THE EFFECT OF INFANT MALNUTRITION ON FUTURE LEARNING OUTCOMES OF CHILDREN IN DEVELOPING COUNTRIES

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ABSTRACT

Well-designed and scalable interventions are required to promote human development in vulnerable populations and break the intergenerational cycle of poverty. Infant malnutrition is a critical issue in developing countries. There is a growing literature that recognizes the adverse impact of malnutrition of children on their future health, educational and labor market outcomes. This paper explores the relationship between infant malnutrition and future schooling outcomes using data from the Young Lives Survey. Using this panel dataset, I track children throughout the first fifteen years of their life and analyze the effect of stunting on future educational achievement. It is important to note that both child malnutrition and future learning outcomes are endogenous variables and influenced by household investment decisions. In the absence of a robust instrumental variables approach, I use a different identification strategy to capture the effect of stunting. Focusing on firstborn Indian male children between the age of 1 and 15, who are known to be favored by parents, I find that children stunted in infancy score lower on reading, mathematics and vocabulary tests. From a policy perspective, my findings are a testimony for the importance of policy programs aimed at combatting malnutrition among children in developing countries.

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Introduction

According to the WHO, in 2017, there were 151 million children under the age of five that were stunted and 51 million children who were severely wasted (WHO, 2017). Besides aggravating child mortality and disease,' malnutrition erodes the very fundamentals of human capital formation: human livelihoods. In fact, child malnutrition is a serious policy challenge across developing countries. An increasing number of economists have started to argue that investing in early childhood nutrition has one of the highest returns in a developing country (Behrman J. , 1993). As we pour money into schools and the education sector, it might make sense to think about diverting some of these funds to addressing malnutrition.

This paper aims to explore the relationship between stunting in infancy and the effect this has on future learning outcomes. Inadequate nutrient intake in the first few years can affect the growth of organs such as the brain and reduce a child's capacity to learn (Birch, 1972). For instance, Liu, Raine, Venables, Dalais and Mednick (2014) find that malnutrition at age 3 years is associated with poor cognition at age 11 years independent of psychosocial adversity. For this reason, many scientists refer to the first 1000 days of life, which includes gestation and the first two years of life, as a critical window of opportunity (Martorell, 2017).

It stands to reason therefore that children who do not get adequate nutrition as an infant face learning challenges later on in life due to poor cognitive growth at this crucial stage. In fact, if the effect of infant malnutrition on future learning outcomes is substantial, it would imply that even if we were to have top-quality schools, learning outcomes would be constrained by infant malnutrition. In addition to my main hypothesis, I also wish to look at the likelihood of future school enrolment as a result of childhood malnutrition. I suspect that children with poor nutrition struggle at school due to the aforementioned reasons. Controlling for other factors, I believe this would make them less likely to be enrolled in school at an early age. Studies have shown that children are more likely to stay in school if they are learning well. This hypothesis is a simple extension of the first hypothesis.

By using the Young Lives dataset, I look at longitudinal data from four countries: Ethiopia, India, Vietnam and Ghana. Controlling for other factors, I find that stunting in infancy is correlated with lower test scores for reading, vocabulary and mathematics in primary school. Furthermore, by focusing on the first-born Indian males subsample I control for unobservable factors such as parental involvement and find that these results continue to remain significant. I also discover that stunted children are less likely to be tested at a later age, implying that they are more likely to have dropped out.

Background

It is widely understood that the process of human capital development starts very early in the life cycle and that the formative years after birth are crucially important (Cunha, Heckman, Lochner, & Masterov, 2006). Poor health in infancy can have a long-lasting impact on an individual's success in later life. It is crucial to consider policies that promote human capital development from very early on, and nutrition is one component that demands particularly close attention. Good nutrition is an essential component of infant health and is vital for growth and development.

The literal meaning of the word “malnutrition” is bad nutrition and is defined by the World Food Programme (WFP) as “a state in which the physical function of an individual is impaired to the point where he or she can no longer maintain adequate bodily performance process such as growth, pregnancy, lactation, physical work and resisting and recovering from disease.” (World Food

Programme, 2000) While technically the term includes both overnutrition and undernutrition, in the context of developing countries, undernutrition is generally the main issue of concern.

Opinions on what constitutes malnutrition—and recommendations for avoiding the problem—have been refined over time. Early studies considered lack of protein to be the most troubling deficiency in the diets of underfed children, especially in developing countries (Semba, 2016). Ingested protein is broken down into amino acids, which are then recycled to build the specific proteins needed by the individual at any given time. Proteins form many structural elements of the body and carry out most cellular processes. By the 1970s, though, investigators had begun to worry about calories as well (The Scientific American, 2015). When deprived of an adequate number of calories, the body breaks down amino acids for energy instead of using them to make new proteins. Proteins are the fundamental building blocks of the human body and when children do not get an adequate amount their growth is compromised. In more recent years, nutrition research has also focused on shortages of vitamins and minerals—particularly vitamin A, iodine and iron— which contribute to significant health problems (Semba, 2016).

Commonly used indicators for malnutrition are based on anthropometry, i.e. the measurement of body parameters to indicate nutritional status. Anthropometric information can be used to determine an individual's nutritional status compared with a reference mean. It also can be used to determine the prevalence of malnutrition in a surveyed population. In 2006 the World Health Organization published updated child growth standards for attained weight and height which are used to calculate malnutrition status (World Food Programme , 2005). A child's reached height (or weight) is standardized and compared to the WHO benchmark. A child is considered ‘stunted’ (too short for age) if their height is two standard deviations below the benchmark; similarly, if their weight is two standard deviations below the benchmark, they are considered ‘wasted’ (too light for age).

Factors that contribute to stunted growth and development include poor maternal health and nutrition, inadequate infant and young child feeding practices, and infection. For instance, if the mother has poor nutrition or health status before, during, or after pregnancy, this can influence her child's growth and development, beginning as early as in the womb. Similarly, wasting can be caused by an insufficient energy intake (e.g. caused by famine), nutrient losses due to infection, or a combination of low intake and high loss. These factors are often closely correlated with poverty: malnutrition is common in most developing countries. Stunting is indicative of long-term malnutrition and is the main indicator used in literature on the subject.

