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Understanding Childhood Malnutrition in Nepal: A Hierarchical Regression Approach

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A HIERARCHICAL REGRESSION APPROACH

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ABSTRACT

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This thesis investigates the determinants of childhood malnutrition in Nepal, with a particular emphasis on the importance of district characteristics relative to household and child characteristics. Using a new dataset constructed from child and household data from the 2006 and 2011 Nepal Demographic and Health Survey (DHS) and community characteristics aggregated from the 2004 and 2010 Nepal Living Standards Survey (NLSS), we estimate a variety of hierarchical regression models, which allow us to partition variance in height-for-age Z-scores between the levels of different hierarchical specifications, and then to partition that variance further, between group-level parameters.

Our findings suggest that the majority of variance in HAZ occurs between children, though the vast majority of variance between districts can be partitioned into variances in agricultural input use and commercialization, healthcare access, and ethnic marginalization, combined with their estimated coefficients. The results generated by models designed to evaluate the robustness of the core estimation strategy also suggest that while variation among children is the largest source of variance, a small but nontrivial proportion of that variance is variance among households.

CHAPTER 1. INTRODUCTION

In Nepal, a very large proportion of children less than five years of age suffer from malnutrition. The incidence of stunting and underweight fell substantially between 2001 and 2011, but even so, 41% of children under five were stunted and 29% experienced underweight in 2011, and 11% were acutely wasted (DHS 2011). A range of individual and household factors likely influence the incidence of child malnutrition. Community factors also shape local dimensions and determinants of malnutrition. This thesis seeks to develop an understanding of the relationship between a range of community factors and specific household factors in determining children's nutritional status.

Studying child malnutrition is important because human capital is a key determinant of economic growth and development (Mankiw, Romer, and Weil 1992). Malnutrition increases the risk of contracting various illnesses and the severity of those illnesses when contracted. Illness, in turn, can deepen a child's level of malnutrition in a highly deleterious disease-hunger feedback loop (Pelletier et al. 1995). This feedback loop is responsible for a substantial proportion of childhood mortality in Nepal and elsewhere (Pelletier et al. 1995), which in itself makes reducing the incidence of malnutrition a worthwhile enterprise. Persistent malnutrition in early childhood can severely hinder children's physical and cognitive development (Black et al. 2013), and at the levels observed in Nepal, this degradation of human capital may have a substantial effect on the national economy. This human capital effect may create a second feedback loop: adults impoverished by their own childhood malnutrition have more difficulty providing for their own children (Harper and Marcus 2003)

To study malnutrition in Nepal I use data from the 2006 and 2011 Nepal Demographic and Health Surveys (DHS), combined with district-level variables from Nepal's National Living Standards Survey (NLSS) data. I estimate the parameters of hierarchical regression models of long-term nutritional outcomes. In this thesis, nutrition is measured by height-for-age Z-scores (HAZ) and I study the incidence of stunting (HAZ< -2.0). Past analyses of malnutrition, in Nepal and across the world, have relied on DHS data due to the rigor of its sampling, its national representativeness and the detail of its household level information. However, because the survey's priority is the collection of health-related information, it does not provide data necessary to assess the role of economic conditions and agricultural characteristics in influencing nutritional outcomes. The inclusion of district level data from the NLSS, which include detailed economic, agricultural and infrastructural variables, allows one to explicitly model the role these factors play in childhood nutrition.

The hierarchical approach has several advantages when compared to classical regression analysis on primary sampling units alone. Because hierarchically structured data violate the independence assumption of standard Ordinary Least Squares (OLS) regression, OLS estimates are potentially unreliable for the data used in this analysis. Using the more precise hierarchical approach can generate more reliable parameter estimates, enhancing the validity of inferences drawn from econometric models. This approach also generates a more complete impression of the sources of variance in the data, compared to OLS, as it decomposes variance into constituent pieces determined by levels of observation, and makes it possible to include covariates at any of these levels. The mechanics and advantages of multilevel models are discussed at length in Chapter 3. Taken together, these advantages mean that in many cases multilevel models do a better job of providing the information necessary for specific and relevant policy analysis than do standard econometric techniques.

This thesis is composed of five chapters, not including this introduction. Chapter 2 discusses existing literature on the specific context of Nepal and on the determinants of malnutrition in developing countries more generally, citing both classical and multilevel empirical work. Chapter 3 discusses the relevant features of multilevel modeling, expounds on the rationale for applying it to this problem and this dataset, and explains the empirical strategy for this research. Chapter 4 describes the data used in the study. Chapter 5 presents the results of the model, describes the rationale for its varied specifications, and discusses the findings. Chapter 6 includes conclusions and discussion of the policy implications of the findings.

