Drama of Life Before Birth *

A Quantile Regression Approach on Indian Adolescents

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Abstract

Least square estimation has typically been used in malnutrition research to determine the average relationship of particular household characteristics on a child's height-for-age z-score. Results are similar across studies, not only in terms of size of coefficients but also in statistical significance. This study discusses the possibility that some of the observed variations in the estimated malnutrition status of a child may reflect the fact that the effect of these characteristics are not the same across a given distribution. To examine this issue, I employed a quantile regression on Young Lives panel data, with two birth cohorts of children of the same age in the Indian state of Andhra Pradesh. Although the constant catch-up effect along the distribution of HAZ could be rejected, the lower end of the quantile indicated a partial catch-up effect in children's past nutritional deficiency. The results suggest no improvement in malnutrition recovery across the two birth cohorts.

Keywords: Height-for-age z-score, Catch-up effect, Quantile regression, Young Lives dataset, India.

JEL classification: C21, I1, I15, I18, O12

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*The title comes from the photo book (1965) *Drama of life before birth* by the Swedish Photographer Lennart Nilsson, ✝ 2017.

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1 Introduction and Motivation

During the past two decades, India has experienced high economic growth, which has resulted in economic, social, demographic, health and nutritional transitions. However, despite the economic growth and numerous policy interventions to improve livelihoods, the country has failed to successfully reach out to the poor and improve children's health. Research has shown that nutritional deficiency in early childhood is associated with low test scores, low educational achievement and small stature in adults. The empirical literature has found a positive relationship between child health and height. Jayachandran and Pande (2017) examined why Indian children are shorter than African children despite the economic growth. The results suggested that the cultural norm of preference for the oldest son caused parents to allocate resources differently to children by birth order and gender.

The sample in this study covered the state of Andhra Pradesh in India, a country where relieving malnutrition has high priority due to its long-term social cost. India was thus an appropriate setting for the study as over the course of many years, the childhood health outcomes had been unsatisfactory by any objective standard. According to World Bank health statistics, in 2014 India's rate of malnutrition was among the worst in the world, with about 39 percent of Indian children below five years of age classified as malnourished. The prevalence of malnourishment among India's population exceeds 15 percent of the total population. This detrimental situation was described by Dreze (2004) as "the catastrophic nature of nutrition in India" and the situation has shown little sign of major improvement over time. Resultant stunting remains a serious source of concern among policy makers in India. The extent to which these early nutritional deficiencies affect future well-being is an empirical question of interest to both policy makers and researchers.

Drawing from these lessons, the aim of this article was to study children's recovery from nutritional deficiency caused by early childhood malnutrition, also known as the catch-up effect, and whether this had improved during a specific period. I used height-for-age z-score (HAZ) as a marker for childhood health where the lagged HAZ captured the catch-up in health, and indicated the children's extent of recovery. The coefficient of catch-up showed whether the child had complete, partial or no recovery from nutritional deficiency (Hoddinott and Kinsey (2001); Fedorov and Sahn (2005); Alderman et al. (2006); Handa and Peterman (2016))

The aim of the study was to determine to what extent children who were malnourished in early childhood (0-8 years old) were able to recover from poor health status caused by early nutritional deficiency when reaching early adolescence (12 years old). I investigated this question by using Young Lives' (henceforth referred to as YL for brevity) longitudinal panel data, where the same child was followed over time and across two waves. The sample used for my analysis included two birth cohorts; an older born in 1994/1995 and a younger, born in 2001/2002. Statistics were used for both birth cohorts at the same ages (8 and 12 years). This enabled me to track the dynamics of child development across time and space. Initially, I analysed the health differences between the waves for each birth cohort, followed by an analysis of the health differences between the birth cohorts. If the younger cohort proved to have better health status at the age of 12 relative to the older birth cohort, it was likely that the younger cohort group had benefited from the high economic growth the country experienced from the early 1990s. In addition to studying differences between cohorts and ages, differences between individual points on the distribution of HAZ values were also studied using a quantile regression model (Koenker and Hallock, 2001). This approach was helpful in studying the differences across the entire distribution of the HAZ. Studying the catch-up effect and conditional distributional effects on the health outcomes was also important, as it yielded two considerations: first, whether a child was able to catch up despite the nutritional deficiency experienced in early childhood by analysing the rate of change in HAZ between the two waves and; second, could the findings of the economic efficiency point on the conditional distribution provide information on where in the distribution to intervene, that is, in which quantile(s) the resources would be most helpful? These analytical tool were thus of relevance in a policy context.

The motivation for employing quantile regression grew from the interest in studying catch-up effects along the entire distribution of nutritional outcomes, that is, how the effects of covariates like maternal education and other household and community characteristics on malnutrition varied along the distribution. The quantile regression was more resistant to outliers than ordinary least square (OLS), a major advantage when working with a large-survey dataset such as YL. The most common objective of interest in econometrics is the conditional mean and its determinants, while estimations of conditional quantiles (e.g. median) is somewhat neglected. However, such an approach enables the researcher to estimate the partial effect of an explanatory variable across different quantiles of the population segments. In addition, quantile regression has advantages over OLS because it allows for the possibility that household income has different marginal effects on the health status of malnourished and well-nourished children. Most of the evidence derives from the conditional distribution departure in the labour market (Martins and Pereira (2004); McGuinness and Bennett (2007); Melly (2005)), but less evidence exists in low income settings (Azam (2012)). Abrevaya and Dahl (2008) were among the first to apply quantile regression to study children's malnutrition measured as birth weight in the USA. This was a natural area for quantile regression, since there was a suspicion that the birth weight distribution of children varied quite substantially. Therefore, the least square estimation of the mean gives an incomplete picture of the conditional distribution.

This article contributes to the existing literature in several ways. First, quantile regression has apparently not yet been applied to study the HAZ for two different birth cohorts. Thus, to my knowledge, this article is the first to examine catch-up effects across two birth cohorts. Secondly, the quantile regression model introduced by Koenker and Hallock (2001) is more flexible than that of a least square estimate and allows study of the effects of a covariate on the entire conditional distribution of the dependent variable. This offers a more complete view of the stochastic relationship among variables. Finally, this article attempts to illustrate the extent to which early nutritional deficiency affects the health status and future well-being of early Indian adolescents.

The key findings of the empirical analysis were that the conditional distribution yielded better information than the conventional average relationship. It allowed me to estimate how, on average, various measures of socioeconomic performance of household and health affected the current child health status. In addition, the conditional HAZ distribution measures indicated how the catch-up growth manifested in different points of the distribution. The coefficient of catch-up growth had a positive and statistically significant effect on the outcome variable, HAZ, but the catch-up growth was close to partial. I also found that this result was similar across the two birth cohorts. This raised awareness that despite economic growth there was little evidence of improved nutrition. I further investigated the finding by interacting a catch-up term with maternal levels of education, which produced the same result. Particular attention should be given to the lower end of the quantile where significant effect is most likely to have an impact. Another consideration was the analysis of gender differences. Preferences for sons over daughters and gender inequality are well-known and still widespread realities in India (Tarozzi, 2008). My results showed no evidence of gender specific catch-up growth. This article contributes to the burgeoning literature on understanding children's malnutrition, and in particular, firmly states in which part of the distribution policy makers are able to make a difference.

The reminder of this article runs as follows. The next section reviews the concept of catch-up growth in a broader social sciences sense and highlights the main findings to date. Section 3 describes the conceptual framework and Section 4 discusses the research setting and data employed. Section 5 sets out the econometric strategy. The empirical evidence and robustness analyses are presented in Sections 6 and 7 respectively. In section

8, I suggest and discuss possible policy implications, with concluding remarks in Section 9.

2 Review of evidence in the literature

This section contains an overview of the related literature and discusses the contribution of this study.

Height as a proxy for the early-life environment

The anthropometric measurements[1] , height and weight are the most common measures used to capture a child's early health status and nutritional development trajectory. To assess children's and adolescents' growth, nutritional status and well-being, either a growth standard and/or a growth reference can be used. A growth standard reflects the optimal growth that all children have the potential to achieve, while a growth reference is simply the distribution used for comparison. For the past four decades, the World Health Organization (WHO) has recommended the use of a growth reference based on z-scores. HAZ measures by how many standard deviations a child deviates from the median reference group. The World Health Organization's Multicentre Growth Reference Study (MGRS) based their reference growth charts on children from six sites around the world: Brazil, Ghana, India, Norway, Oman and the USA.

HAZ is a widely used indicator of the long-term nutritional and epidemiological environment of the child (Case et al. (2005); Case and Paxson (2010)). It reflects the health of a child relative to an internationally healthy child, incorporating past and present inputs into health, and provides a cumulative picture of overall health status. A child is classified as stunted when HAZ is more than two standard deviations below the median of the reference population (Onis, 2006). Early stunting is indicative of the nutritional deficiency of a child. I was thus able to fully exploit information conveyed by this variable.

Anthropometric assessments provide an indication of the size and shape of the human body as a mirror of the cumulative shocks the child has experienced over its lifetime. In the health economic literature, HAZ is used to study the association of malnutrition in early years on later outcomes, such as performance at school as well as in the labour and marriage markets (Case and Paxson (2008); Tarozzi (2008); Almond and Currie (2011)).

[1] Anthropometric measurements include both height-for-age z-score and weight-for-age z-score. However, this article exclusively studied the children's height-for-age z-score (HAZ).

Most of the studies of nutritional recovery from moderate and chronic malnutrition employ HAZ as an indicator for capturing past input, such as prenatal and postnatal care and health-related behaviors [2]. These important attributes are shaped in childhood and have a key role in determining adult outcomes. For example, research on famine provides convincing evidence on the harmful effects of experiencing hunger in early life on long-term health (Almond et al. (2010); Dercon and Porter (2014)). Chen and Zhou (2007) showed that children born or conceived in famine decreased in height by 3.03 standard deviations and experienced fewer hours worked and lower wage rates as a result.

Is India experiencing catch-up growth from childhood malnutrition?

The empirical evidence on the catch-up effect as an indication of the ability to correct for nutritional deficiency is growing, and has shown that early childhood malnutrition is associated with a range of adverse outcomes in later life. More recently, the economic literature has taken an interest in children's catch-up growth potential to study rapid physical growth to compensate for past insults to health, and the potential impact on future outcomes. To date, the study of catch-up growth has been more common in the medical, clinical and nutritional fields. The term catch-up was introduced in the early 1960s to describe a phase of rapid linear growth under favourable circumstances, which allows a child to accelerate commensurate to his or her pre- illness growth. Three types of catch-up growth are defined in nutritional literature as height velocity above the statistical limits of normality for age and/or maturity during a defined period of time when growth retardation ceases. This follows a transient period of growth inhibition. The three types of catch-up growth are: The first type A is the classical example, which is present in infancy and childhood, where the height velocity increases to return to the normal height velocity in relation to the child's age. The second, type B occurs in adolescents during which growth development is delayed and height velocity is small or shows no increase. And the third, type C is a mixture of the two previous types, consisting of both a delay and prolongation of growth (Boersma and Wit, 1997).

The lack of evidence in economic literature about the catch-up effect is mainly due to data requirements. In order to capture the child's potential catch-up effects, the empirical modelling relies upon a dynamic child-health relationship. Consequently, panel data is

[2] Prenatal behaviour included the number of prenatal care visits, whether the pregnant women received tetanus shots and iron supplementation and delivered the baby at a facility. Investments in postnatal care included check-ups within the first two months of life and whether the children received iron supplements and vaccinations, as well as adequate micronutrition.

required to estimate current health status as a function of previous period health status and current period prices, resources and exogenous characteristics. The existing literature has found evidence of catch-up effects in China, Nicaragua, South-Africa (Handa and Peterman, 2016), Zimbabwe (Alderman et al., 2006) and Indonesia (Mani, 2012). Mani (2012), defines child health as a child's height in centimeters in the current period, and the catch-up effects as height in the lagged time period. The other two studies use the more common HAZ measure for child health. However, the results are not influenced by the discrepancy in the definitions.

Hitherto, the majority of studies have emphasized interventions and directions to policy makers about the optimal time to invest to prevent child malnutrition. Many of the studies include recommendations such as pre and post-natal care and behavioral changes in parenting (Currie, 2011). Evidence suggests that to improve child health, investment in parental education, especially in maternal education (Glewwe (1999); Glewwe (2002); De (2017)) is beneficial, as is better provision of health care services (Strauss and Thomas (1998); Thomas and Frankenberg (2002)), better composition of food intake (Desai et al. (2016); Aurino (2017)) and more recently, access to sanitation (Spears (2013); Andres et al. (2017)). The results from these studies were mainly derived from cross-sectional data. However, studies derived from longitudinal data confirm that low birth weight combined with poor infant and young child nutrition cause poor growth trends and rarely allow children to catch up.

Methodologically, the height distribution has been overlooked by the conditional average effect. One way to calibrate the average effect is to examine the conditional distributional effect of catch-up growth on children's health. This substantially increases the depth of understanding of which children are lagging behind in height distribution. Consequently, addressing children's catch-up effect requires not only panel data but also treating the lagged dependent variable for potential endogeneity. Several econometric techniques address this concern by applying an instrumental variable approach and/or Arellano-Bond estimation.