Literature Review

For many years, scientists had studied the connection between nutrition and intellectual development with reference to the first two years of a child’s life. This is because the majority of brain growth occurs during this period and many important neural connections are established (Gale, O’Callaghan, Godfrey, Law, & Martyn, 2004). It stands to reason, therefore, that inadequate nutrition during this critical period would inflict severe and lasting damage on an infant's cognitive development. However, in recent years, evidence suggests that brain growth continues much later into childhood and it is possible for catch-up growth to take place (Sowell, et al., 2004). Thus, the emphasis has shifted to adequate nutrition intake over a much longer period of a child’s life.

A lot of research has explored the learning outcomes of children and identified factors that play a role in determining these (Kasirye, 2009). The theoretical economic model of the behavior of schools specify a level of achievement, usually measured by students' test scores, as the typical output, and characteristics of the teaching and learning environment as typical inputs (Todd & Wolpin, 2003). We can aggregate "inputs" for this model into four categories: individual-level characteristics such as age or gender; household characteristics such as the parents' education or income; school-level factors such as class size or teacher qualifications; and finally, national level characteristics such as GDP per-capita and net spend on education (Kasirye, 2009).

Extensive literature reviews by Pollitt (Pollit, 1990) and Behrman (Behrman J. R., 1996) identify a significant positive association between child nutritional status and school performance. Children's performance on tests of cognitive function and educational achievement are also a strong indicator of long-term academic potential as well as future productivity. For example, Liddell and Rae showed that each additional standard deviation scored in Grade 1 exams resulted in children being 4.8 times as likely to reach Grade 7 without repeating a year of schooling (Liddel & Rae, 2001). Similarly, a study of wages in South Africa finds that an increase of 1 standard deviation in literacy and numeracy scores were associated with a 35% increase in wages (Moll, 1998). According to the WHO, a 1% loss in adult height as a result of childhood stunting is associated with a 1.4 percent loss in productivity (WHO, 2014).

However, Behrman et al. (1996) note that although there is a strong association between proper nutrition and learning outcomes, this does not imply causality as both variables are endogenous. One source of the endogeneity is unobserved individual effects that create a correlation between child nutrition and the error term in regression analyses. Furthermore, both childhood nutrition and learning outcomes are not randomly assigned, but in fact, influenced by human investment decisions. Education and nutrition in childhood can both be considered goods which a household consumes and subject to a household budget constraint. Family members, in particular, the head of the household, usually determine the optimum amount of consumption and this amount is subject to unobserved preferences and tastes. These unobserved characteristics are the main factors causing the endogeneity of child health in schooling performance analysis. For example, parents may choose to provide the eldest son with better nutrition as a baby and also provide him better educational opportunities in subsequent years. Thus, the effect we would be captured in our standard regression would be biased by parental preferences.

Alderman et al. (2009) recommend the use of an instrumental variables approach such as using price shocks during the infancy of a child to account for stunting status. Similarly, Glewwe and King (2001) use prices for four commodities reported every six months as well as rainfall as identifying instruments. The exogenous variation captured by these instrument account for the endogeneity between a child's health and schooling opportunities arising out of household resource allocation. Studies using this instrumental variable approach report that the relationship between child health and subsequent schooling is actually much larger than those implied by naive estimates that do not account for behavioral choices (Alderman, Hoogeveen, & Rossi, 2009).

The returns on investing in nutrition are substantial. In an analysis of cohorts across 17 countries, Hoddinott et al (2013) find the benefits to cost ratio of nutrition interventions range from 3.5 to 40 dollars returned on every dollar spent. The variations depend on the country's current level of income, projected growth rate, the current rate of stunting, and other parameters. Another study by Alderman et al (2017) finds the economic value of reducing undernutrition to be substantial even if we make low-return assumptions and use a small discount rate. According to the World Bank malnutrition can cause a loss of 2-3 percent to the gross domestic product (GDP) of a country (World Bank, 2006).

Empirical Approach and Results

Overview

In this section go through my conceptual approach and discuss my empirical results. Using data from the Young Lives Survey I explore the effect of stunting in infancy on test scores of children in later years. I first present my empirical model and discuss the variables I have used. After discussing how the independent and dependent variable are measured, I also go through the control variables and justify their inclusion in the model. I then present the results of my regressions on the total sample and follow this up with robustness checks.

Empirical Model

The basic empirical model is as follows:

$$Y_i = \alpha + \rho Stunted + \delta X_i + \lambda + \eta + \varepsilon$$

Y_i is the test score for child i for a given subject and round, α is a constant and ρ is our coefficient of interest on an indicator variable for stunted infants. X_i is a vector of our control variables, with λ and η representing country and community fixed effects respectively. Our error term is represented by ε.

If the effect of stunting is significant, we expect ρ to be negative and have a small p-value in our regressions. I run a pooled regression which aggregates the test score for a subject across all four countries for a single round.[1] The dataset reports anthropometric measures at age one (from Round

[1] Appendix 2 contains the results for separate country-wise regressions

1), and cognition tests score of the same children at ages five (Round 2), eight (Round 3), eleven (Round 4) and fifteen (Round 5), which are the main variables I use in the analysis.

For my dependent variable, I will use the anthropometric measures collected by the Young Lives team to create an indicator variable for "stunted" children. This is the accepted practice in studies related to malnutrition and uses a child's measured height to calculate stunting rate. The measured height is standardized using the World Health Organization's (WHO) universal growth standards for children aged five years, which is based on the median of the gender- and age-specific reference population. A child is considered stunted if he or she lies two standard deviations below the standard reference population i.e. has a z-score of −2 or lower (WHO, 2006). The dataset contains height-for-age measures as continuous standardized scores ranging from -6 to +6. I will create an indicator variable for stunted children which will take a value of 1 if the child has a standardized score lower than −2. The coefficient of interest will be on these indicator variables.