CHAPTER 2. BACKGROUND

2.1 National Context

Nepal's geography is very diverse, especially for a country of its size. It is divided into three distinct ecological zones: mountains, hills, and a broad plain, known as the terai. The mountains are perhaps Nepal's best-known feature, but due to their effective remoteness, which make the provision of most goods and services very difficult, only about seven percent of the country's population resides in that zone. The hill zone includes altitudes from 610 to 4,876 meters above sea level, making it quite diverse in itself, and its valleys, especially the Kathmandu valley, are fertile and densely populated. Finally, the terai are an extension of the Gangetic plains of northeastern India, and are home to fifty percent of the country's population. The terai's relatively mild terrain and placement near India has made it an attractive location for the development of new industries, as the infrastructure necessary for such development is more prevalent there (DHS 2011). Agriculture accounts for 76% of Nepal's employment, and approximately 83% of the population lives in rural areas, so a very large number of citizens are deeply affected by the country's topography and physical characteristics (DHS 2011). Nepal is also divided into five regions on its north-south axis, and these five regions are combined with the three ecological zones to generate thirteen subregions. Subregions are made up of Nepal's seventy-five districts, and districts are in turn made up of a variety of smaller administrative units. Figure 1 shows these geographic designations, and Figure 2 shows means of height-for-age Z-score, a measure of long-term childhood malnutrition, at the district level, along with bars indicating overall mean value, the cutoff value for being considered stunted, and the healthy population mean of zero.

Figure 1: Map of Nepal with Ecological Zones, Subregions, and Districts
Source: Reliefweb 2000

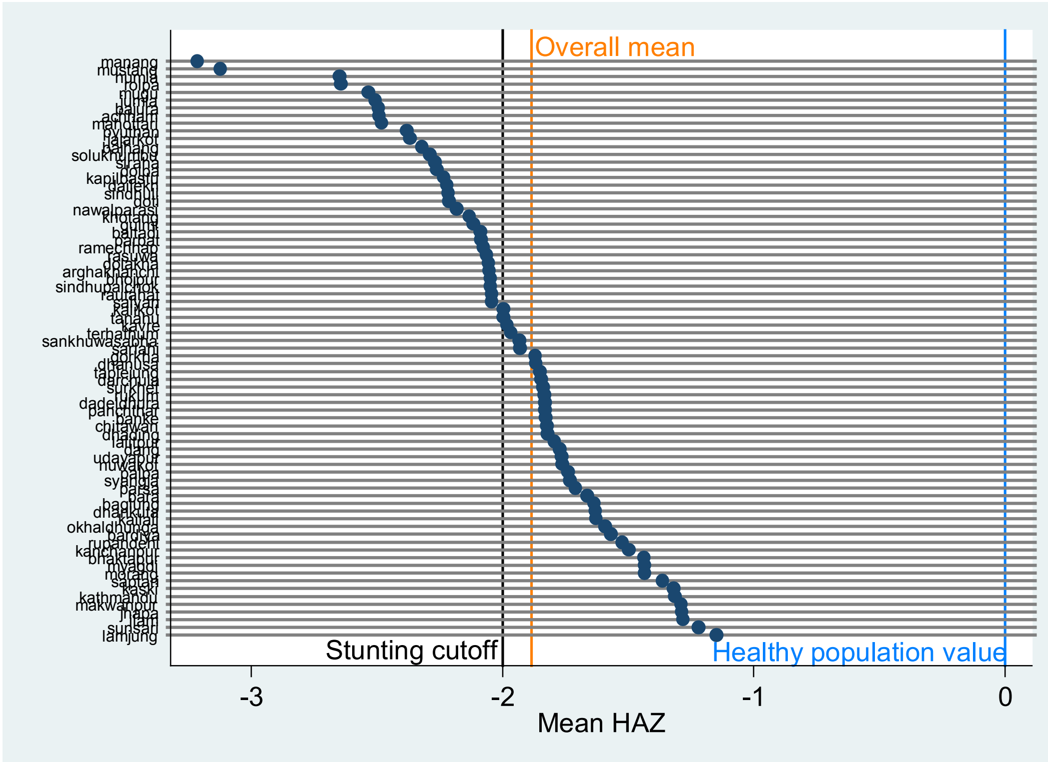

Figure 2: Mean HAZ by District

Since the 1980's, Nepal has undergone a major political and economic transition, from a monarchy with a highly centralized economic system to a parliamentary democracy with a market economy. Instituted through structural adjustment initiated inthe mid-1980's, this economic liberalization has had far-reaching effects in the agricultural sector, as under the previously highly-centralized government, various agricultural inputs and investments had been heavily subsidized (Khanal et al. 2005). The loss of subsidies had very serious effects on the fertilizer market and investment in shallow tube wells. Fertilizer prices rose rapidly during the 1990s, seemingly leading to a drop in already-low levels of nutrient application on a per hectare basis (Khanal et al. 2005). The effect on the installation of shallow tube wells, which facilitates irrigation, was even more substantial: the number of shallow tube wells installed dropped from