To the best of my knowledge, there is only one study addressing children's catch-up effect in India. Subha et al. (2016), investigated the catch-up relationship across all four YL countries [3] using quantile regression instrument variables (QR-IV). The results suggested that children exhibited different levels of catch-up along the distribution of anthropometric outcomes and that the effect varied across countries. India exhibited low levels of catch-up at the bottom quantiles and higher catch-up at the top quantiles. There has been little investigation into the catch-up effect on child malnutrition because

[3] Ethiopia, India, Peru and Vietnam.

so far, it is unclear from previous literature what the causing mechanism of malnutrition is. Despite advancement in empirical evidence, there is still a need to understand a child's ability to overcome malnutrition. Therefore catch-up growth is an interesting aspect to study to suggest a way to correct the impaired health of children, since so many children are entering early adolescence with nutritional deficiencies and their ability to catch up later on is thus important. So far, much of the research has focused on early childhood and adults, and less on whether children are able to catch-up in puberty before early adolescence. The aforementioned studies and their various methods of capturing child health suggest that early childhood nutritional deprivation has adverse long-term effects.

3 Conceptual Framework

In order to better understand the mechanisms through which children can catch up in health, I outlined a framework that served to systematize my thinking and helped me to summarize the vast literature on how early childhood health influenced late childhood health [4]. I described a stylized framework of the households' economic decision making in a dynamic framework, as suggested by Cunha and Heckman (2007) and Strauss and Thomas (2007).

To elucidate issues surrounding the early life growth deficiency, I laid out a simplified two-period dynamic conditional health production function. In economic models, health is perceived as a multidimensional composition with both stock and flow variables. Health as a stock variable illustrates long term inputs that can be carried out into the future periods such as height, weight or resistance to diseases. Flow inputs are short-term inputs that are produced and consumed in the current period *(t)* such as caloric intakes (Currie and Vogl, 2013). Therefore, a child's current health status is a composition of these stock variables, which reflects both the current and previous periods of health inputs from $t = 0$ [5]

To set up a simplistic dynamic conditional household production function, I assumed that a household seeks to maximize its utility given its budget constraints. I also assumed that the utility increases at a diminishing rate. The caregivers, often the parents, are the key decision makers and have a set of genetic endowments, knowledge and skills that they use

[4] In reality, there are more than two periods in early childhood: conception, in utero, prenatal and postnatal periods

[5] Previous evidence suggests that the cumulative process of health *stock* inputs are likely to be influenced by the mother's health status (nutritional inputs of the mother) during pregnancy (in utero). This indicates that $t = 0$ goes back in time before the period of birth. For simplicity, I assumed that stock inputs started to accumulate at birth $t = 0$ (Almond and Currie, 2011).

to allocate the available resources and make optimal choices for health inputs. To produce health inputs, the household faces various specific constraints such as income, time and prices. In addition, the household is also constrained by the locality's characteristics such as the availability of preventive and curative health care providers and the prevalence of infectious diseases.

When summarized, this gave me the reduced form of child health demand function. It systematized the household's access to technology and how it was transformed into health. The current health status HAZ_t which I estimated empirically, was the outcome of the initial attributes of the child and all prior investments into the child's health status.

$$HAZ_{i,t} = h[HAZ_{t-1}, X_t, E_t|G] \tag{1}$$

The above function states that the current health status measured by $HAZ_{i,t}$,t is a function of lagged HAZ_{t-1}, current period inputs X_t and current periods exogenous characteristics E_t, conditional on exogenously determined genetic endowments G. Since I followed each child over time (t), it was natural to extend the analysis by introducing the dynamic relationship. Each household is obliged to solve an inter-temporal utility maximization problem over T time periods. The household utility depends on the allocation of the optimal amount of consumption C_t, leisure goods L_t and health inputs X_t that enter into the health stock of children H_t. The utility function was assumed to be intertemporally separable and each subutility u_t was increasing and quasi-concave (Foster (1995); Fedorov and Sahn (2005)).

$$\max_{\{C_t, L_t, X_t\}} \quad U[u_1(C_1, L_1, X_1), u_2(C_2, L_2, X_2), ..., u_T(C_T, L_T, X_T)] \tag{2}$$

The household's dynamic budget constraint in each time period (t) was calculated as follows:

$$P_t^C C_t + P_t^X X_t = w_t(N_t - L_t) + Y_t + A_{t-1}(1 + r_t) - A_t, \quad t = 1, ..., T \tag{3}$$

where variables on the left represented prices of consumption goods $P_t^C C_t$ and health inputs $P_t^X X_t$. Monetary related variables, wage rate w_t, time endowment N_t, non-labor income L_t, current and past period assets A_t, A_{t-1} and real interest rate r_t were represented on the right. In my empirical framework, I only observed the household's wealth index and disregarded other arguments in the budget constraint without any significant impact on the relationship to be estimated.

Maximizing (2) subject to Equations (1) and (3) yielded the optimal number of health inputs at each time period (t) , X_t^*.

$$X_t^* = x[H_{t-1}, P_t^C, P_t^X, w_t, N_t, Y_t, A_t, A_{t-1}, r_t] \tag{4}$$

Finally, substituting (4) into Equation (1), yielded the dynamic conditional health demand function

$$H_t = h[H_{t-1}, x(H_{t-1}, P_t^C, P_t^X, w_t, N_t, Y_t, A_t, A_{t-1}, r_t), E_t|G] \tag{5}$$

Arriving at the dynamic child health demand function, Equation (5), which describes the relationship between the current child health status as a function of previous child health status; prices of consumption goods and health inputs; wage rates; time endowments; non-labour income; assets, and exogenous characteristics conditional on genetic endowments. The goal was to estimate the relationship between the child's current health status as a function of past health status and its determinants, by employing the dynamic health demand function yielded by Equation (6).

$$HAZ_t = h[HAZ_{t-1}, X_{it}, X_{ht}, X_{ct}] \tag{6}$$

where X_{it} represents a vector of child-level characteristics and X_{ht} and X_{ct} represent time-specific household and community level variables. All three variables in Equation (6) are associated with child nutrition.

4 Research setting and Data

This paper uses of YL data. The data set has several strengths for my purposes. First, it covered two birth cohorts. Second, the longitudinal nature of the data helped greatly in dealing with problems estimating and identifying policy impacts. Third, the data enabled me to identify the ages of the younger cohort that needed to be matched with the older cohort. As I discuss later, these elements were critical for identifying the period of catch-up growth of younger children. To my knowledge no other baseline surveys existed with which I could compare children of the same age but from different birth cohorts and subsequently obtain a better estimate. This, in itself made the YL data important.

4.1 Data overview - Young Lives Study

(Insert Figures 1 and 2)

The YL data originated from a large-scale longitudinal survey conducted as part of a study of child poverty, trends and trajectories, run by the University of Oxford in the UK and jointly funded by the Department for International Development (DFID) and the Netherlands Ministry of Foreign Affairs. The data contained detailed information on children, households, and the communities in which they lived. Data collection began in 2002 and followed 12,000 children from Ethiopia Peru, Vietnam and the state of Andhra Pradesh, including Telangana, in India for a period of 15 years. Figure 2 shows a time line of the five waves for both birth cohorts of the survey. To date, the study has conducted five waves of data collection and the last wave is currently being cleaned. The two birth cohorts of children have been followed in each country in order to collect information on each stage of childhood.

The YL baseline sample in India in 2002 consisted of 1000 children born between 1994 and 1995 for the older cohort, while the younger cohort consisted of 2000 children born between 2001 and 2002 in Andhra Pradesh (Barnett et al., 2013). Andhra Pradesh and Telangana are located on the south-east coast of India (see Figure 1) and are home to approximately 85 million inhabitants, which make up 7 percent of the Indian population (Azubuike and Briones, 2016). The state has three distinct agro-climatic zones; Coastal Andhra, Rayalaseema, and Telangana (which became a separate state in June 2014). The YL data was gathered from seven districts representative of the state. The sample selection was representative of all the aspects of poor and rural settings in the state. Both birth cohorts were sampled at random from the same 20 sentinel sites in each of the four countries and only one child per household was selected. Comparing the YL sample and the nationally representative samples from the Demographic and Health Surveys (DHS) that are closest to YL baseline data collection, YL children were slightly better off (Barnett et al., 2013). There was one persistent difference between the two birth cohorts in YL, namely that, measured by HAZ, the older cohort was shorter than the younger cohort.

The YL data offered a unique opportunity to examine child trajectories and development by providing numerous measurements of child health, nutritional status, and cognitive and non-cognitive ability. In addition, it contained a rich set of household characteristics, including measures of material investments in children, household resources, and household structures. Longitudinal panel data offers numerous advantages, however, issues such as attrition levels are often their Achilles heel. In the YL data, there is very limited attrition, particularly compared to other longitudinal surveys undertaken in low resource contexts. This is because a great effort was made by the field research assistants to motivate the participants to remain throughout all waves of the survey. The low attrition of the YL survey in India ranged from 1 percent for the younger cohort and 2 percent for the older cohort for the waves included in this analysis. My empirical model relied on observing changes in children's malnutrition status across the two birth cohorts, therefore maintaining low attrition was essential for the validity of the results.

4.2 Sample and Descriptive Statistics

Main outcome variable

(Insert Figures 3, 4, 5 and 6)

The younger cohort was born within an 18-month age range between January 2001 and June 2002. The main outcome variable was the anthropometric measure, height-for-age z-score (HAZ) at the age of 12, capturing the children's malnutrition. Cleaned HAZ Waves I and II for the older cohort and Waves III and IV for the younger cohort were included in the analyses. About 33 and 34 percent of children in the older cohort were stunted in Waves I and II respectively, and approximately 29 percent were stunted in Waves III and IV for the younger cohort. The few questionable z-scores in the YL data above 6 and below -6 were recoded as missing.

Figure 3 provides a first visual summary of the HAZ variable, which shows that there was little difference between the two waves in HAZ for the younger cohort compared to HAZ for the older cohort, which had larger variation. This indicated a sign for catch-up in malnutrition between the birth cohorts. Figure 4 shows the empirical cumulative density function (CDF) of HAZ for younger and older cohorts, which appeared reasonably symmetrical. HAZ was roughly -3, slightly above -2 and approximately 0 at the 10^{th}, 50^{th} and 90^{th} quantiles , while the younger cohort's empirical CDF corresponded to roughly below -2, roughly above -2 and approximately 0 z-scores for each quantile. This indicated an improvement when comparing the two birth cohorts, as the younger cohort was better nourished than their counterparts born in 1994/1995.

Figures 5 - 6 describe two different levels of change in HAZ. Figure 5 shows the relationship in HAZ between the two waves. The left panel illustrates the change for the younger cohort and the right panel for the older cohort. The fitted line shows a negative HAZ relationship, implying that in the four years between the waves, there had been a slight improvement in the level of nourishment. However, the younger cohort showed a greater improvement rate relative to the children in the older cohort.

Figure 6 depicts the relationship between change in HAZ and HAZ at baseline when the children were 8 years old. The positive relationship that the fitted line portrays, validates the evidence shown in Figure 5. The longitudinal nature of the data was an advantage for finding these stunting patterns. The data revealed that of the YL children who were stunted in Wave I and Wave III (aged 8), 50 percent were still stunted at Wave II and Wave IV (aged 12). Among those children who were stunted in both waves, approximately 84 percent of the older cohort and 85 percent of the younger cohort lived in urban sites; 16.3 percent of the older cohort and 13.5 percent of the younger cohort lived in rural sites. In contrast, of the YL children who were not stunted at Waves I and III, 25.3 percent and 27.2 percent of rural children and 75 percent and 71 percent of urban children were stunted by Waves II and IV. Thus, there appeared to be more malnourished children in urban areas than in rural areas.

Explanatory variables

(Insert Tables 1, 2, 3, and 4)

A range of relevant explanatory variables that are known in the literature to affect HAZ or stunting outcomes were included. The variables were sorted into three categories: anthropometric information, household, and community characteristics. The anthropometric information was disaggregated by birth cohort for both waves to capture the health trajectory between cohorts. Household and community characteristics were derived from Waves II and IV for older and younger cohorts respectively, when the children were 12 years old [6].

The descriptive statistics comparing the two birth cohorts can be found in Table 1 panels A and B, containing means, standard deviations and min. and max. values for both cohorts. Apart from HAZ, the anthropometric information included a range of characteristics associated with child health and well-being, such as body mass index (BMI), which measures the child's weight in relation to its height, stunting, severe stunting, thinness, severe thinness, underweight, and severe underweight. The younger cohort showed, on average, better health outcomes within and across age groups, although there were no significant differences. This was in line with what previous YL data evidence had shown (Vellakkal et al. (2015)).

[6] The covariates from Waves I and III were tested but the estimations did not show any differences in results

Overall, children had improved in many of the observable variables, although YL children in the older cohort were significantly shorter on average than the international standard. Table 2 shows the stunting pattern across waves for each birth cohort. Overall, both birth cohorts showed similar average stunting rates across waves with only marginal improvement between the cohorts.

Table 3 shows the proportion of malnourishment across waves by gender. A higher proportion of younger cohort female children were stunted compared to male children. While the stunting rate was persistent across the waves and birth cohorts for females, the opposite occurred for male children. Girls performed worse than boys in general, a result consistent with the much larger, nationally representative sample of the National Family Health Survey (NFHS) from India (Jayachandran and Kuziemko (2011); Jayachandran (2015); Jayachandran and Pande (2017)).