For my controls, I will use characteristics at the individual and household levels consistent with the literature on the learning outcomes. As previously mention I will also include community and country fixed effects in the model to account for heterogeneity. The control variables have been grouped as follows:

- Individual:
    - Gender of a child
    - Indicator for serious illness as an infant
    - Indicator for birth in hospital or health facility

- Household:
    - Years of education received by a caregiver
    - Wealth Index in Round 1 of the survey
    - Wealth Index in the current round of the survey
    - Number of Members
    - Years lived in the community
    - Indicator for Urban Household
    - Indicator for whether household faced a serious shock when child was infant

For my independent variable, I use reported test scores. The team designed separate cognition tests and used these to measure numeracy and literacy of the children. The tests include a Peabody Picture Vocabulary Test, a Mathematics test and a Reading comprehension test (Young Lives, 2017). Details of these tests and the methodology behind their design have been covered by the Young Lives team. The dataset contains both raw scores as well as measures of correct answers. I used the standardized scores for each test and ran a separate regression for each subject in order to be able to make effective comparisons. It should be noted that for Rounds 2 and 3 the standardized score is reported in a Rasch form whereas for Rounds 4 and 5 it is reported as a percentage. Thus, we cannot compare the coefficient on test scores across rounds with different standardization techniques.

Data Description and Descriptive Statistics

To carry out the analysis, this paper uses data from the Young Lives Survey. The Young Lives survey is a longitudinal study that is tracing the changing lives of 12,000 children in Ethiopia, India, Peru, and Vietnam over a 15-year period. It aims to shed light on the drivers and impacts of child poverty and generate evidence to help policymakers design programs that make a real difference to poor children and their families (Young Lives, 2017).

As part of this study, the Young Lives team has collected at the household level for each child as well as each community these households belong to (a total of 20 communities were selected in each country). As a result, the final dataset is rich and contains information on household composition; maternal and infant health; child-care and health, household income and livelihoods; socioeconomic status and so on. It also contains community level data on the physical and social environment, and the facilities available to the inhabitants of each region (Young Lives, 2017). The descriptions of the variables that have been used for the analytical model in this paper are presented in Appendix A. The descriptive statistics are presented in Appendix B.

Empirical Results

The main results are reported in Tables 1-4 on the following pages, with each table corresponding to results from a different round of the Young Lives survey. This allows us to see the effects of stunting in Round 1 on cognitive test scores in subsequent rounds.

My single variable OLS regression estimates show a negative effect of stunting as an infant on future test scores, in accordance with other studies done on the subject (Pollit, 1990). However, regressing test scores on only a childhood stunting lead to omitted variable bias as there are a lot of factors correlated with child malnutrition and these are present in the error term. To account for this, we control for factors at the individual child and household level as previously discussed. We also add in community and country fixed effects to account for heterogeneity among the different areas where the survey was carried out.

After running our full OLS model with controls and fixed effects, we see that the effect of stunting on future test scores remains significant though it is diminished. The lowering of the coefficient confirms that omitted variable bias was occurring in the single variable model. The effect seems to diminish during later rounds of the survey, whereby the standard errors are getting larger. Although this seems to indicate that the effect of infant malnutrition on learning is greater when a child is younger and diminishes with time, it is likely the result of selection bias occurring.

Although the attrition rate of the Young Lives survey is low (Young Lives, 2017), there is still a risk of selection bias occurring. Malnourished children are often from poorer households, and these children are also more likely to drop out of the survey process in subsequent rounds. Even if these children did not drop out, there is still a likelihood that these children might not be tested for other reasons. To check for this, I ran a logistical model which predicted the probability of not being tested on stunting in Round 1. The results are indicated in Appendix D and suggest that stunted infants are less likely to be tested in future rounds and this result holds at the 1% level. This helps explain why the magnitude of the coefficient on our dependent variable falls in later rounds.

Appendix C contains results from separate regressions run for each country. The results indicate that stunting is a stronger factor in determining test outcomes in India as compared to other countries. Stunting rates in our sample are higher for India and Ethiopia as compared to Vietnam and Peru, and it would follow that malnutrition has a greater impact on the test scores in these two countries. However, the test scores in the sample are lower for Ethiopian students on average, indicating that learning outcomes are poorer in that country. This is in line with other studies on the topic with Indian students performing better on cognitive testing (Iyer, 2017). In Ethiopia, the weaker schooling system and infrastructure mean that test scores are lower on the whole, whereas India has a relatively better educational infrastructure and a high rate of stunting. Thus, we see a larger impact of stunting on the Indian children in the Young Lives sample.

Table 1: Pooled OLS Estimates for Round 2

	(1)	(2)	(3)	(4)
	Round 2 Reading	Round 2 Vocabulary	Round 2 Reading	Round 2 Vocabulary
Stunted in Round 1	-10.75***	-17.00***	-4.543***	-6.451***
	(1.303)	(1.477)	(1.318)	(1.327)
Individual Controls	-	-	Yes	Yes
Household Controls	-	-	Yes	Yes
Community Fixed Effects	-	-	Yes	Yes
Country Fixed Effects	-	-	Yes	Yes
Observations	7,030	5,710	6,823	5,566
R-squared	0.010	0.023	0.166	0.341

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.10

Table 2: Pooled OLS Estimates for Round 3

	(1)	(2)	(3)	(4)	(5)	(6)
	Round 3 Reading	Round 3 Vocabulary	Round 3 Maths	Round 3 Reading	Round 3 Vocabulary	Round 3 Maths
Stunted in Round 1	-4.821***	-5.796***	-6.239***	-2.593***	-2.702***	-3.528***
	(0.394)	(0.364)	(0.375)	(0.405)	(0.344)	(0.354)
Individual Controls	-	-	-	Yes	Yes	Yes
Household Controls	-	-	-	Yes	Yes	Yes
Community Fixed Effects	-	-	-	Yes	Yes	Yes
Country Fixed Effects	-	-	-	Yes	Yes	Yes
Observations	6,916	5,810	7,383	6,678	5,636	7,122
R-squared	0.021	0.042	0.036	0.156	0.364	0.291

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.10

Table 3: Pooled OLS Estimates for Round 4

	(1) Round 4 Reading	(2) Round 4 Vocabulary	(3) Round 4 Maths	(4) Round 4 Reading	(5) Round 4 Vocabulary	(6) Round 4 Maths
Stunted in Round 1	-7.964***	-6.462***	-8.668***	-2.078***	-2.577***	-2.867***
	(0.527)	(0.357)	(0.542)	(0.429)	(0.333)	(0.506)
Individual Controls	-	-	-	Yes	Yes	Yes
Household Controls	-	-	-	Yes	Yes	Yes
Community Fixed Effects	-	-	-	Yes	Yes	Yes
Country Fixed Effects	-	-	-	Yes	Yes	Yes
Observations	7,029	7,198	7,093	6,822	6,988	6,875
R-squared	0.031	0.044	0.035	0.465	0.345	0.305