6,800 in 1988/89 to 2,000 by 2000, falling far short of the target of 8,800 (Khanal et al. 2005). Despite these setbacks, the agricultural sector has increased its productivity since the mid 1990's, though it has lagged behind other South Asian countries (Khanal et al. 2005).

Economic liberalization was implemented in a way that some stakeholders saw as exclusive. The changes it brought about deepened existing inequalities substantially over a fairly short time period. Gains from liberalization and inflows of development aid accrued disproportionately to urban areas, both in monetary and infrastructural terms (Sharma 2006). This deepening of inequalities was particularly pronounced in the mid-western and far-western regions of Nepal (Murshed and Scott 2004). In 1996, conflict broke out between Maoist insurgents and the central government. The insurgents rapidly gained strength due to their ability to recruit from the disaffected rural population, the government's ineffective response, and their links to the Naxalite Maoist insurgency in India. Both sides victimized the civilian population, and it is estimated that over thirteen thousand people were killed between the start of the conflict and its official end in 2006 (Bhatt and Murshed 2009). In addition to these deaths, the conflict caused substantial displacement, property damage, and general uncertainty, all of which had substantial, if not explicitly measured, economic effects (Sharma 2006).

2.2 Determinants of Childhood Malnutrition

A variety of social, economic, and physiological factors contribute to childhood malnutrition, and understanding the roles these diverse, though often interconnected, factors play in determining nutritional status has interested researchers from a variety of disciplines for some time. Understanding the impact of these factors, and their interactions, informs the development of the empirical model discussed in detail in chapters 3 through 5. Developing an understanding of interventions appropriate for improving nutritional conditions relies similarly on the substantial literature on past nutrition-related interventions.

Smith and Haddad (1999) divide the determinants of malnutrition into three categories: *immediate* determinants, *underlying* determinants, and *basic* determinants. Immediate determinants are the proximate, physical components of nutrition, such as disease and micronutrient intake, and they are influenced by underlying determinants. Underlying determinants are factors which help define immediate determinants by shaping endowments and their distributions. They generally occur at the household level, and include factors like food security, childcare, and health environment. These underlying determinants are, in turn, influenced by basic determinants. Basic determinants are features of the communities and countries in which households reside. They affect nutrition through their influence on underlying determinants. They include factors such as natural resources, institutions, cultural values, and general economic conditions like labor market performance and access to technology (Smith and Haddad 1999). Each of these levels consists of a variety of factors, and this framework represents a convenient way to organize the literature on the varied determinants of malnutrition. This conceptual structure is also especially useful here because it translates smoothly into a multilevel regression model. For this reason I use it throughout this thesis as a guiding conceptual and technical framework for approaching the measurement and explanation of malnutrition in Nepal.

Household economic status is perhaps the most obvious underlying determinant of children's nutritional status, and it has been studied extensively. Wealth and income play a substantial role in determining the quantity and quality of food available to an individual child, while contributing to the levels of most other underlying determinants (Haddad et al. 2002, Haddad, Hoogeveen, and Rossi 2006). This broad effect creates a conceptual challenge, however, because income can be a source of explanatory variable endogeneity. In a regression setting, this often necessitates the use of other indicators of economic wellbeing, which have their own shortcomings, or the use of instrumental variable regression. The most common alternative indicator is an asset index, in which a household's assets are tallied and then assigned a value for comparison with other households. Various measures of actual consumption, in monetary terms, also sidesteps the endogeneity of income and similar variables (Filmer and Pritchett 2001, Smith, Ruel and Ndiaye 2004, Shrestha 2007). Index values are generally transformed into quartiles or quintiles, and membership in these groups is expressed as a set of binary indicators. This is convenient both because it is simple in its own right, and because it lends itself to the generation of interaction terms with other categorical variables of interest.