The descriptive statistics of stunting patterns by gender is illustrated in Table 4. When observing stunting patterns by gender, we observed discrepancies within and across birth cohorts. In the younger birth cohort, female children became less stunted, (catch-up over four years) while the male children became more stunted, although the male group had been advantaged at the baseline year of 8 years old. The same pattern was observed in the older cohort. Taking everything into account, Tables 2 to 4 indicate some improvements between the two birth cohorts in child health measurements. In particular, the HAZ showed an advantage for the younger cohort and for male children.

(Insert Table 5)

In Table 5, I disaggregated the children's characteristics by birth cohort to illustrate the portion for each of the included variables. Gender composition was similar across birth cohorts. The birth order of siblings in the household showed a large difference between the two cohorts. The age distribution was equally distributed in the older cohort, while in the younger cohort, it was skewed towards the child being the youngest with no siblings in the household. A high proportion of the children lived in rural areas, approximately 75 percent in both birth cohorts. Children were equally represented in all three regions. The majority of the children were Hindu and came from Backward castes. Their common language was Telugu, which is the language most spoken in Andhra Pradesh.

(Insert Table 6)

The household characteristics used, gave the parents' age and levels of education, mother's age at birth, gender composition of siblings and household size from the baseline cohort. The level of education of the parents was divided into three categories: no education, elementary, and secondary education. The omitted category was no education, so coefficients could be interpreted relative to this category. The parents' level of education was similar across the birth cohorts – generally an elementary education. The household size indicated the number of household members, which was also similar across the cohorts, as were the structures and composition of household members (See Table 6).

Household characteristics provided details about wealth and whether or not households had access to basic services such as safe drinking water, sanitation, electricity and adequate fuel for cooking. The wealth index was a continuous variable, composed from three sub-indices measuring housing quality, access to services and ownership of consumer durables, all of which had equal weights in the estimation of the wealth index. The indices were estimated consistently across waves. Therefore, only variables that were present in all waves were included in the estimation (Azubuike and Briones (2016)). Overall, the younger cohort born in 2001/2002 experienced better economic conditions in their households than their counterparts born in 1994/1995.

5 Econometric Strategy

I turn now to characterizing my econometric strategy. The goal of the empirical analysis was to examine the catch-up growth of the child between the birth cohorts.

5.1 Least squares estimation

My point of departure was a standard linear specification that captured the average relationship as follows:

$$HAZ_{it} = \alpha_0 + \beta_1 HAZ_{i,t-1} + \beta_2 \mathbf{X}_{i,t} + \beta_3 Z_i + \varepsilon_i \tag{7}$$

$$where = \begin{cases} \beta_1 = 0 & \text{complete catch-up} \\ 0 < \beta_1 < 1 & \text{partial catch-up} \\ 1 \leqslant \beta_1 & \text{no catch-up} \end{cases}$$

where the outcome variable of interest was HAZ_{it} of child i in birth cohort t. The lagged dependent variable $HAZ_{i,t-1}$ referred to child i's HAZ in the previous wave $(t-1)$. The β_1 coefficient captured the catch-up effect. A coefficient of zero indicated "a complete catch-up"; i.e. no persistence in health across time. This would imply that children malnourished at a young age had not experienced permanent growth retardation.

A coefficient of one on the lagged HAZ indicated "no catch-up", that is, malnourishment early in childhood implied permanent negative growth incidence. And a coefficient of between zero and one indicated "partial catch-up", which implied that the children recovered to some degree, but not fully from the effects of early nutritional deficiencies. The time varying covariates: child's age, household wealth index, and community characteristics such as the availability of sanitation and safe drinking water were denoted by $\mathbf{X}$, while, Z captured the time invariant characteristics such as gender. Assuming that ε_i was the model prediction error, ordinary least squares (OLS) would minimize $\sum_i \varepsilon_i^2$. ε_i which captured the influence of all unobserved factors on child's malnutrition.

In my baseline specification, I estimated Equation (7) using OLS. I also expanded the set of controls to check the robustness of my results, as described in Section 7 below. The key assumption when the catch-up growth effect was studied using the standard linear specification, was that the explanatory variables were assumed to have the same impact across the entire distribution of anthropometric measurements and other covariates. Consequently, researchers and policy makers would only need to observe effects on the conditional mean of HAZ. From a public policy perspective, however, the conditional mean is not necessarily indicative of the size and nature of the effects on the lower or upper tail of the HAZ distribution. Therefore, it was also interesting to study a relationship where the lagged dependent variable $HAZ_{i,t-1}$ and other covariates were allowed to depend upon the q quantile of interest (Cameron and Trivedi (2009)).

Thus, to resolve the problem of only observing the conditional mean on HAZ and therefore to capture the conditional distributional effect of covariates on HAZ, and to allow for the catch-up effect to vary along the distribution of HAZ, I estimate a quantile regression model.

5.2 Quantile estimation

The descriptive statistics in Section 4 showed that the distribution of HAZ in the two birth cohorts was quite complex. Thus, to resolve the problem of only observing the conditional mean on HAZ and to enable me to capture the conditional distributional effect of covariates on HAZ, as well as allow for the catch-up effect to vary along the distribution of HAZ, I estimated a quantile regression model (QR). This method estimated the effects of covariates on the outcome variable, HAZ, at different points of its conditional distribution. This was in contrast to a standard linear regression technique, which summarizes the average relationship between a set of covariates and the outcome variable based on the conditional mean function $E(HAZ|x)$, which only provides a partial view of the relationship. However, when the interest is in describing the relationship at different points in the conditional distribution of y, a QR is a robust method to extract this relationship.

Analogous to the conditional mean function of linear regression, the quantile regression examines the relationship between covariates and outcomes, using the conditional median function $Q_q(HAZ_i|X_i)$, for quantile q of the empirical distribution. The quantile $q \in (0, 1)$ splits the data into proportions q below and $1-q$ above. Thus, not surprisingly, the median regression, which is also known as the least absolute deviations (LAD) regression, minimizes $\sum_i |\varepsilon_i|$, whereas quantile regression in general minimizes a sum that gives asymmetric penalties $(1-q)|\varepsilon_i|$ for over-prediction and $q|\varepsilon_i|$ for under-prediction. The quantile regression estimator is asymptotically normally distributed, is more robust to non-normal errors and outliers than its counterpart least squares regression, and is semi-parametric, as it avoids assumptions about the parametric distribution of the error process. It is also able to capture heterogeneity in the set of predictors at different quantile levels of the outcome distribution, HAZ, caused by heteroscedastic variance (Angrist and Pischke, 2009).

The quantile regression estimator for quantile q minimizes the objective function as described by Koenker and Bassett (1978), Koenker and Bassett (1982) and Koenker and Hallock (2001). This non-differentiable function is minimized via the simplex method, which is guaranteed to yield a solution in a finite number of iterations. Although the estimator has been proven to be asymptotically normal with an analytical variance-covariance matrix (VCE), the expression for the VCE is awkward to estimate. Bootstrap standard errors are often used in place of analytic standard errors, as the errors may be heteroscedastic. In my estimations, the number of replications, m, was set to 100.

$$Q_q(HAZ_i|X_i) = X_i\beta_q, \quad q \in (0,1) \tag{8}$$

$$\widehat{\beta}_q = \arg\min_{\beta} \left[\sum_{i:HAZ_i \geq \mathbf{x}_i^{'}\beta}^{N} q|HAZ_i - \mathbf{x}_i^{'}\beta_q| + \sum_{i:HAZ_i < \mathbf{x}_i^{'}\beta}^{N} (1-q)|HAZ_i - \mathbf{x}_i^{'}\beta_q| \right] \tag{9}$$

where $HAZ_{i,t}$ was the outcome variable: the children's current health status. $\mathbf{X}_i$ was the vector of covariates as in least square estimation and the β was the slope coefficients vector, which would differ depending on the particular quantiles being estimated. Thus, the statistical model (8) showed the conditional quantile of HAZ as a linear function of the covariates. It should be pointed out that the quantile coefficients yielded the effects on the distribution and not on the individuals. These effects had no causal interpretation as such, since they might have included omitted variables bias problems. For example, many maternal choices such as proper prenatal diet, or awareness in general were omitted from the regression specification. They might also have been correlated with observed variables that were included. For example, an increase in the maternal level of education was likely to have a beneficial effect on HAZ by improving the maternal choices mentioned.

6 Empirical Evidence

In this section, I start by documenting the key fact that underlies the standard linear relationship: the catch-up rate for children with malnutrition measured as the change in HAZ between 8 and 12 years old for each birth cohort. To achieve this, I estimated the same set-up in a framework of a family of conditional quantile functions.

6.1 Baseline results

(Insert Table 7)

Table 7 shows the result from estimating Equation (7). In column 1, I displayed results for the younger cohort and in column 2 those for the older cohort. The coefficient of the lagged HAZ portrayed the catch-up effect in malnutrition with similar results across the birth cohorts. The catch-up effects were less than partial, 0.7 ($0.5 < \beta_1 < 1$), an effect that was statistically significant at the 1 percent level. The result yielded the average effect of the lagged HAZ on the current health status of the child, conditional on the covariates. As discussed in my proposition, the malnourishment remained unchanged across the birth cohorts.

Turning to gender differences, the gender coefficient showed an unexpected result for boys. The magnitude of the coefficient indicated that boys were, on average, more malnourished relative to girls. The coefficient was negative and larger for the older birth cohort than for the younger, and the effect was statistically significant for both birth cohorts at the 1 and 5 percent levels, respectively.

The mother's age at birth had a negative and statistically significant effect on HAZ for both birth cohorts. The maternal level of education had a positive impact for children in the older birth cohort. That is, children belonging to households where the mother had no formal education were more likely to be malnourished than children from households with mothers who had at least elementary or secondary education (statistically significant at 5 percent level). This result was not surprising and has been well established in previous research (Currie, 2009). However, the result turned out to have no statistical influence for children in the younger cohort. Finally, access to sanitation had a positive and statistically significant effect on the children's health status at the 10 percent level in the younger cohort.

6.2 Conditional quantile effects

(Insert Table 8 and Table 9)

I turn now to the results of estimating the quantile regression Equation (8). The results are presented in Table 8 for the younger cohort and in Table 9 for the older cohort. Columns 1–5 contain results for the five quantiles $\tau = 0.10$, $\tau = 0.25$, $\tau = 0.50$, $\tau = 0.75$ and $\tau = 0.90$. The quantile regression estimated the partial effect of covariates of the anthropometric distribution across the quantiles, which was its main advantage over the linear estimator. The estimated coefficients measured the impact of each covariate on the entire distribution. This implied, for example, that the coefficient of the catch-up effect at the median represented the percentage increase in health that would keep an "average" child's health at the median if the child's level of malnutrition decreased by one standard deviation.

The quantile regression results for the younger cohort suggested some important differences across the points in the conditional distribution of the children's HAZ. I found that children in the younger cohort exhibited different rates for β - coefficient of catch-up effect along the anthropometric distribution. At the lower end of the distribution, the coefficient suggested a slightly higher catch-up rate, while the higher quantiles of the HAZ distribution had lower catch-up rates. The results for all five quantiles (translated with high HAZ in comparison to the median HAZ of the reference group) were statistically significant at the 1 percent level, but the interpretation of their differences was not straightforward. What the results from Table 8 implied was that children in the lower quantiles were already malnourished, and thus more likely to partially catch-up. In contrast, those children in the higher quantiles were already well-nourished, thus the results indicated that children in these quantiles were less likely to catch up as they were already in good health.

Turning to the gender differences; the coefficients for males were negative and statistically significant at the 1 percent level for the two lowest quantile distributions of HAZ. However, for the quantile, this was positive and statistically significant at the 1 percent level. This result was not as puzzling as it seemed. Since I used quantile regression, the fact that nutritional investments were lower for boys than for girls in lower quantiles, while the inverse pattern emerged in the higher quantiles, clearly captured the persistent gender differences across quantiles and households. The differences in nutritional intake between the genders were also likely to reflect past differences in investment conditioned by gender. Girls were at a disadvantage compared to boys in the higher quantiles, while in the lower quantiles, both genders experienced low HAZ, although boys were more likely to be malnourished than girls. These effects at lower quantiles were underestimated by OLS.

Another notable result was maternal age at birth. The parameter estimate was negative and statistically significant at the 1 percent level for $\tau = 50\%$ and $\tau = 0.75\%$ quantiles. This implied that children born to younger mothers were disadvantaged compared to children born to older mothers in the two conditional quantiles, rather than the mean. Contrary to what was indicated in the baseline results, the maternal level of education only affected children's health at the highest quantile (statistically significant at the 1 percent level). The urban dummy had a positive and statistically significant effect at the 1 percent level for the lowest quantile: children living in urban areas were less malnourished than children living in rural area. Among the other dummy variables included in the regression analysis, it was only the availability of sanitation that had a statistically significant impact on children's health for the three highest quantiles at the 10, 5 and 1 percent levels. Children from the highest quantiles experienced a positive impact on their health (were less malnourished) when their households had access to sanitation.