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.10

Table 4: Pooled OLS Estimates for Round 5

	(1) Round 5 Reading	(2) Round 5 Vocabulary	(3) Round 5 Maths	(4) Round 5 Reading	(5) Round 5 Vocabulary	(6) Round 5 Maths
Stunted in Round 1	-6.121***	-5.131***	-7.413***	-0.902	-1.779***	-1.868***
	(0.679)	(0.424)	(0.472)	(0.648)	(0.393)	(0.438)
Individual Controls	-	-	-	Yes	Yes	Yes
Household Controls	-	-	-	Yes	Yes	Yes
Community Fixed Effects	-	-	-	Yes	Yes	Yes
Country Fixed Effects	-	-	-	Yes	Yes	Yes
Observations	3,407	5,221	7,168	3,230	5,002	6,944
R-squared	0.023	0.027	0.033	0.331	0.297	0.288

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.10

Robustness Checks

There is an endogeneity problem with respect to the dependent and independent variable in our model as previously discussed. One source of the endogeneity is unobserved individual effects that create a correlation between child nutrition and the error term in regression analyses. To deal with this issue, we can use an instrumental variables approach.

Unfortunately, despite testing multiple candidates, I could not find an adequate instrument to control for the endogeneity in the model. The literature on the subject makes use of instruments such as maternal height, the occurrence of natural disasters and rainfall data to predict stunting rates among children. The Young Lives dataset contains data on both maternal height as well as natural disasters occurring during pregnancy and the first year of the index child collected in Round 1. However, the former is correlated with our dependent variable, test scores, whereas the disaster data does not accurately predict stunting in the first stage of our IV regression with an F-value of 2.02. I also attempted to create composite variables by interacting variables such as maternal height and years of school education; however, this instrument was also weak and under-identified. (see, Table D1).

Another approach to deal with the bias introduced by parental preferences is to focus on the Indian subsample. Various studies have documented favoritism toward first-born male children in India. Jayachandran and Pande have explored the prevalence of stunting in India and noted that the height disadvantage increases sharply with birth order (Jayachandran & Pande, 2017). By subsampling the India data and limiting our analysis to first-born male children, we can remove the bias introduced by parental investment decisions. There is a large body of evidence indicating that first-born male children are allocated greater household resources, and this means on average we can assume that the eldest son’s nutrition status is not subject to parental choice in the same way as it is for other children.

By subsampling the India data and limiting our analysis to first-born male children, we can remove the bias introduced by parental investment decisions. There is a large body of evidence indicating that first-born male children are allocated greater household resources, and this means on average we can assume that the eldest son's nutrition status is not subject to parental choice in the same way as it is for other children.

By narrowing our focus to India, I was also able to introduce some additional controls to account for other factors that could influence testing outcomes. In addition to the controls used in the cross-country model, the following OLS estimates also include controls for caste status, the mother tongue of the child and language in which he or she was tested. This allows us to overlook any bias that might arise due to language barriers during testing. In Rounds 4 and 5 I also control for whether the child goes to a public or private school, which has been shown to influence learning outcomes in children.

Employing this approach, we see that most of our results continue to remain significant and the results are presented in Tables 5-8 on the following pages. The coefficients are smaller as compared to the whole country sample, which indicates the effect of parental investment decisions. As we know that first-born Indian males are favored by parents and are prioritized when there is limited food and get better educational opportunities. The subsample controls for these unobserved factors and this leads to a shrinking of the coefficients (Andrabi, Das, Khwaja, Zajonc, & Vishwanath, 2009).

Table 5: OLS Estimates using first-born Indian males subsample for Round 2

	(1) Round 2 Reading	(2) Round 2 Vocabulary	(3) Round 2 Reading	(4) Round 2 Vocabulary
Stunted in Round 1	-15.21***	-11.05**	-11.85***	-7.819*
	(4.310)	(4.706)	(4.329)	(4.164)
Individual Controls	-	-	Yes	Yes
Household Controls	-	-	Yes	Yes
Community Fixed Effects	-	-	Yes	Yes
Observations	543	497	524	484
R-squared	0.022	0.011	0.256	0.400

Standard errors in parentheses

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

Table 6: OLS Estimates using first-born Indian males subsample for Round 3

	(1)	(2)	(3)	(4)	(5)	(6)
	Round 3 Reading	Round 3 Vocabulary	Round 3 Maths	Round 3 Reading	Round 3 Vocabulary	Round 3 Maths
Stunted in Round 1	-4.808***	-4.992***	-5.420***	-2.542**	-1.844	-2.917**
	(1.292)	(1.465)	(1.291)	(1.224)	(1.382)	(1.202)
Individual Controls	-	-	-	Yes	Yes	Yes
Household Controls	-	-	-	Yes	Yes	Yes
Community Fixed Effects	-	-	-	Yes	Yes	Yes
Observations	552	440	559	537	429	543
R-squared	0.025	0.026	0.031	0.309	0.397	0.376

Standard errors in parentheses

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

Table 7: OLS Estimates using first-born Indian males subsample for Round 4

	(1)	(2)	(3)	(4)	(5)	(6)
	Round 4 Reading	Round 4 Vocabulary	Round 4 Maths	Round 4 Reading	Round 4 Vocabulary	Round 4 Maths
Stunted in Round 1	-5.988***	-4.489***	-5.484***	-2.917**	-1.970*	-0.541
	(1.600)	(1.092)	(2.006)	(1.484)	(1.079)	(1.946)
Individual Controls	-	-	-	Yes	Yes	Yes
Household Controls	-	-	-	Yes	Yes	Yes
Community Fixed Effects	-	-	-	Yes	Yes	Yes
Observations	549	560	552	527	530	528
R-squared	0.004	0.029	0.013	0.186	0.223	0.248

Standard errors in parentheses

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

Table 8: OLS Estimates using first-born Indian males subsample for Round 5

	(1)	(2)	(3)	(4)
	Round 5 Reading	Round 5 Maths	Round 5 Reading	Round 5 Maths
Stunted in Round 1	-3.661*	-4.218***	-3.092*	-2.369
	(1.515)	(1.556)	(1.640)	(1.528)
Individual Controls	-	-	Yes	Yes
Household Controls	-	-	Yes	Yes
Community Fixed Effects	-	-	Yes	Yes
Observations	547	547	541	531
R-squared	0.005	0.011	0.203	0.287