Regardless of which indicator a researcher chooses to capture economic wellbeing, a substantial body of research suggests that economic wellbeing has a positive effect on children's nutritional status (Haddad et al. 2002, Haddad, Hoogeveen, and Rossi 2006, Shrestha 2007, Smith, Ruel, and Ndiaye 2004). In a study of Ethiopian households, Christiaensen and Alderman (2004) found that the natural log of expenditures was positively and significantly correlated with HAZ in a variety of model specifications, some of which controlled for the prices of a variety of local food products. The effect of expenditures was fairly small, however – the authors note that according to their results, a 10% increase in expenditures would only move the average HAZ score 0.7% closer to the reference standard (Christiaensen and Alderman, 2004). Haddad et al. (2002) reach a similar conclusion in a study using both cross-country and household level data to study the role of income in malnutrition: they note that a sustained 2.5% increase in incomes across the developing world could reduce undernutrition rates by 27%, but this scenario is unlikely, as only three of the twelve countries observed in the study had sustained that level of income growth in the high-growth 1990's (Haddad et al., 2002). A study of Mozambican households found that consumption expenditures had a positive and significant effect on calorie availability and HAZ (Garrett and Ruel, 1999) Alderman, Hoogeveen, and Rossi (2006) observed a similar effect in a household study in Tanzania: using logged expenditures as the indicator for wealth, they found a significant and positive effect, but as in the other studies, the effect was too small to plausibly generate a substantial reduction in malnutrition in the near term. These findings seem fairly intuitive, but as Alderman (1990) points out, through the late 1980's, the role of income in determining nutritional status lacked clear empirical support, so they are important.

Studies which use asset indices as indicators of wealth reach similar conclusions about the role of wealth in the determination of childhood malnutrition. Using this approach, Shrestha (2007) finds a significant, positive, and large correlation between wealth and short-term nutritional status, measured by weight-for-age Z-score, but an ambiguous relationship for long-term nutritional status, measured by HAZ. Shrestha uses asset index quintile indicator variables as his measure of wealth, with the first quintile as the reference value, and in his overall model, the indicators are all significant, with positive and large odds ratios. He is skeptical of this result, however, because using multiple specifications of the model suggested that despite the intent of asset indices' mitigating endogeneity issues, their effect is mediated through maternal education. In models where both are included, the wealth index values get credit for effects of maternal education, overestimating wealth coefficients and underestimating education coefficients (Shrestha 2007). Fotso and Kuate-Defo (2004) use both a household-level wealth index value and community level averages to explain nutritional status across several countries. They find that both are important, but are at least somewhat conditional on the presence of other determinants, such as healthcare and infrastructure access (Fotso and Kuate-Defo 2004). Several other cross-country studies of childhood malnutrition employing hierarchical models generate somewhat ambiguous results, due largely to questionable data quality and massive unobserved heterogeneities between countries. In some cases, these multicountry hierarchical modelling studies find large and significant effects, which suggests that the use of asset indices is a legitimate approach for the purposes of this analysis (Madise, Matthews and Margetts 1999, Griffiths et al. 2003, Harttgen and Misselhorn 2006).

Economists have understood that the presence of food supplies large enough to feed a population are not sufficient to ensure food security, as actual access to food supply is dependent upon wealth, infrastructure, and institutions, as well as the existence of food products in a given area. At the same time, if a shortfall in food supply occurs, as it may in Nepal, where many areas are quite remote and cannot easily import food, it will have a substantial effect on consumption, and thus nutritional status. Smith and Haddad (2001) find that at the national level, food supply, measured in calories available per capita, has a significant and positive impact on child nutrition, and that the elasticity of the relationship between food supply and childhood malnutrition grows smaller as the starting food supply level grows. This is unsurprising from a physiological standpoint, but it demonstrates the policy-relevant fact that, in their words, “as per-capita food supplies are increased in any country, they become an increasingly blunt tool for reducing malnutrition.” While their emphasis of this study is on cross-country comparison rather than the development of country-specific policy prescriptions, they do note that their analysis, which includes data from Nepal, designates South Asia as a ‘high impact’ area for food supply increase, due to its combination of relatively low levels of calories per capita and high levels of childhood malnutrition.

Sen (1981) approaches the widespread hunger occurring during famines as a combined failure of what he terms ‘direct entitlements’ and ‘trade entitlements’, that is, the widespread inability to produce enough food for oneself and/or one’s household, combined with an inability to purchase food from markets. While Sen was interested in discrete famine events and this thesis is concerned with long-term nutrition, his observations remain relevant: this dual entitlement approach underscores the importance of food markets in determining nutritional status, rather than seeing food access only as an equilibrium problem, predicated on agricultural productivity. The evidence on market extension is mixed, however, because extending markets in the developing world often requires smallholders to begin selling crops, and in many cases, newly commercialized farmers are net buyers of food.The literature on agricultural commercialization, which is often associated with increased input use and rising incomes, is somewhat ambiguous, as Kennedy (1994) finds that while children in commercialized households did not display worse nutrition, they are not substantially better off either, as one might expect given the increases in income associated with selling goods. She argues that other factors, which either interact with agricultural factor or are independent of them, explain nutritional status. In a study of commercialization in the Philippines, Bouis and Haddad (1990) find that the income gains from commercialization do improve nutrition among preschool children, but only by a modest amount. Taken together, these findings suggest two different stylized facts, because they measure different things: at the household level, increases in market oriented activity has a neutral or slightly positive impact on nutrition, but at the community level, increased market access and resilience may be helpful if it lowers prices for net buyers and reduces the likelihood of trade entitlement failures.