Table 9 describes results for the older cohort. Most of the results were similar to those for the younger cohort and were in line with previous research. There were a few exceptions that were noteworthy from a policy perspective and I elaborate on these briefly in Section 8. The coefficients of the catch-up effect had almost the same pattern as those for the younger cohort. Consistent with many other findings, but with different methodological set-ups, my results were in line with previous evidence about recovery from nutritional deficiency. There was no change in catch-up effect between birth cohorts. Thus, the results revealed what is a known fact: the high persistence of malnourishment in India. The sibling composition showed a negative and statistically significant outcome at the 5 percent level for the lowest quantiles, indicating that boys with female siblings were better off than girls with male siblings. The coefficient for boys was negative and statistically significant at the 1 percent level for the two lowest quantiles. This implied that boys were more malnourished than girls in the lowest quantiles. This unexpected sign of the gender coefficient was consistent with results of the younger birth cohort.

Maternal age at birth reported similar result to those for the younger birth cohort. This result was in line with previous evidence on the association between maternal age and childbirth. Turning to maternal education levels – this was more likely to impact the children's level of malnutrition for the higher quantiles in the older birth cohort, unlike the results for the younger cohort. In $\tau = 0.50$, $\tau = 75$ at $\tau = 0.90$ quantiles, children whose mothers had received elementary or secondary schooling (with the effect even stronger if the mothers had secondary schooling), were relatively healthier compared to children whose mothers had had no level of education. This result was somewhat different from that for the younger birth cohort, possibly because the older birth cohort was likely to be poorer.

The urban residency dummy had negative and statistically significant impacts at the 5 percent level for the three highest quantiles. The average YL child living in an urban area was disadvantaged compared to the child living in rural areas. Indeed, this result was counter-intuitive. However, children born in the 1994/1995 birth cohort in Andhra Pradesh were likely to have experienced poorer circumstances in urban areas compared to rural areas. The government in Andhra Pradesh recently implemented several programmes to promote the well-being of children, which may be the reason for the different results for the younger cohort. Unfortunately, however, I did not have information on policy variables that could capture the programme effects. Household access to sanitation had a negative impact and was statistically significant at 1 percent level for the highest quantile. This implied that children in the higher quantiles were harmed if they did have access to sanitation, while access to sanitation for children in the lowest quantile had a positive effect on HAZ. The effect was statistically significant at the 1 percent level. It could be suggested that intervention to improve access to sanitation should not be given high priority for the top end of the quantile distribution.

(Insert Figures 7 and 8)

Figures 7 and 8 show how the coefficients for each covariate varied across quantiles, and contrasts this with the (fixed) OLS estimates. More specifically, they illustrate how the effect of lagged HAZ and other covariates varied over quantiles and show how the magnitude of the effects at various quantiles differed considerably from the OLS coefficients, even in terms of the confidence intervals around each coefficient. It was important to analyses whether or not the coefficients for different quantiles were significantly different from the OLS coefficients. If the quantile regression coefficient was outside the OLS confidence interval, we have a statistically significant difference between the quantile and OLS coefficient. The figures show that the effects of covariates differ by quantiles for younger and older cohorts. I have confined my discussion to only a few of the covariates for both birth cohorts. For example, in the first panel of the figures, the intercept of the model may be interpreted as the estimated conditional quantile function of HAZ of girls born to mothers with no education, from a Scheduled caste, living in a rural area, with no access to sanitation, electricity or cooking fuel.

The second panel captures the catch-up effect in malnutrition. According to the OLS estimates of the mean effect, the catch-up was approximately 0.75 standard deviation from the mean reference group. However, as it was clear from the quantile regression results that the differences were much smaller in the lower quantiles of the distribution and considerably larger than 0.85 standard deviation in the upper tail of the distribution. For example, the catch-up effect was 0.62 standard deviation at the $\tau = 0.05$ quantile but was about 0.82 standard deviation larger at the $\tau = 0.95$ quantile. This result indicated that the confidence interval of the conventional least squares provided a poor representation of the range of the disparities.

The gender effects of the dummy variable were substantial. At the10^{th} percentile of the conditional distribution, the difference in HAZ was roughly 0.40 standard deviation from the mean of the reference group. Maternal level of education beyond elementary school was associated with a modest increase in HAZ. Secondary education had a uniform effect over the whole range of the distribution of about 0.10 standard deviation. For this effect, the quantile estimate was consistent with the least squares results, but this was the exception, not the rule.

Several of the remaining covariates were of substantial policy interest. These included household access to sanitation, electricity and cooking fuel. However, as pointed out in Section 5, in the corresponding least squares analysis, the interpretation of their causal effects may be somewhat controversial. The key point shown in these figures is that effects differ by quantiles, and that OLS in general may not be a good representation of the impact of covariates on HAZ. In almost all the panels of Figures 7 and 8, the quantile regression estimates lay at some point outside the confidence intervals for the ordinary least squares regression, suggesting that the effects of these covariates may not have been constant across the conditional distribution of the covariates.

6.3 Interaction effects

(Insert Table 10 and 11)

This section introduces the possibility that catch-up growth varies with family background. Tables 10 and 11 illustrate the interaction term between catch-up growth and maternal level of education. Previous evidence about determinants of child health focused largely on the various ways maternal education could have an impact on child health (Strauss and Thomas (1995); Case and Paxson (2010); Alderman and Headey (2017)). Mothers with education possess certain characteristics that are decisive for child health such as bargaining power, position in the labour market (earnings)[7] and access to information. Presumably, the mother's level of education interacts with an ability to correct childhood malnutrition. I tested this hypothesis by interacting the two covariates. In both birth cohorts, the results suggested some important differences across different points in the conditional distribution when including the interaction term. This implied that growth of the catch-up effect was higher ($\beta < 0.5$), indicating that children whose mothers had elementary education or higher were more likely to experience less nutritional deficiency than they would otherwise, compared to the base category of no maternal level of education.

6.4 Extracting marginal quantiles

(Insert Table 12)

Having analysed the conditional quantile effects of covariates on children's HAZ. I turned to investigating the marginal quantiles. Table 12 illustrates the transition from conditional quantiles to marginal quantiles. Column (1) shows results for the younger cohort and (2) for the older cohort. This estimation fulfilled two purposes. In the first place, child health related to marginal effect is interesting in itself. Secondly, it can be seen as a robustness check to show the link between the conditional quantile and marginal quantile estimation. According to Table 12, the calculated marginal effects in terms of the underlying covariates implied that the child's health increased by 0.314 (0.267) z-score, given one z-score increase in the catch-up coefficient for the younger (older) birth cohort. Translating this, the result indicated that if the child were less malnourished in the past by one standard deviation closer to the reference group, the HAZ would have been higher by 0.267 standard deviation, that is the child would have had a better health status than it would otherwise have had.

A male child's health decreased by -0.0147 (-0.003) z-score. In addition, sibling gender composition had negative marginal effects on the child's health status. However, the wealth index, maternal level of education and access to sanitation or to electricity all

[7] Better position at the labour market comes with higher opportunity costs. For example, it can lead to a negative effect on breast feeding and on child care in general because of lost future earnings (Jayachandran and Kuziemko, 2011).

had positive marginal effects on child health. This implied, for example, that children whose mothers had at least elementary schooling had 0.012 (0.044) z-score better health relative to children with uneducated mothers. A specific concern was access to cooking fuels, which had a negative marginal effect on the child's health. In fact the health of the child decreased by -0.022 (-0.044) z-score. The negative marginal effect reflected the current research on the impact of cooking fuel on health (Rinne et al., 2007).

7 Robustness analysis

My results showed that there was a discrepancy in determinants of child health across the conditional quantiles yielding a larger spectrum of information to policy makers beyond the conventional conditional mean effect. In this section, I discuss potential heterogeneous effects within the sample split according gender.

The gender-health disparities among children in India remains unresolved (Tarozzi (2008); Aurino (2017)). Dividing the sample according to gender allowed me to capture the heterogeneous impact on the catch-up effect, which was important, in addition to controlling for gender as I did in the previous estimations. I thus repeated the main analysis with the sample split according to gender. Thus far, results for both birth cohorts have only revealed a partial catch-up effect.

The results of this exercise are presented in Tables A.1 - A.2 for the younger cohort and A.3 - A.4 for the older cohort. In all the tables, column (1) reports the least square whereas quantile estimation results are found in the subsequent columns (2)-(6) for each respective birth cohort and gender. In general, the results were similar to those discussed in Section 6: the catch-up coefficients of least square showed close to no change in catch-up growth rate for both genders. Tables A.1 - A.3 contain results for females. Both the least square and conditional quantile yielded similar β coefficients of catch-up effect and were statistically significant at the 1 percent level for both genders. Tables A.2 - A.4, contain results for the male gender. These results shared the same pattern as those for the female child across the cohorts. This suggested that the catch-up effect was neither gender- nor birth-cohort specific.

Although the catch-up coefficient continued to predict a partial effect on children's current health status conditional to a wide range of covariates, it was interesting to note what the exceptions were. Strikingly, the households with no access to sanitation and safe water had no different statistically significant malnutrition status across gender and birth cohorts. This suggested that once the catch-up effect, sibling composition, wealth, mother's age at birth, maternal education, caste and area of residence were accounted for, the remaining differences on the child malnutrition status across population groups in conditional quantiles (average) in Andhra Pradesh is small. Likewise, the predictive power of maternal education disappeared for certain quantiles. I found that for girls, maternal education levels only had predictive power at the higher end of the conditional distribution. Similar results were revealed for boys. Finally, the results showed no statistically significantly impact of caste in either gender groups.

8 Discussion

On a larger scale, according to the World Bank's 2014 health statistics indicator, the Indian health expenditure was 4.7 percent of the total GDP, where the public expenditure represented only 1.4 percent compared to private expenditure, amounting to 3.3 percent. This implied that out-of-pocket health expenditure (% of private expenditure on health) was 89.2 percent. However, the distribution of resources across states in India varies widely, thus the effectiveness of this spending is of vital importance to health policy makers. Previous results on this issue focused on how increased health spending affects the average child's health performance and other covariates of interest for policy makers. The finding presents very few positive effects.

My results suggest that some measures of childhood health may have positive effects at points in the conditional distribution of HAZ other than the average effect. The most noteworthy of my findings can determine where resources may matter, not just whether or not they matter on average. For instance, my results suggest that the marginal rupees allocated towards per child expenditures raises the health (decreases the child malnutrition) at the lower portion of the conditional distribution, yet neither of these resource measures impact the average child health outcome. However, it should be noted that the way in which per child health expenditure is spent, and how the additional rupee is used, will obviously determine how effective the policies are in decreasing child malnutrition in the relevant points of conditional distribution. My most robust result on the effect of β_1 or the catch-up effect on the conditional distribution of HAZ carries some intriguing implications. A simple interpretation of this finding is that there is no decrease in child malnutrition across the two birth cohorts (only a marginal change). Further reflection, however, suggests another plausible explanation, as the interaction term illustrates a different story. Interacting the catch-up variable with maternal education levels seemingly decreases the level of malnutrition, although the pattern in the two birth cohorts remains the same. One policy implication of my findings is that if an additional rupee were invested in a region such as in Kerala or another state where the health policy has done better work, for example, it is unlikely that HAZ would decrease much. Furthermore, if my interpretation is correct, the largest decrease in HAZ will be at the bottom of the conditional distribution, where the 0.10 quantile estimate is higher than the estimates for the other quantiles.

The policy challenge for decreasing child malnutrition is considerable. The challenges include (not exhaustively) changing preferences, attitudes, knowledge and behaviour and in particular empowering women of child-bearing age. Therefore, public policies that alter development trajectories in disadvantaged sub-populations such as those derived from the pro-poor sample population that YL data present, are an interesting example. The results presented in this paper are likely to allow more flexibility to reach out to those most in need, as health in childhood has both short-term and longer-term economic consequences. Childhood health is a function of a broad set of policies: investment decisions, parental choices, parental health stock and economic background.

9 Concluding remarks

This article studied the extent to which children were able to recover from nutritional deficiency in early childhood, the so called catch-up. I studied this by using two waves for two birth cohorts from a panel dataset where children were of the same age at each wave. The setting for the study was the state of Andhra Pradesh in India, a country where malnutrition remains a dilemma. The catch-up effect has remained difficult to capture as it has required large and detailed data.

The predictor of interest in this study was the child's HAZ and whether the HAZ indicated any improvement across waves for two birth cohorts. The results from the linear specification showed that the catch-up effect was non-increasing, which was in line with previous results. The main contribution of this study to the catch-up growth literature was to investigate how the effects of the current health status varied along the entire distribution of health. To illustrate this I used quantile regression. My regression specification followed the standard dynamic conditional health production function approach to relate child health outcomes to a vector of household and community specific controls and was based on the data from the Young Lives study.

The estimation results from the quantile regression revealed some interesting findings. They suggested that the null of the homogeneous catch-up effect along the entire distribution of anthropometric measurements could be rejected, and that there could be differential health quality effects at different points in the HAZ throughout the conditional distribution. I found, for example, that healthy children (those further to the right in the conditional distribution of HAZ) had a lower catch-up effect but that this varied significantly only along the lower to middle quantiles. In fact, the interaction terms showed much better coefficient results on the catch-up effect. However, this pattern was consistent with previous evidence that, despite high economic growth, children had not recovered from nutritional deficiency across the birth cohorts.

Other confounders, which had not been controlled for in the analysis, may also exert an effect on the relationship between child health status and catch-up growth rate. For example, the maternal health status before conception and the child's innate health endowment.