Standard errors in parentheses

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

Limitations and Inferential Challenges

One of the main challenges in establishing a link between infant malnutrition and future learning outcomes is to account for possible correlations between the observed indicators and unobserved variables such as parental involvement. As our model is endogenous there is always a risk that the effect we are capturing as the effect of an observed variables, is in fact due some unobserved factor. The ideal solution to this would have been to find an effective instrument, but unfortunately that was not possible with this data. As an alternative this paper looked at a subsample of first-born Indian males to account for parental involvement. While there is substantial evidence that first-born Indian males are favored by parents, subsampling leads to a much smaller pool of observations. Moreover, this approach does not account for other sources of endogeneity in our model apart from parental preferences. There might be other unobserved factors that affect household decisions that are not accounted for by this approach.

Measurement error is another concern for our results. Stunting is the most widely used predictor of malnutrition and is based on the height of children. To get accurate stunting figures, it is essential for height measurements to be accurate and precise. However, in practice, this can often be a difficult task due to lack of equipment or maintenance of available ones, the feasibility of implementation and training of personnel. These factors can lead to measurement error occurring in practice which can contribute to a downward bias in our estimates.

Conclusions

Malnutrition is a serious issue in developing countries. Lack of nourishment compromises both physical and mental growth in children and undermines an individual's productivity in later life. This paper explores the effect of infant malnutrition on future learning outcomes and finds that stunted infants score lower in cognitive tests at later stages of their lives. These effects are also significant in the case of children who benefit from parental investment decisions such as first-born Indian sons. My research indicates that stunted children are at a significant disadvantage in their educational opportunities and have poorer learning outcomes.

This paper also contributes to the growing body of evidence which suggests that better health and nutrition may pay off in terms of economic growth and help improve educational performance of poor people in the developing world. Policymakers, therefore, should seriously consider how various policies affect child health and nutrition and identify those policy changes that would improve it. Targeted nutrition programs will help improve the physical work capacity, cognitive development, school performance, and health of poor people across the world. Not only will this contribute to economic development but also help reduce inequality as the effects of malnutrition are borne disproportionately by the poorest of the poor.

Appendix A: Description of Variables

Table A1: Description of variables used from Young Lives Survey Round 1

Variable Name	**Description**
Height for age	The height-for-age z-score for the child calculated using WHO standards
Stunted (%)	Percentage of children with a z-score with less than -2
Male (%)	Percentage of children who are male
Mother's Education (Years)	Years of education received by the mother of the child
Wealth Index	This value is calculated as the average of the Housing Quality Index, the Consumer Durables Index and the Services Index.
Consumer Durables Index	This value is based on the number of assets owned by the household. A typical set of assets is considered – productive assets (e.g., sewing machines) are not included in this calculation. For each asset owned by the household, a 1 is added to the index; the result is then divided by total categories of assets to give a value between 0 and 1.
Housing Quality Index	This value is based on the number of rooms per person in the household and the main materials used for the walls, roof, and floor. The number of rooms is divided by the size of the household. This result is divided by 1.5 to allow for rooms such as kitchens and bathrooms not used for general living. If the result of this calculation is greater than 1, it is set to 1. If the walls are made of brick or concrete, then 1 is added to the index. If the roof is made of iron, concrete, tiles or slate, then 1 is added to the index. If the floor is made of cement or is tiled or laminated, then 1 is added to the index. This gives a value between 0 and 4 which is then divided by 4 to give a housing quality index of between 0 and 1.

Variable Name	Description
Height for age	The height-for-age z-score for the child calculated using WHO standards
Housing Services Index	This value is based on whether or not the dwelling has electricity, the source of drinking water, type of toilet facility and the main type of fuel used for cooking. If the dwelling has electricity, then 1 is added to the index. If drinking water is piped into the dwelling or the yard, then 1 is added. If the household has their own toilet facility (not shared with other households), then 1 is added and if paraffin, kerosene, gas or electricity is used for cooking another 1 is added. The result is then divided by 4 to give a value between 0 and 1.
Household Size	Number of people living in the household
Unplanned pregnancy	When you became pregnant with the index child, did you want to become pregnant at that time?
Delivery at Health Facility	Was the child delivered at a health facility or not?
Serious illness or injury	Has the child ever had a serious illness or injury where you really thought they might die?
Long Term Health Condition	Does the child have any long-term health problems?
Bad Event	Since the mother was pregnant with this child has the household experienced an event which decreased food availability?

Table A2: Description of variables used from Young Lives Survey Rounds 2 and 3

Variable Name	**Description**
Math Rasch Score	Rasch score on Mathematics test
Vocabulary Rasch Score	Rasch score on Peabody Vocabulary test
Reading Rasch Score	Rasch score on Reading test
Stunted (%)	Percentage of children with a z-score with less than -2
Wealth Index	This value is calculated as the average of the Housing Quality Index, the Consumer Durables Index and the Services Index.
Attended Preschool	Has the child attended any preschool?
Started School	Has the child formally started his or her schooling?

Table A3: Description of variables used from Young Lives Survey Rounds 4 and 5

Variable Name	**Description**
Math Score (%)	Percentage of correct answers on Mathematics test
Vocabulary Score (%)	Percentage of correct answers on Peabody Vocabulary test
Reading Score (%)	Percentage of correct answers on Reading test
Stunted (%)	Percentage of children with a z-score with less than -2
Wealth Index	This value is calculated as the average of the Housing Quality Index, the Consumer Durables Index and the Services Index.