These findings suggested that the catch-up effect appeared to have no consequence for the average HAZ but may indeed matter at other points of the conditional distribution of the HAZ. To shed light on the catch-up mechanism, and to conciliate my findings with the existing literature, I integrated the analysis by studying gender differences across the birth cohorts. Some studies found gender differences in nutrient intake and nutritional status. Aurino (2017) demonstrated that while there were no gender-based disparities in the intra-household allocation of food during childhood, the disparities emerged for boys in mid-adolescence. My results indicated that neither gender nor birth cohort had an impact on catch-up growth.

To sum up, my study contributes to the existing literature by focusing on the context of children's potential to catch-up in health across quantiles. In this light, my results are consistent with the evidence of several studies on persistency of malnutrition despite India's economic growth. Further, the evidence from my study underlines the importance of maternal education, how it interacts with catch-up effect and how it defines female skills and empowerment.

To conclude, rather than trying to isolate causal effects, this article instead focused on the differences between the incremental effects of covariates at different quantiles of the conditional HAZ distribution. The extent to which these differences existed for the causal effects is an interesting topic and requires further investigation. Sadly, I must leave exploration of these and other possible mechanisms to future work.

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Tables

Table 1: Sample descriptive statistics of the study population by birth cohort

Panel A : Younger cohort

Variables	Mean	Std. Dev	Min	Max	Obs
8 years old					
Height-for-age	-1.445	1.026	-4.87	3.12	1922
Weight-for-age	-1.868	1.055	-4.87	3.12	1928
Height (cm)	118.588	6.263	62.00	154.40	1925
Weight (kg)	19.664	3.056	11.60	43.70	1929
BMI [calculated BMI = weight/height^2]	13.929	1.624	4.58	41.36	1929
Thinness	0.278	0.448	0	1	1929
Severe thinness	0.065	0.247	0	1	1929
Underweight	0.459	0.498	0	1	1929
Severe underweight	0.134	0.340	0	1	1929
Stunting	0.289	0.453	0	1	1929
Severe stunting	0.055	0.229	0	1	1929
12 years old					
Height-for-age	-1.442	1.020	-4.96	2.61	1904
Height (cm)	140.036	7.605	82.20	169.20	1909
Weight (kg)	31.074	6.869	15.00	72.00	1910
BMI [calculated BMI = weight/height^2]	15.814	4.563	9.87	180.69	1910
Thinness	0.331	0.471	0	1	1910
Severe thinness	0.108	0.310	0	1	1910
Underweight	-	-	-	-	-
Severe underweight	-	-	-	-	-
Stunting	0.293	0.455	0	1	1910
Severe stunting	0.061	0.239	0	1	1910
Maternal age	30.6	4.3	19	55	1913
Maternal level of education	1.8	0.8	1	3	1861
Father's age	36.4	5.2	27	78	1888
Father's level of education	2.1	0.8	1	3	1779
Household size	5.4	2.3	2	30	1931
Number of adults in household	3.5	1.8	1	14	1919
Number of school aged children in household	0.7	1.0	0	6	1920

Note: Sample population from young cohort, Waves III and IV when YL child is 8 and 12 years old, respectively. The variable thinness is defined as BMI-for-age z-score $\leqslant$ - 2 and severe thinness as BMI-for-age z-score $\leqslant$ - 3. The variable underweight is defined as WAZ $\leqslant$ - 2 and severe underweight as WAZ $\leqslant$ - 3. The variable stunted is defined as HAZ $\leqslant$ - 2 and severely stunted as HAZ $\leqslant$ - 3. Parents' characteristics are derived from Wave IV. Source: Author's calculations based on the YL dataset

Panel B: Older cohort

Variables	Mean	Std. Dev	Min	Max	Obs
8 years old					
Height-for-age	-1.560	1.031	-4.60	2.01	1006
Weight-for-age	-1.950	1.030	-4.80	2.35	1006
Height (cm)	118.004	6.335	71.40	140.80	1008
Weight (kg)	19.453	2.991	12.10	38.70	1008
BMI [calculated BMI = weight/height^2	13.931	1.652	9.332	46.88	1008
Thinness	0.261	0.439	0	1	1008
Severe thinness	0.063	0.242	0	1	1008
Underweight	0.473	0.500	0	1	1008
Severe underweight	0.155	0.362	0	1	1008
Stunting	0.331	0.471	0	1	1008
Severe stunting	0.075	0.264	0	1	1008
12 years old					
Height-for-age (12 yrs old)	-1.530	1.039	-4.50	2.42	977
Height (kg)	141.498	7.566	101.20	167.95	985
Weight (cm)	32.338	10.699	15.6	153.20	985
BMI [calculated BMI = weight/height^2]	27.916	167.332	11.068	2971.73	985
Thinness	0.335	0.472	0	1	985
Severe thinness	0.097	0.297	0	1	985
Underweight	-	-	-	-	-
Severe underweight	-	-	-	-	-
Stunting	0.342	0.475	0	1	985
Severe stunting	0.072	0.259	0	1	985
Maternal age	30.6	5.6	18	60	978
Maternal level of education	1.4	0.6	1	3	973
Father's age	36.8	6.3	25	65	947
Father's level of education	1.6	0.8	1	3	913
Household size	5.5	2.0	2	24	1008
Number of adults in household	2.8	1.4	1	13	1008
Number of school aged children in household	1.4	1.0	0	7	1008

Note: Sample population from older cohort, Waves I and II when YL child is 8 and 12 years old, respectively. The variable thinness is defined as BMI-for-age z-score $\leqslant$ - 2 and severe thinness as BMI-for-age z-score $\leqslant$ - 3. The variable underweight is defined as WAZ $\leqslant$ - 2 and severe underweight as WAZ $\leqslant$ - 3. The variable stunted is defined as HAZ $\leqslant$ - 2 and severely stunted as HAZ $\leqslant$ - 3. Parents' characteristics are derived from Wave IV. Source: Author's calculations based on the YL dataset.

Table 2: Children's stunting pattern across waves

Variables	Younger cohort	N	Older cohort	N
8 years old	-2.606	561	-2.668	335
12 years old	-2.606	560	-2.618	332

Note: Children's stunting measured as height-for-age z-score (HAZ -2) from wave I and II for older YL child and III and IV for younger YL child. Source: Author's calculations based on the YL dataset.

Table 3: Children's malnutrition across wave and by gender

Variables	Younger cohort	N	Older cohort	N
Female, HAZ				
8 years old	16.7%	1922	16.6%	1006
12 years old	15.8%	1904	16.1%	977
Male, HAZ				
8 years old	12.5%	1922	16.7%	1006
12 years old	13.6%	1904	17.9%	977

Note: Children's malnutrition across waves and by gender. The percentage yields proportion of malnourishment (stunting) by gender in each wave and birth cohort. Source: Author's calculations based on the YL dataset.

Table 4: Stunting pattern across waves and by gender

	Younger cohort	N	Older cohort	N
HAZ, 8 years old				
Girls	-1.477	1031	-1.550	494
Boys	-1.407	891	-1.569	512
HAZ, 12 years old				
Girls	-1.434	1026	-1.438	484
Boys	-1.450	878	-1.620	493

Note: Children's stunting across waves by gender, where stunting is measured as HAZ. The HAZ shows the average standard deviation from the mean. Source: Author's calculation based on the YL dataset.

Table 5: Child characteristics disaggregated by birth cohort in percentages

Variables	Older cohort (Wave I)	Younger cohort (Wave III)
Child's gender		
Female	49.11	53.55
Male	50.89	46.45
Age order of siblings in the household		
Index child is the eldest	26.68	0.16
Index child is a middle child	25.58	0.47
Index child is the youngest	39.42	43.78
Index child has no siblings in the household	8.32	55.59
Child's first language		
Telugu	84.21	81.52
Urdu	5.73	6.18
Other: Hindi, Oria, Kannada, Marati, Tamil	6.14	6.96
Local dialect	3.92	5.35
Child's caste/ethnicity		
Scheduled castes	21.03	18.12
Scheduled tribes	10.81	12.88
Backward castes	68.15	69.00
Child's religion		
Hindi	87.4	91.87
Muslim	6.94	7.20
Other: Christian, Buddhist, Protestant, Orthodox, Sikh	5.65	0.93
Area of residence		
Urban	24.90	25.44
Rural	75.10	74.56
Region of residence		
Coastal Andhra	34.72	35.16
Rayalaseema	30.46	29.36
Telangana	34.82	35.48

Note: The Table presents child characteristics in percentage at 8 years old and the variables are constant across the waves. The data is derived from Wave I for older cohort and Wave III for younger cohort. Index child indicates surveyed child. Source: Author's calculation based on Young Lives dataset.

Table 6: Sample descriptive of the study population by household characteristics

Panel A: Younger cohort

Variables	Mean	Std. Dev	Min	Max	Obs
Wealth index	0.585	0.166	0.090	0.946	1915
Dummy for the availability of adequate fuels for cooking	0.428	0.495	0	1	1915
Dummy for the availability of electricity	0.976	0.153	0	1	1915
Dummy for the availability of sanitation	0.407	0.491	0	1	1915
Dummy for the availability of safe drinking water	0.989	0.107	0	1	1915

Panel B: Older cohort

Variables	Mean	Std. Dev	Min	Max	Obs
Wealth index	0.468	0.199	0.007	0.926	994
Dummy for the availability of adequate fuels for cooking	0.272	0.445	0	1	994
Dummy for the availability of electricity	0.892	0.310	0	1	994
Dummy for the availability of sanitation	0.346	0.476	0	1	994
Dummy for the availability of safe drinking water	0.953	0.212	0	1	994

Note: Sample population from Wave IV and Wave II for younger and older cohorts respectively, when the YL child is 12 years old. Wealth index variable includes housing quality index, access to services index and consumer durables index. Source: Author's calculations based on the YL dataset.

Table 7: The ordinary least square coefficients for children's height-for-age z-score in two birth cohorts

Variables	(1) HAZ Younger cohort	(2) HAZ Older cohort
HAZ (t-1)	0.746***	0.754***
	(0.025)	(0.029)
Sibling composition	-0.028	0.010
	(0.038)	(0.045)
Gender (Boys = 1)	-0.070**	-0.142***
	(0.032)	(0.044)
Wealth	0.267	0.228
	(0.171)	(0.217)
Maternal age at birth of child	-0.008**	-0.005
	(0.004)	(0.004)
Maternal education: Elementary	0.028	0.133**
	(0.037)	(0.059)
Maternal education: Secondary	0.042	0.165**
	(0.046)	(0.066)
Child's ethnicity: Scheduled tribes	0.003	-0.105
	(0.060)	(0.073)
Child's ethnicity: Backward castes	-0.014	-0.044
	(0.042)	(0.053)
Dummy for area of residence	0.021	-0.097
	(0.052)	(0.067)
Dummy for the availability of sanitation	0.087*	0.014
	(0.052)	(0.068)
Dummy for the availability of safe water	-0.032	-0.008
	(0.085)	(0.076)
Dummy for the availability of fuels for cooking	-0.027	-0.084
	(0.044)	(0.086)
Constant	-0.319**	-0.202
	(0.152)	(0.158)
Observations	1,746	918
R-squared	0.603	0.598

*** p<0.01, ** p<0.05, * p<0.1

Note: The table reports standard linear regression estimates of children's catch-up effect in malnutrition measured as HAZ at time *t-1*, at year 2002 for older cohort and 2009 for younger cohort. The robust standard errors are reported in parentheses. The outcome variable HAZ stands for height-for-age z-score at time *t*, in year 2006 for older cohort and 2013 for younger cohort. The reference category for Maternal education is that the mother has no education, and the reference category for the child's ethnicity is scheduled castes. The dummy variable for area of residence is rural or urban, all other dummy variables indicate either the households have availability of sanitation, water and fuels for cooking or they don't.

Table 8: Quantile regression estimates of height-for-age z-score for younger cohort

Variables	(1) $\tau = 10\%$	(2) $\tau = 25\%$	(3) $\tau = 50\%$	(4) $\tau = 75\%$	(5) $\tau = 90\%$
HAZ (t-1)	0.728***	0.824***	0.845***	0.858***	0.815***
	(0.025)	(0.014)	(0.013)	(0.016)	(0.021)
Sibling composition	0.000	-0.030	-0.038	-0.006	0.009
	(0.056)	(0.033)	(0.030)	(0.040)	(0.049)
Gender (Boys = 1)	-0.263***	-0.232***	-0.041	0.049	0.110***
	(0.060)	(0.034)	(0.027)	(0.031)	(0.040)
Wealth	0.570	0.183	0.082	-0.078	0.062
	(0.365)	(0.177)	(0.129)	(0.172)	(0.233)
Maternal age at birth	-0.002	-0.005	-0.007***	-0.010***	-0.007
	(0.007)	(0.004)	(0.003)	(0.003)	(0.005)
Maternal education: elementary	-0.065	0.013	0.034	0.050	0.150***
	(0.073)	(0.036)	(0.030)	(0.035)	(0.054)
Maternal education: secondary	-0.040	0.013	0.067	0.035	0.065
	(0.069)	(0.050)	(0.041)	(0.051)	(0.052)
Child's ethnicity: Scheduled tribes	-0.079	-0.008	0.056	0.073	0.136
	(0.112)	(0.070)	(0.040)	(0.055)	(0.094)
Child's ethnicity: Backward castes	-0.051	-0.036	-0.007	0.039	-0.006
	(0.067)	(0.037)	(0.033)	(0.040)	(0.051)
Dummy for area of residence	0.230***	0.033	0.035	0.005	-0.076
	(0.071)	(0.046)	(0.041)	(0.054)	(0.080)
Dummy for the availability of sanitation	0.073	0.013	0.093**	0.147***	0.181***
	(0.083)	(0.052)	(0.043)	(0.054)	(0.061)
Dummy for the availability of safe water	-0.178	0.091	0.089	0.135	-0.072
	(0.329)	(0.080)	(0.069)	(0.166)	(0.172)
Dummy for the availability of fuels for cooking	-0.011	0.002	-0.059*	-0.008	-0.016
	(0.078)	(0.043)	(0.035)	(0.045)	(0.063)
Observations	1,746	1,746	1,746	1,746	1,746
R-squared	0.335	0.411	0.452	0.460	0.423

*** p<0.01, ** p<0.05, * p<0.1

Note: The table reports standard linear regression estimates of children's catch-up effect in malnutrition measured as HAZ at time t-1, at year 2002 for older cohort and 2009 for younger cohort. The robust standard errors are reported in parentheses. The outcome variable HAZ stands for height-for-age z-score at time t, in year 2006 for older cohort and 2013 for younger cohort. The reference category for maternal education is that the mother has no education, and the reference category for the child's ethnicity is scheduled castes. The dummy variable for area of residence is rural or urban, all other dummy variables indicate either the households have access to sanitation, water and fuels for cooking or they don't.

Table 9: Quantile regression estimates of height-for-age z-score for older cohort

Variables	(1) $\tau = 10\%$	(2) $\tau = 25\%$	(3) $\tau = 50\%$	(4) $\tau = 75\%$	(5) $\tau = 90\%$
HAZ (t-1)	0.719***	0.805***	0.826***	0.849***	0.824***
	(0.028)	(0.022)	(0.017)	(0.023)	(0.033)
Sibling composition	-0.110**	0.029	-0.011	0.028	0.064
	(0.046)	(0.047)	(0.039)	(0.042)	(0.070)
Gender (Boys = 1)	-0.301***	-0.210***	-0.046	-0.012	-0.059
	(0.044)	(0.046)	(0.041)	(0.043)	(0.067)
Wealth	0.645***	0.150	0.064	-0.133	-0.098
	(0.230)	(0.210)	(0.177)	(0.179)	(0.328)
Maternal age at birth	-0.009**	-0.006	-0.005	-0.001	0.001
	(0.005)	(0.004)	(0.003)	(0.004)	(0.007)
Maternal education: elementary	0.081	0.085	0.136***	0.120**	0.165*
	(0.058)	(0.056)	(0.045)	(0.057)	(0.093)
Maternal education: secondary	0.070	0.109	0.184***	0.178***	0.174*
	(0.095)	(0.083)	(0.071)	(0.054)	(0.095)
Child's ethnicity: Scheduled tribes	-0.139	-0.126	-0.088	0.020	0.004
	(0.088)	(0.078)	(0.060)	(0.072)	(0.120)
Child's ethnicity: Backward castes	-0.119*	-0.083	-0.033	0.016	0.117
	(0.070)	(0.056)	(0.040)	(0.065)	(0.072)
Dummy for area of residence	0.092	0.023	-0.139**	-0.174**	-0.320**
	(0.063)	(0.079)	(0.067)	(0.078)	(0.127)
Dummy for the availability of sanitation	0.149***	0.130*	0.032	-0.061	-0.306***
	(0.046)	(0.069)	(0.061)	(0.052)	(0.074)
Dummy for the availability of safe water	-0.126	-0.005	0.023	0.069	0.149
	(0.120)	(0.080)	(0.052)	(0.095)	(0.104)
Dummy for the availability of fuels for cooking	-0.240**	-0.089	-0.136*	0.003	0.151
	(0.096)	(0.084)	(0.073)	(0.083)	(0.144)
Observations	918	918	918	918	918
Pseudo R-squared	0.377	0.416	0.428	0.418	0.382

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Note: The table reports quantile regression estimates of children's catch-up effect in malnutrition measured as HAZ. Robust standard errors are reported in parentheses. The outcome variable HAZ stands for height-for-age z-score. The reference category for education is mother has no level of education and for the child's ethnicity is scheduled caste. The dummy variable for area of residence is rural or urban, all other dummy variables indicate either the households have access to sanitation, water and fuels for cooking or they don't.

Table 10: Interaction effect: Quantile regression estimates of height-for-age z-score for younger cohort

Variables	(1) $\tau = 10\%$	(2) $\tau = 25\%$	(3) $\tau = 50\%$	(4) $\tau = 75\%$	(5) $\tau = 90\%$
$HAZ(t-1)$	0.791***	0.808***	0.810***	0.834***	0.733***
	(0.070)	(0.035)	(0.028)	(0.039)	(0.049)
$HAZ(t-1)$ * Maternal education	-0.040	0.012	0.023	0.012	0.050*
	(0.034)	(0.018)	(0.017)	(0.020)	(0.026)
Sibling composition	0.015	-0.031	-0.046	0.003	-0.016
	(0.057)	(0.033)	(0.033)	(0.038)	(0.050)
Gender (Boys = 1)	-0.268***	-0.227***	-0.035	0.048	0.115***
	(0.061)	(0.033)	(0.028)	(0.032)	(0.041)
Wealth	0.675*	0.188	0.009	-0.098	-0.025
	(0.355)	(0.183)	(0.129)	(0.172)	(0.236)
Maternal age at birth	-0.003	-0.004	-0.007**	-0.011***	-0.007
	(0.007)	(0.004)	(0.003)	(0.004)	(0.005)
Maternal education: elementary	-0.141	0.028	0.080**	0.076	0.206***
	(0.107)	(0.050)	(0.040)	(0.049)	(0.069)
Maternal education: secondary	-0.135	0.051	0.139**	0.077	0.150*
	(0.165)	(0.084)	(0.059)	(0.081)	(0.085)
Child's ethnicity: Scheduled tribes	-0.081	-0.005	0.068*	0.077	0.090
	(0.087)	(0.071)	(0.041)	(0.058)	(0.083)
Child's ethnicity: Backward castes	-0.060	-0.032	-0.004	0.042	-0.050
	(0.062)	(0.038)	(0.033)	(0.042)	(0.054)
Dummy for area of residence	0.229***	0.045	0.049	0.015	-0.115
	(0.070)	(0.045)	(0.042)	(0.052)	(0.074)
Dummy for the availability of sanitation	0.060	0.019	0.098**	0.153***	0.167***
	(0.080)	(0.052)	(0.044)	(0.053)	(0.056)
Dummy for the availability of safe water	-0.186	0.081	0.096	0.126	-0.064
	(0.317)	(0.071)	(0.062)	(0.144)	(0.197)
Dummy for the availability of fuels for cooking	-0.046	0.010	-0.040	0.001	0.007
	(0.070)	(0.043)	(0.035)	(0.046)	(0.061)
Pseudo R-squared	0.336	0.4107	0.4511	0.4593	0.425
Observations	1,746	1,746	1,746	1,746	1,746

*** p<0.01, ** p<0.05, * p<0.1

Note: The table reports quantile regression estimates of children's catch-up effect in malnutrition measured as HAZ. Robust standard errors are reported in parentheses. The outcome variable HAZ stands for height-for-age z-score. The reference category for Maternal education is mother has no level of education and for the child's ethnicity is scheduled castes. The dummy variable for area of residence is rural or urban, all other dummy variables indicate either the households have availability of sanitation, water and fuels for cooking or they don't.

Table 11: Interaction effect: Quantile regression estimates of height-for-age z-score for older cohort

Variables	(1) $\tau = 10\%$	(2) $\tau = 25\%$	(3) $\tau = 50\%$	(4) $\tau = 75\%$	(5) $\tau = 90\%$
$HAZ(t-1)$	0.541***	0.711***	0.753***	0.817***	0.678***
	(0.070)	(0.045)	(0.042)	(0.052)	(0.077)
$HAZ(t-1)$ * Maternal education	0.107***	0.065**	0.052*	0.026	0.090**
	(0.037)	(0.029)	(0.028)	(0.030)	(0.041)
Sibling composition	-0.119**	0.024	0.016	0.013	0.067
	(0.054)	(0.037)	(0.038)	(0.048)	(0.069)
Gender (Boys = 1)	-0.275***	-0.235***	-0.063	-0.016	-0.069
	(0.053)	(0.041)	(0.039)	(0.047)	(0.081)
Wealth	0.537*	0.129	-0.029	-0.117	-0.075
	(0.284)	(0.168)	(0.181)	(0.213)	(0.298)
Maternal age at birth	-0.006	-0.009**	-0.007**	-0.000	0.001
	(0.005)	(0.004)	(0.004)	(0.004)	(0.008)
Maternal education: elementary	0.297**	0.199***	0.223***	0.181**	0.266***
	(0.123)	(0.075)	(0.057)	(0.081)	(0.083)
Maternal education: secondary	0.384**	0.315***	0.355***	0.281**	0.437***
	(0.170)	(0.119)	(0.100)	(0.136)	(0.137)
Child's ethnicity: Scheduled tribes	-0.124	-0.153***	-0.063	-0.020	-0.027
	(0.103)	(0.045)	(0.072)	(0.074)	(0.126)
Child's ethnicity: Backward castes	-0.084	-0.082**	-0.010	-0.014	0.099
	(0.071)	(0.041)	(0.040)	(0.068)	(0.093)
Dummy for area of residence	0.071	0.004	-0.094	-0.143	-0.311**
	(0.089)	(0.061)	(0.063)	(0.088)	(0.147)
Dummy for the availability of sanitation	0.113	0.132**	0.052	-0.070	-0.302***
	(0.081)	(0.055)	(0.060)	(0.058)	(0.110)
Dummy for the availability of safe water	-0.045	-0.019	0.026	0.092	0.102
	(0.103)	(0.052)	(0.055)	(0.091)	(0.173)
Dummy for the availability of fuels for cooking	-0.186*	-0.136*	-0.101	0.002	0.185
	(0.108)	(0.073)	(0.069)	(0.097)	(0.150)
Pseudo R-squared	0.3819	0.4175	0.4284	0.4182	0.3846
Observations	918	918	918	918	918

*** p<0.01, ** p<0.05, * p<0.1

Note: The table reports quantile regression estimates of children's catch-up effect in malnutrition measured as HAZ. Robust standard errors are reported in parentheses. The outcome variable HAZ stands for height-for-age z-score. The reference category for Maternal education is mother has no level of education and for the child's ethnicity is scheduled caste. The dummy variable for area of residence is rural or urban, all other dummy variables indicate either the households have availability of sanitation, water and fuels for cooking or they don't.

Table 12: Marginal effects in terms of underlying covariates on child health (HAZ)

Variables	Height-for-age z-score	
	Younger cohort	Older cohort
	(1)	(2)
HAZ (t-1)	0.314	0.267
Gender of siblings	-0.014	-0.003
Gender (Boys=1)	-0.015	-0.015
Wealth Index	0.030	0.021
Maternal age at birth	-0.003	-0.002
Maternal level of education: elementary	0.012	0.044
Maternal level of education: secondary	0.025	0.060
Child's ethnicity: Scheduled tribe	0.021	-0.029
Child's ethnicity: Backward castes	-0.002	-0.011
Area of residency	0.013	-0.045
Access to sanitation	0.034	0.010
Access to electricity	0.033	0.007
Access to cooking fuels	-0.022	-0.044

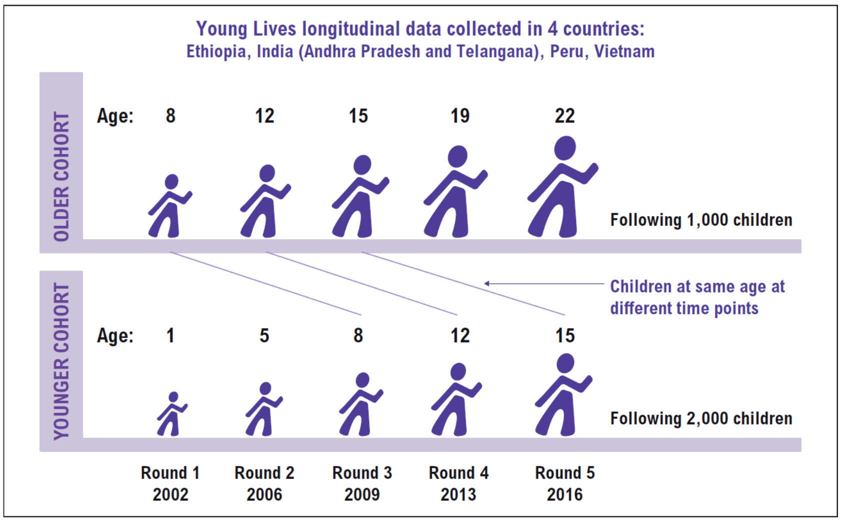
Note: The table reports the marginal effect of covariates on children's health measured as height-for-age z-score for younger and older cohorts respectively.