Appendix B: Summary Statistics

Table B1: Descriptive statistics of variables used from Young Lives Survey Round 1

	Ethiopia	India	Peru	Vietnam
N	1917	1970	2035	1983
Age (Months)	11.65 (3.55)	11.77 (3.48)	11.54 (3.54)	11.64 (3.16)
Height for age	-1.53 (1.85)	-1.30 (1.48)	-1.30 (1.30)	-1.12 (1.26)
Stunted (%)	42.0	30.7	28.4	20.8
Male	52.3	53.6	50.0	51.2
Mother's Education (Years)	2.43 (3.59)	3.33 (4.47)	7.70 (4.37)	6.46 (3.52)
Wealth Index	0.21 (0.18)	0.41 (0.20)	0.41 (0.20)	0.44 (0.22)
Household Size	5.71 (2.16)	5.42 (2.37)	5.71 (2.34)	4.89 (1.83)
Wanted Index Child (%)	63.7	91.9	54.1	82.6
Birth in Health Facility (%)	17.2	49.7	67.9	78.4
Years lived in community	15.36 (10.54)	9.10 (7.69)	15.83 (11.12)	17.42 (11.52)
Serious Illness as an infant (%)	30.7	22.2	32.0	12.9

Table B2: Descriptive statistics of variables used from Young Lives Survey Round 2

	Ethiopia	India	Peru	Vietnam
N	1912	1950	2032	1970
Age (months)	61.86 (3.85)	64.27333 3.889001	63.47988 4.701809	63.05533 3.745793
Vocabulary Rasch Score	299.67 (49.90)	300.27 (49.75)	299.98 (49.86)	300.01 (49.97)
Reading Rasch Score	298.88 (49.40)	300.54 (50.18)	300.05 (50.03)	300.05 (50.05)
Attended preschool (%)	24.1	86.9	83.5	90.5
Started school (%)	3.7	44.4	9.3	7.3

Table B3: Descriptive statistics of variables used from Young Lives Survey Round 3

Round 3				
	Ethiopia	India	Peru	Vietnam
N	1885	1931	1943	1964
Age (months)	97.49 (4.05)	95.41067 3.835297	95.43134 3.603272	96.56279 3.776313
Math Rasch Score	299.80 (14.97)	300.27 (14.90)	300.01 (14.92)	300.06 (14.86)
Vocabulary Rasch Score	304.06 (12.34)	300.20 (15.01)	304.56 (11.55)	303.51 (11.13)
Reading Rasch Score	299.75 (14.84)	300.24 (14.97)	299.92 (14.98)	300.03 (14.92)

Table B4: Descriptive statistics of variables used from Young Lives Survey Round 4

Round 4				
	Ethiopia	India	Peru	Vietnam
N	1872	1915	1902	1929
Age (months)	145.49 (3.90)	143.8 (3.81)	143.01 (3.74)	146.37 (3.72)
Math Score (%)	37.45 (21.62)	44.38 (22.64)	55.61 (18.93)	47.85 (16.76)
Vocabulary Score (%)	69.71 (15.87)	75.80 (13.56)	68.50 (14.10)	76.68 (11.01)
Reading Score (%)	27.88 (15.20)	55.95 (18.76)	60.07 (14.89)	49.33 (16.94)

Table B5: Descriptive statistics of variables used from Young Lives Survey Round 5

Round 5				
	Ethiopia	India	Peru	Vietnam
N	1812	1905	1860	1941
Age (months)	181.02 (3.73)	180.00 (3.78)	179.24 (3.76)	182.41 (3.64)
Math Score (%)	29.85 (15.04)	33.39 (16.56)	36.21 (15.89)	46.34 (21.31)
Vocabulary Score (%)	75.32 (15.02)	83.24 (13.76)	77.11 (13.76)	-
Reading Score (%)	51.53 (21.23)	-	62.69 (14.75)	-

Appendix C: Country-wise OLS Estimates

Ethiopia:

Table C1: OLS Estimates using Ethiopia subsample for Round 2

	(1)	(2)
	Round 2 Reading	Round 2 Vocabulary
Stunting in Round 1	-2.238	-3.974
	(2.629)	(3.082)
Individual Controls	Yes	Yes
Household Controls	Yes	Yes
Community Fixed Effects	Yes	Yes
Observations	1,346	735
R-squared	0.271	0.440

Robust standard errors in parentheses

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

Table C2: OLS Estimates using Ethiopia subsample for Round 3

	(1) Round 3 Reading	(2) Round 3 Vocabulary	(3) Round 3 Maths
Stunting in Round 1	-1.282	-1.153	-1.846***
	(0.793)	(0.701)	(0.596)
Individual Controls	Yes	Yes	Yes
Household Controls	Yes	Yes	Yes
Community Fixed Effects	Yes	Yes	Yes
Observations	1,325	684	1,599
R-squared	0.256	0.575	0.502

Robust standard errors in parentheses

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

Table C3: OLS Estimates using Ethiopia subsample for Round 4

	(1) Round 4 Reading	(2) Round 4 Vocabulary	(3) Round 4 Maths
Stunting in Round 1	-1.596**	-0.908	-1.805*
	(0.735)	(0.628)	(1.040)
Individual Controls	Yes	Yes	Yes
Household Controls	Yes	Yes	Yes
Community Fixed Effects	Yes	Yes	Yes
Observations	1,379	1,450	1,428
R-squared	0.381	0.549	0.359

Robust standard errors in parentheses

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

Table C4: OLS Estimates using Ethiopia subsample for Round 5

	(1)	(2)	(3)
	Round 5 Reading	Round 5 Vocabulary	Round 5 Maths
Stunting in Round 1	-0.467	-1.722***	-1.182*
	(0.946)	(0.626)	(0.687)
Individual Controls	Yes	Yes	Yes
Household Controls	Yes	Yes	Yes
Community Fixed Effects	Yes	Yes	Yes
Observations	1,481	1,426	1,509
R-squared	0.409	0.501	0.361

Robust standard errors in parentheses

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

India:

Table C5: OLS Estimates using India subsample for Round 2

	(1)	(2)
	Round 2 Reading	Round 2 Vocabulary
Stunting in Round 1	-9.823***	-9.155***
	(2.425)	(2.271)
Individual Controls	Yes	Yes
Household Controls	Yes	Yes
Community Fixed Effects	Yes	Yes
	(20.98)	(32.49)
Observations	1,767	1,594
R-squared	0.203	0.390

Robust standard errors in parentheses

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

Table C6: OLS Estimates using India subsample for Round 3

	(1)	(2)	(3)
	Round 3 Reading	Round 3 Vocabulary	Round 3 Maths
Stunting in Round 1	-1.967***	-3.371***	-3.664***
	(0.705)	(0.726)	(0.674)
Individual Controls	Yes	Yes	Yes
Household Controls	Yes	Yes	Yes
Community Fixed Effects	Yes	Yes	Yes
Observations	1,794	1,515	1,822
R-squared	0.267	0.347	0.361