Figures

Figure 1: Map of Andhra Pradesh and Telangana, India

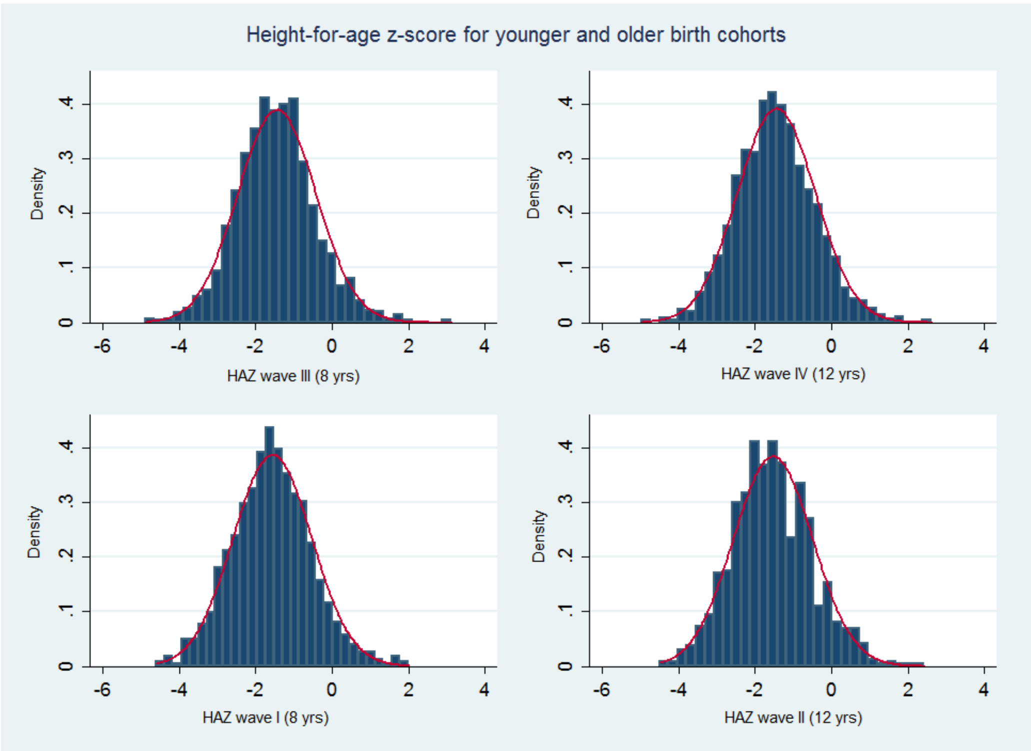
Note: Andhra Pradesh is a state in south-east India. The YL data includes seven districts with 20 unidentified villages. The state's distinguishing features can be categorized into three agro-climatic regions; Coastal Andhra, Rayalaseema and Telangana where the YL dataset captured interregional variations. The sub-ecological zones in Andhra Pradesh are described as mainly coastal and inland plains. The two states, Andhra Pradesh and Telangana were amalgamated until June 2014, after which Telangana, the north-western part of Andhra Pradesh, separated to form a new state. Together they have the fifth largest population in India.

Figure 2: Young Lives cohorts



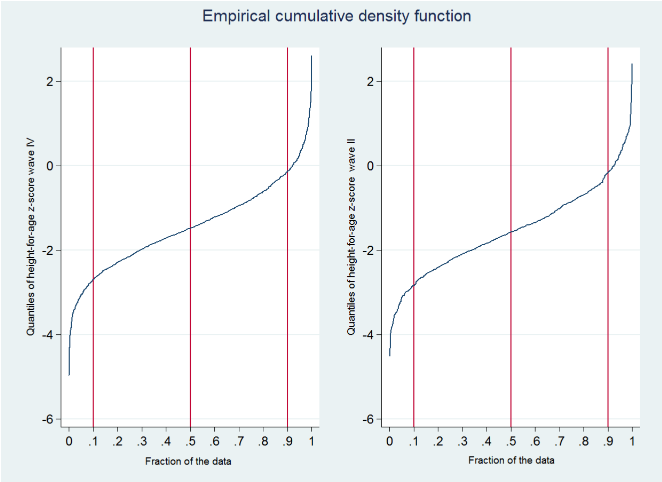
Note: The sample is restricted to Wave I and Wave II from the older cohort and Wave III and Wave IV from the younger cohort. The YL children were 8 years old in Waves I and III and 12 years old in Waves II and IV. Source: Young Lives Study.

Figure 3: Height-for-age z-score for younger cohort



Note: The first panel shows the histogram of the height-for-age z-score for the younger cohort for Wave III and Wave IV. The second panel shows the histogram of the height-for-age z-score for the older cohort for Wave I and Wave II. I have excluded the questionable outliers: HAZ $\geq$ 6 and HAZ $\leqslant$ -6. The red line captures the normal distribution. The sample is clustered around the mean of HAZ. Source: Author's calculations based on the YL dataset.

Figure 4: The empirical cumulative density function

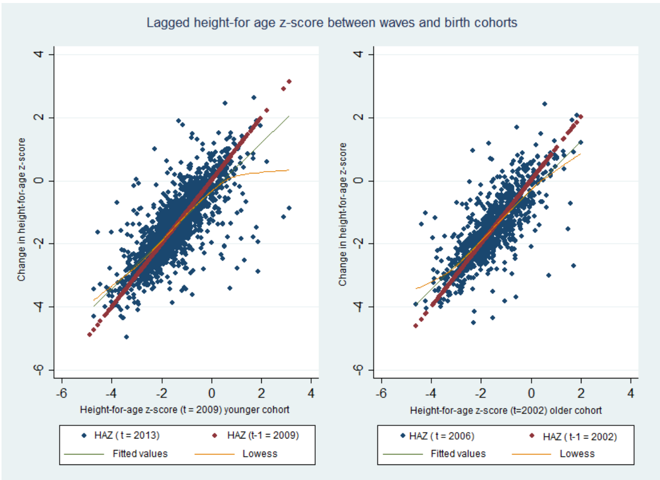


Note: The empirical cumulative density function for younger and older birth cohorts respectively at 12 years old. Source: Author's calculations based on the YL dataset.

Figure 5: Change in height-for-age z-score between waves and birth cohorts

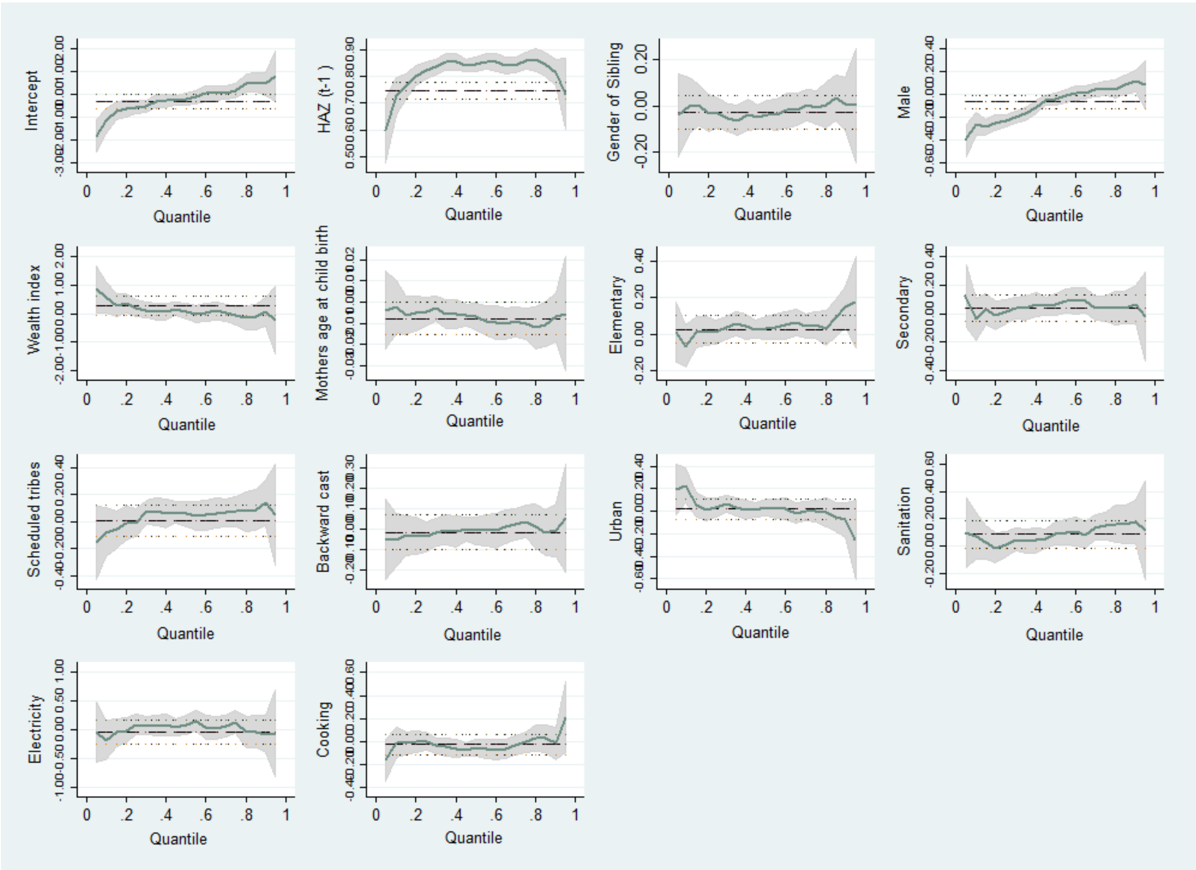
Note: The figure shows the change in HAZ between waves and birth cohorts. The fitted values display a negative relationship in HAZ between waves 2009 and 2013 for the younger cohort and between waves 2002 and 2006 for the older cohort. The comparison in HAZ between the birth cohorts suggests little improvement across the waves. Source: Author's calculations based on the YL dataset.

Figure 6: Lagged height-for-age z-score between waves and birth cohorts



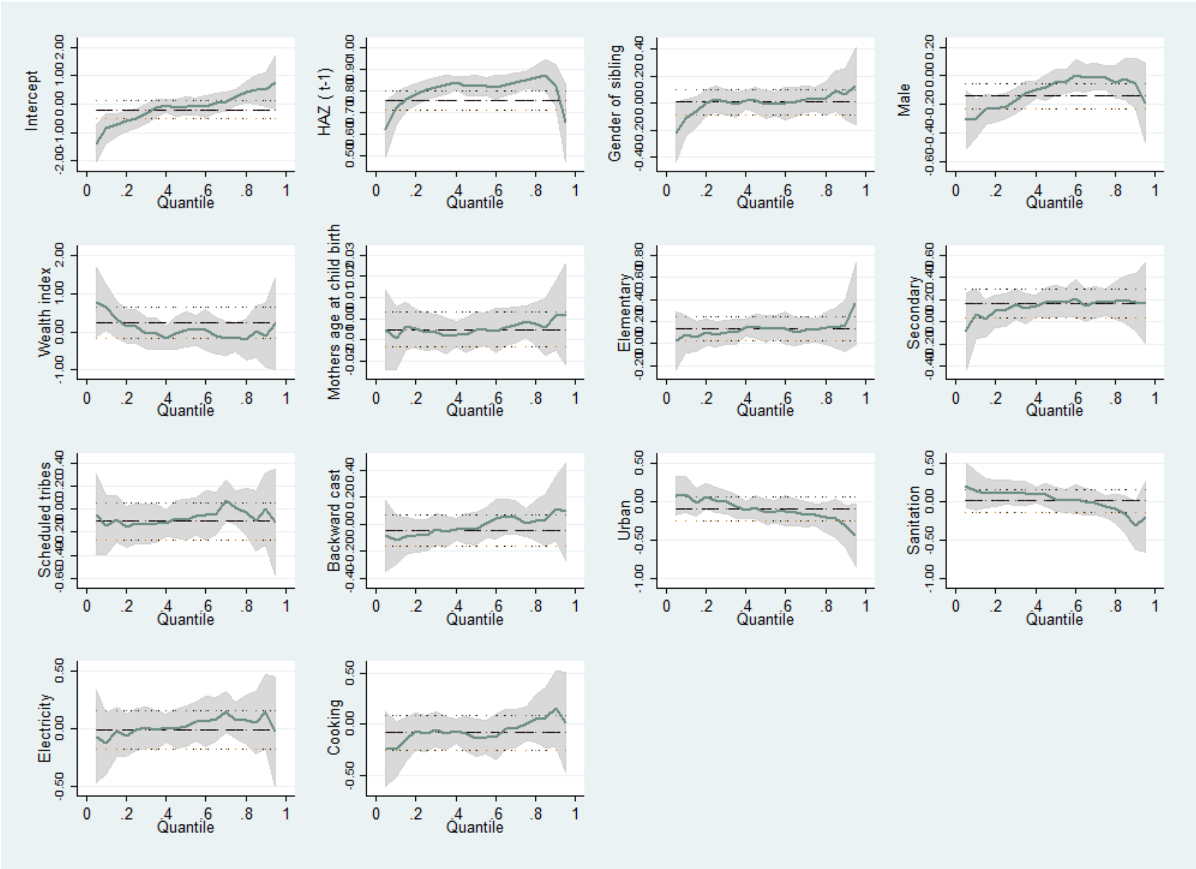
Note: The figure shows the lagged HAZ between waves and birth cohorts. The relationship between change in HAZ and HAZ year 2009 for the younger cohort and year 2002 for the older cohort is positive. The fitted values between the birth cohorts display a similar slope. Source: Author's calculations based on the YL dataset.