Robust standard errors in parentheses

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

Table C7: OLS Estimates using India subsample for Round 4

	(1)	(2)	(3)
	Round 4 Reading	Round 4 Vocabulary	Round 4 Maths
Stunted in Round 1	-3.054***	-2.783***	-3.822***
	(0.955)	(0.663)	(1.084)
Individual Controls	Yes	Yes	Yes
Household Controls	Yes	Yes	Yes
Community Fixed Effects	Yes	Yes	Yes
Observations	1,781	1,821	1,778
R-squared	0.212	0.252	0.282

Robust standard errors in parentheses

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

Table C8: OLS Estimates using India subsample for Round 5

	(1)	(2)
	Round 5 Vocabulary	Round 5 Maths
Stunted in Round 1	-1.155*	-1.893**
	(0.685)	(0.786)
Individual Controls	Yes	Yes
Household Controls	Yes	Yes
Community Fixed Effects	Yes	Yes
Observations	1,809	1,762
R-squared	0.158	0.261

Robust standard errors in parentheses

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

Peru:

Table C9: OLS Estimates using Peru subsample for Round 2

	(1)	(2)
	Round 2 Reading	Round 2 Vocabulary
Stunting in Round 1	-2.656	-3.567
	(2.732)	(2.255)
Individual Controls	Yes	Yes
Household Controls	Yes	Yes
Community Fixed Effects	Yes	Yes
Observations	1,907	1,651
R-squared	0.223	0.565

Robust standard errors in parentheses

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

Table C10: OLS Estimates using Peru subsample for Round 3

	(1) Round 3 Reading	(2) Round 3 Vocabulary	(3) Round 3 Maths
Stunting in Round 1	-2.337***	-2.353***	-2.441***
	(0.850)	(0.593)	(0.741)
Individual Controls	Yes	Yes	Yes
Household Controls	Yes	Yes	Yes
Community Fixed Effects	Yes	Yes	Yes
Observations	1,680	1,652	1,817
R-squared	0.220	0.451	0.365

Robust standard errors in parentheses

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

Table C11: OLS Estimates using Peru subsample for Round 4

	(1)	(2)	(3)
	Round 4 Reading	Round 4 Vocabulary	Round 4 Maths
Stunting in Round 1	-2.360***	-2.573***	-2.054**
	(0.786)	(0.640)	(0.982)
Individual Controls	Yes	Yes	Yes
Household Controls	Yes	Yes	Yes
Community Fixed Effects	Yes	Yes	Yes
Observations	1,804	1,808	1,804
R-squared	0.301	0.437	0.287

Robust standard errors in parentheses

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

Table C12: OLS Estimates using Peru subsample for Round 5

	(1)	(2)	(3)
	Round 5 Reading	Round 5 Vocabulary	Round 5 Maths
Stunting in Round 1	-1.772**	-0.931	-2.147**
	(0.851)	(0.688)	(0.873)
Individual Controls	Yes	Yes	Yes
Household Controls	Yes	Yes	Yes
Community Fixed Effects	Yes	Yes	Yes
Observations	1,731	1,745	1,779
R-squared	0.228	0.361	0.236

Robust standard errors in parentheses

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

Vietnam:

Table C13: OLS Estimates using Vietnam subsample for Round 2

	(1) Round 2 Reading	(2) Round 2 Vocabulary
Stunting in Round 1	-2.019	-7.222***
	(2.673)	(2.477)
Individual Controls	Yes	Yes
Household Controls	Yes	Yes
Community Fixed Effects	Yes	Yes
Observations	1,803	1,586
R-squared	0.290	0.445

Robust standard errors in parentheses

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

Table C14: OLS Estimates using Vietnam subsample for Round 3

	(1)	(2)	(3)
	Round 3 Reading	Round 3 Vocabulary	Round 3 Maths
Stunting in Round 1	-2.073**	-1.330**	-4.215***
	(0.834)	(0.551)	(0.733)
Individual Controls	Yes	Yes	Yes
Household Controls	Yes	Yes	Yes
Community Fixed Effects	Yes	Yes	Yes
Observations	1,852	1,760	1,857
R-squared	0.289	0.450	0.394

Robust standard errors in parentheses

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

Table C15: OLS Estimates using Vietnam subsample for Round 4

	(1)	(2)	(3)
	Round 4 Reading	Round 4 Vocabulary	Round 4 Maths
Stunting in Round 1	-0.797	-1.964***	-3.309***
	(0.922)	(0.625)	(0.861)
Individual Controls	Yes	Yes	Yes
Household Controls	Yes	Yes	Yes
Community Fixed Effects	Yes	Yes	Yes
Observations	1,826	1,877	1,834
R-squared	0.259	0.319	0.331

Robust standard errors in parentheses

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

Table C16: OLS Estimates using Vietnam subsample for Round 5

	(1)
	Round 5 Maths
Stunting in Round 1	-0.964
	(1.200)
Observations	1,860
Individual Controls	Yes
Household Controls	Yes
Community Fixed Effects	Yes
R-squared	0.269

Robust standard errors in parentheses

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

Appendix D: Testing Selection Bias on Stunted Kids

Table D1: Logistical Model estimates for probability of child not being tested in Round 2 on infant stunting indicator

	Not tested for Reading Round 2	Not tested for Vocabulary Round 2
Stunting in Round 1	0.433***	0.629***
	(0.0741)	(0.0528)
Observations	7,905	7,905

Robust standard errors in parentheses

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

Table D2: Logistical Model estimates for probability of child not being tested in Round 3 on infant stunting indicator

	Not tested for Reading Round 3	Not tested for Vocabulary Round 3	Not tested for Maths Round 3
Stunting in Round 1	0.605***	0.440***	0.570***
	(0.0696)	(0.0538)	(0.0921)
Observations	7,905	7,905	7,905

Robust standard errors in parentheses

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

Table D3: Logistical Model estimates for probability of child not being tested in Round 4 on infant stunting indicator

	(1)	(2)	(3)
	Not tested for Reading Round 4	Not tested for Vocabulary Round 4	Not tested for Maths Round 4
Stunting in Round 1	0.604***	0.445***	0.588***
	(0.0732)	(0.0812)	(0.0757)
Observations	7,905	7,905	7,905

Robust standard errors in parentheses

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

Table D4: Logistical Model estimates for probability of child not being tested in Round 5 on infant stunting indicator

	(1)	(2)	(3)
	Not tested for Reading Round 5	Not tested for Vocabulary Round 5	Not tested for Maths Round 5
Stunting in Round 1	-0.242***	-0.314***	0.517***
	(0.0492)	(0.0530)	(0.0793)
Observations	7,905	7,905	7,905

Robust standard errors in parentheses

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

Appendix E: Instrumental Variables Approach

Table E1: Summary results for first-stage regressions using natural disaster data to instrument for stunting in infancy

	Under-identification	Weak Identification	
Variable	F (1,2425)	SW Chi-SQ.	SW F (1,2425)
Stunting in Round 1	2.02	2.05	2.02

Table E2: Summary results for first-stage regressions using composite instrument variable composed of interaction term between maternal height and maternal years of schooling

	Under-identification	Weak Identification	
Variable	F (1,4420)	SW Chi-SQ.	SW F (1,4420)
Stunting in Round 1	1.88	1.90	1.88

Bibliography

Alderman, H., Hoogeveen, H., & Rossi, M. (2009). Preschool Nutrition and Subsequent Schooling Attainment: Longitudinal Evidence from Tanzania. *Economic Development and Cultural Change* .

Andrabi, T., Das, J., Khwaja, A., Zajonc, T., & Vishwanath, T. (2009). *Learning and Educational Achievements in Punjab Schools (LEAPS): Insights to inform the education policy debate.* World Bank.

Barker, D. (2007). Introduction: The Window of Opportunity . *The Journal of Nutrition, Volume 137, Issue 4*, 1058-1059.

Behrman, J. (1993). The economic rationale for investing in nutrition in developing countries. *World Development, Vol 21 Issue 11*, 1749-1771.

Behrman, J. R. (1996). The Impact of Health and Nutrition on Education. *The World Bank Research Observer Vol. 11, No. 1*, 23-37.

Birch, H. G. (1972). Malnutrition, learning, and intelligence. *American Journal of Public Health*, 773–784.

Cunha, F., Heckman, J., Lochner, L., & Masterov, D. (2006). Interpreting the Evidence on Life Cycle Skill Formation. In *Handbook of the Economics of Education* (pp. 697-812). Chicago: Elsevier.

Gale, C., O'Callaghan, F. J., Godfrey, K. M., Law, C. M., & Martyn, C. N. (2004). Critical periods of brain growth and cognitive function in children. *Brain, Volume 127, Issue 2*, Pages 321–329.

Glewe, P., King, E., & Jacoby, H. (2001). Early childhood nutrition and academic achievement: a longitudinal analysis. *Journal of Public Economics, vol. 81, issue 3*, 345-368.

Interpreting the Evidence on Life Cycle Skill Formation. (2006). In E. A. Hanushek, & F. Welch, *Handbook of the Economics of Education, Volume 1* (pp. 697-812).

Iyer, P. (2017). Measuring learning quality in Ethiopia, India and Vietnam: from primary to secondary school effectiveness. *Compare: A Journal of Comparative and International Education*, 908-924.

Jayachandran, S., & Pande, R. (2017). Why Are Indian Children So Short? The Role of Birth Order and Son Preference. *American Economic Review*, 2600-2629.

Kasirye, I. (2009). Determinants of learning achievement in Uganda. *CSAE Conference, Economic Development in Africa.* Oxford: Economic Policy Research Centre.

Liddel, C., & Rae, G. (2001). Predicting early grade retention: a longitudinal investigation of primary school progress in a sample of rural South African children. *British Journal of Educational Psychology*, 413-428.

Liu, J., Raine, A., Venables, P., Dalais, C., & Mednick, S. A. (2014). Malnutrition at Age 3 Years and Lower Cognitive Ability at Age 11 Years. *Archives of Pediatrics & Adolescent Medicine*, 593-600.

Martorell, R. (2017). Improved Nutrition in the First 1000 Days and Adult Human Capital and Health. *American Journal of Human Biology*.

Moll, P. (1998). Primary Schooling, Cognitive Skills and Wages in South Africa. *Economica*, 263-284.

Pollit, E. (1990). *Malnutrition and infection in the classroom.* UNESCO.

Prado, E., & Dewey, K. (2014). Nutrition and Brain Development in Early Life, Volume 72, Issue 4. *Nutrition Reviews*, 267.

Semba, R. (2016). The rise and fall of protein malnutrition in global health. *Annals of Nutrition & Metabolism*, 79-88.

Sowell, E. R., Thompson, P. M., Leonard, C. M., Welcome, S. E., Kan, E., & Toga, A. W. (2004). Longitudinal Mapping of Cortical Thickness and Brain Growth in Normal Children. *Journal of Neuroscience*.

The Scientific American. (2015). Avoiding Malnutrition. In *Understanding Child Development.* Scientific American.

Todd, P., & Wolpin, K. (2003). On the Specification and Estimation of the Production Function for Cognitive Achievement. *The Economic Journal*, 3-33.

Victora, C., Adair, L., Fall, C., Hallal, P., Martorell, R., Richter, L., & Sachdev, H. (2008). Maternal and child undernutrition: consequences for adult health and human capital. *The Lancet*, 340–357.

WHO. (2006). *WHO Child Growth Standards: Methods and Development.* Geneva: WHO.

WHO. (2014). *WHA Global Nutrition Targets 2025: Stunting Policy Brief.* WHO.

WHO. (2017). *Global Health Observatory (GHO) data*. Retrieved from World Health Organization: https://www.who.int/gho/child-malnutrition/en/

World Food Programme . (2005). *A Manual: Measuring and Interpreting Malnutrition and Mortality.* World Food Programme.

World Food Programme. (2000). *Food and Nutrition Handbook.* Rome.

Young Lives. (2017). Retrieved from Young Lives Study: https://www.younglives.org.uk/content/round-4-questionnaires

Young Lives. (2017). *Young Lives Study*. Retrieved from https://www.younglives.org.uk/content/round-1-questionnaires