Figure 7: OLS and quantile regression estimates for height-for-age z-score for the younger cohort



Note: The dashed line in each figure represents the ordinary least squares estimate of the conditional mean effect. The two dotted lines represent the conventional 90 percent confidence intervals for the least squares estimate. The shaded grey area depicts a 90 percent pointwise confidence band for the quantile regression estimates, while the continuous green line shows the conditional quantile estimate. The figure shows covariates and how they differ across the quantiles for the younger cohort. Source: Author's calculations based on the YL dataset.

Figure 8: OLS and quantile regression estimates for height-for-age z-score for the older cohort



Note: The dashed line in each figure represents the ordinary least squares estimate of the conditional mean effect. The two dotted lines represent the conventional 90 percent confidence intervals for the least squares estimate. The shaded grey area depicts a 90 percent pointwise confidence band for the quantile regression estimates, while the continuous green line shows the conditional quantile estimate. The figure shows covariates and how they differ across the quantiles for the younger cohort. Source: Author's calculations based on the YL dataset.

A Appendix

Robustness analysis

Table A.1: Heterogeneous effects for females - younger cohort

Variables	(1) OLS	(2) 10%	(3) 25%	(4) 50%	(5) 75%	(6) 90%
HAZ (t-1)	0.775***	0.718***	0.824***	0.854***	0.881***	0.842***
	(0.032)	(0.037)	(0.012)	(0.015)	(0.020)	(0.024)
Sibling composition	0.020	0.077	0.007	0.023	0.037	0.016
	(0.049)	(0.079)	(0.032)	(0.033)	(0.050)	(0.057)
Wealth	0.247	0.186	0.150	0.177	0.024	0.237
	(0.214)	(0.375)	(0.180)	(0.149)	(0.205)	(0.211)
Maternal age at birth	-0.009*	-0.009	-0.002	-0.006*	-0.012***	-0.010*
	(0.005)	(0.008)	(0.003)	(0.003)	(0.004)	(0.006)
Maternal education: elementary	0.050	0.024	0.039	0.064**	0.060	0.146*
	(0.045)	(0.075)	(0.042)	(0.032)	(0.045)	(0.080)
Maternal education: secondary	0.098*	0.041	0.018	0.093**	0.116*	0.218**
	(0.059)	(0.081)	(0.054)	(0.047)	(0.068)	(0.097)
Child's ethnicity: Scheduled tribes	-0.070	-0.234	-0.091	0.009	0.061	0.188**
	(0.071)	(0.180)	(0.083)	(0.049)	(0.068)	(0.076)
Child's ethnicity: Backward castes	-0.054	-0.062	-0.070**	-0.064	0.031	-0.023
	(0.051)	(0.079)	(0.030)	(0.040)	(0.047)	(0.048)
Dummy for area of residence	0.051	0.197**	0.063	0.017	0.020	-0.153
	(0.068)	(0.086)	(0.050)	(0.045)	(0.070)	(0.108)
Dummy for the availability of sanitation	0.057	0.105	0.029	0.038	0.063	0.074
	(0.066)	(0.087)	(0.054)	(0.046)	(0.067)	(0.069)
Dummy for the availability of safe water	0.027	0.105	0.072	0.130	0.129	-0.113
	(0.106)	(0.296)	(0.066)	(0.119)	(0.258)	(0.072)
Dummy for the availability of fuels for cooking	-0.117**	-0.156*	-0.061	-0.140***	-0.034	-0.097
	(0.060)	(0.081)	(0.042)	(0.039)	(0.058)	(0.072)
Observations	957	957	957	957	957	957
Pseudo R squared	0.651	0.369	0.463	0.515	0.512	0.472

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Note: The table illustrates least square and quantile regression estimates of children's catch-up effect in malnutrition measured as HAZ. Robust standard errors are indicated in parentheses. Bootstrap standard error with 100 replications was employed with no difference in the coefficients exempt for larger standard error. The outcome variable HAZ stands for height-for-age z-score. The sample is split by gender and birth cohort. The reference category for Maternal education is mother has no level of education and for the child's ethnicity is Scheduled castes. The dummy variable for area of residence is rural or urban. All other dummy variables indicate either that the households have availability of sanitation, water and fuels for cooking or they don't.

Table A.2: Heterogeneous effects for males - younger cohort

Variables	(1) OLS	(2) 10%	(3) 25%	(4) 50%	(5) 75%	(6) 90%
HAZ (t-1)	0.712***	0.679***	0.826***	0.825***	0.812***	0.741***
	(0.041)	(0.052)	(0.026)	(0.027)	(0.022)	(0.029)
Sibling composition	-0.092	0.027	-0.087*	-0.138**	-0.066	-0.038
	(0.059)	(0.111)	(0.052)	(0.062)	(0.059)	(0.067)
Wealth	0.266	0.658	0.279	0.166	-0.183	-0.430*
	(0.277)	(0.543)	(0.297)	(0.284)	(0.265)	(0.225)
Maternal age at birth	-0.006	0.004	-0.008	-0.008	-0.010	-0.000
	(0.006)	(0.011)	(0.005)	(0.006)	(0.006)	(0.008)
Maternal education: elementary	-0.007	-0.141	-0.015	-0.009	0.045	0.116
	(0.061)	(0.137)	(0.058)	(0.064)	(0.061)	(0.085)
Maternal education: secondary	-0.023	0.035	0.034	0.031	-0.058	-0.117*
	(0.070)	(0.130)	(0.080)	(0.076)	(0.061)	(0.067)
Child's ethnicity: Scheduled tribes	0.070	0.015	0.168	0.077	0.072	0.188
	(0.103)	(0.203)	(0.144)	(0.084)	(0.096)	(0.119)
Child's ethnicity: Backward castes	0.030	-0.024	-0.033	0.051	0.069	0.139
	(0.069)	(0.108)	(0.065)	(0.073)	(0.056)	(0.111)
Dummy for area of residence	0.004	0.146	0.002	0.014	-0.012	-0.030
	(0.083)	(0.144)	(0.097)	(0.083)	(0.064)	(0.109)
Dummy for the availability of sanitation	0.131	0.011	0.013	0.134	0.229***	0.260***
	(0.083)	(0.169)	(0.101)	(0.091)	(0.073)	(0.064)
Dummy for the availability of safe water	-0.117	-0.340	0.037	0.058	0.113	0.156
	(0.136)	(0.346)	(0.094)	(0.183)	(0.179)	(0.249)
Dummy for the availability of fuels for cooking	0.091	0.149	0.066	0.020	0.057	0.238***
	(0.066)	(0.142)	(0.075)	(0.075)	(0.064)	(0.074)
Observations	789	789	789	789	789	789
Pseudo R squared	0.559	0.3064	0.3645	0.3872	0.4031	0.3844

*** p<0.01, ** p<0.05, * p<0.1

Note: The table illustrates least square and quantile regression estimates of children's catch-up effect in malnutrition measured as HAZ. Robust standard errors are indicated in parentheses. Bootstrap standard error with 100 replications was employed with no difference in the coefficients exempt for larger standard error. The outcome variable HAZ stands for height-for-age z-score. The sample is split by gender and birth cohort. The reference category for Maternal education is mother has no level of education and for the child's ethnicity is Scheduled castes. The dummy variable for area of residence is rural or urban. All other dummy variables indicate either that the households have availability of sanitation, water and fuels for cooking or they don't

Table A.3: Heterogeneous effects for females - older cohort

Variables	(1) OLS	(2) 10%	(3) 25%	(4) 50%	(5) 75%	(6) 90%
HAZ (t-1)	0.783***	0.731***	0.822***	0.832***	0.838***	0.849***
	(0.035)	(0.053)	(0.028)	(0.028)	(0.031)	(0.074)
Sibling composition	0.003	-0.126*	-0.016	-0.055	0.065	0.004
	(0.061)	(0.072)	(0.067)	(0.067)	(0.093)	(0.143)
Wealth	0.222	0.446	0.263	-0.054	-0.458	0.065
	(0.338)	(0.418)	(0.288)	(0.304)	(0.381)	(0.667)
Maternal age at birth	-0.005	-0.012	-0.004	-0.008	-0.004	-0.007
	(0.005)	(0.009)	(0.005)	(0.006)	(0.007)	(0.012)
Maternal education: elementary	0.227***	0.079	0.160**	0.102	0.155	0.653***
	(0.083)	(0.094)	(0.073)	(0.073)	(0.131)	(0.200)
Maternal education: secondary	0.205**	-0.019	0.008	0.224***	0.259**	0.427
	(0.093)	(0.133)	(0.121)	(0.085)	(0.121)	(0.278)
Child's ethnicity: Scheduled tribes	0.001	0.069	-0.005	-0.034	0.034	0.026
	(0.096)	(0.152)	(0.119)	(0.113)	(0.196)	(0.265)
Child's ethnicity: Backward castes	0.020	0.063	0.004	0.072	0.058	0.022
	(0.075)	(0.097)	(0.060)	(0.060)	(0.136)	(0.171)
Dummy for area of residence	-0.168*	0.098	-0.129	-0.141	-0.268**	-0.556*
	(0.098)	(0.154)	(0.119)	(0.104)	(0.118)	(0.283)
Dummy for the availability of sanitation	-0.031	0.030	0.045	0.059	-0.070	-0.428*
	(0.100)	(0.118)	(0.099)	(0.107)	(0.113)	(0.252)
Dummy for the availability of safe water	0.008	0.172	-0.115	0.018	0.101	0.006
	(0.106)	(0.204)	(0.134)	(0.097)	(0.148)	(0.211)
Dummy for the availability of fuels for cooking	-0.280**	-0.198	-0.329**	-0.214**	-0.028	-0.255
	(0.122)	(0.167)	(0.143)	(0.105)	(0.160)	(0.233)
Observations	463	463	463	463	463	463
Pseudo R squared	0.649	0.431	0.485	0.486	0.449	0.405

*** p<0.01, ** p<0.05, * p<0.1

Note: The table illustrates least square and quantile regression estimates of children's catch-up effect in malnutrition measured as HAZ. Robust standard errors are indicated in parentheses. Bootstrap standard error with 100 replications was employed with no difference in the coefficients exempt for larger standard error. The outcome variable HAZ stands for height-for-age z-score. The sample is split by gender and birth cohort. The reference category for Maternal education is mother has no level of education and for the child's ethnicity is Scheduled castes. The dummy variable for area of residence is rural or urban. All other dummy variables indicate either that the households have availability of sanitation, water and fuels for cooking or they don't

Table A.4: Heterogeneous effects for males - older cohort

Variables	(1) OLS	(2) 10%	(3) 25%	(4) 50%	(5) 75%	(6) 90%
HAZ (t-1)	0.726***	0.677***	0.747***	0.840***	0.860***	0.824***
	(0.049)	(0.045)	(0.032)	(0.036)	(0.031)	(0.047)
Sibling composition	0.033	0.024	0.012	0.117	0.022	0.054
	(0.067)	(0.097)	(0.067)	(0.074)	(0.065)	(0.072)
Wealth	0.155	0.288	-0.103	-0.286	0.117	0.066
	(0.275)	(0.501)	(0.303)	(0.331)	(0.278)	(0.233)
Maternal age at birth	-0.005	-0.015*	-0.006	-0.005	0.001	0.011
	(0.007)	(0.008)	(0.007)	(0.007)	(0.005)	(0.011)
Maternal education: elementary	0.050	0.043	0.042	0.066	0.120	-0.040
	(0.083)	(0.098)	(0.092)	(0.094)	(0.084)	(0.076)
Maternal education: secondary	0.125	0.148	0.204*	0.049	0.150	0.018
	(0.094)	(0.134)	(0.109)	(0.104)	(0.114)	(0.121)
Child's ethnicity: Scheduled tribes	-0.205*	-0.319*	-0.334***	-0.234*	-0.059	-0.024
	(0.106)	(0.165)	(0.079)	(0.125)	(0.094)	(0.152)
Child's ethnicity: Backward castes	-0.124*	-0.403***	-0.226***	-0.065	-0.020	0.248***
	(0.075)	(0.102)	(0.076)	(0.079)	(0.076)	(0.077)
Dummy for area of residence	-0.084	0.063	-0.001	-0.094	-0.098	-0.316*
	(0.094)	(0.111)	(0.100)	(0.125)	(0.096)	(0.176)
Dummy for the availability of sanitation	0.045	0.291***	0.161	0.081	-0.083	-0.220
	(0.099)	(0.104)	(0.116)	(0.104)	(0.080)	(0.134)
Dummy for the availability of safe water	-0.013	-0.239	-0.069	0.105	0.219	0.060
	(0.109)	(0.193)	(0.087)	(0.097)	(0.175)	(0.159)
Dummy for the availability of fuels for cooking	0.122	0.066	0.193	0.192	0.063	0.215
	(0.118)	(0.178)	(0.145)	(0.151)	(0.118)	(0.180)
Observations	455	455	455	455	455	455
Pseudo R squared	0.553	0.349	0.374	0.376	0.387	0.381

*** p<0.01, ** p<0.05, * p<0.1

Note: The table illustrates least square and quantile regression estimates of children's catch-up effect in malnutrition measured as HAZ. Robust standard errors are indicated in parentheses. Bootstrap standard error with 100 replications was employed with no difference in the coefficients exempt for larger standard error. The outcome variable HAZ stands for height-for-age z-score. The sample is split by gender and birth cohort. The reference category for Maternal education is mother has no level of education and for the child's ethnicity is Scheduled caste. The dummy variable for area of residence is rural or urban. All other dummy variables indicate either that the households have availability of sanitation, water and fuels for cooking or they don't