Healthcare environment and, more broadly, the quality of infrastructure and institutions in a child's community also act as important underlying determinants of childhood malnutrition, due to the role they play in determining health, which in turn helps determine nutritional outcomes. In their Tanzania household study cited above, Alderman, Hoogeveen, and Rossi find large and significant effects for road access, healthcare availability (proxied by ratio of vaccinated children in a community), and the presence of feeding posts in the community, all of which can be considered service variables. The authors, like many other researchers, are interested in the role of service availability compared to generalized income growth. They find that, in this case, services are much stronger predictors of malnutrition than logged mean expenditures, an indicator of consumption (Alderman, Hoogeveen, and Rossi 2006). Christiaensen and Alderman find a somewhat contradictory result, as the coefficients they estimate for distances from health centers are insignificant in all specifications of their model. However, they note that this is inconclusive, both because the distance variable measures only access and cannot capture any information about quality, and because there was very little variance in these variables in their dataset, perhaps creating a false negative (Christiaensen and Alderman 2004). It seems reasonable to accept the findings of the first paper and to concur with the authors of the second paper in being skeptical of their null result, because while vaccination ratios do not provide a full picture of the management or resources of local health systems, the fact that they measure the actual occurrence of a specific intervention, rather than just the presence of a building, means that this indicator captures at least some of the quality of healthcare as well as acting as a strong indicator of its penetration. Shrestha (2007) finds a significant correlation between a child being underweight (WAZ < -2.0) and households saying that they have difficulty accessing health services, but no statistically significant relationship between difficulty and HAZ. This result suggests that for whatever reason, easier access to healthcare improves nutrition for Nepali children in the short term, but does not necessarily help them in the long term (Shrestha 2007).

In a cross-country study of income, Haddad et al. (2002) note that income should, intuitively, improve infrastructure. In projections they generate, accounting for this secondary effect of income growth produces a substantial increase in the rate at which malnutrition drops. Moreover, in their final discussion, they note that specific health interventions and infrastructure, which they lacked the data to study explicitly, may play a key role in reducing malnutrition past the point they predict regular income growth will push it. They recommend this as a future area for productive research. In a more general cross-country study, Smith and Haddad (1999) use access to safe water as a proxy for infrastructure and health environment, due to the important role it plays in avoiding a variety of tropical diseases and parasites. They find that it has a significant and positive impact on improved nutrition, but that compared to other variables they analyze, the effect is small, and consequently should be a secondary priority in developing future interventions and policy.

The social and economic status of mothers is the most commonly discussed underlying determinant of childhood malnutrition across the literature, and is very often found to be the most important determinant in multivariate empirical analyses. These factors are difficult to quantify totally, but the overwhelming majority of childhood malnutrition studies discussed here use some measure of maternal education as an indicator of both women's status, and of mothers' human capital endowments. Even apart from its importance as an indicator of women's general status, the human capital effect of education deserves attention, as it helps determine children's malnutrition through its effects on income and on childcare decisions that drive direct determinants of malnutrition (Haddad 1999, Christaensen and Alderman 2004). Measuring maternal education is also convenient from a policy perspective, because its effect has clear policy relevance, and augments the case for an already uncontroversial intervention, rather than suggesting a difficult or expensive change in course. Many studies also attempt to measure women's status in households explicitly, often through a binary variable capturing whether or not the head of the household is female, which theoretically mitigates the negative effects of intra-household gender discrimination and/or gendered differences in spending on health and nutrition inputs (Meinzen-Dick et al. 2012, Haddad 1999).

Women's status in households, captured in some combination of these variables, determines childhood malnutrition indirectly, through a variety of other underlying and direct determinants. Control of income, which is reduced both by being unable to command a male's wage due to limited educational opportunities and by having limited influence in the deployment of household finances, is the most important of these pathways, as it allows mothers to direct income into better care for children, and to balance resources between children when shocks occur (Haddad 1999). Improving women's status also creates strong intergenerational effects, due to increased investment in girls when women have more of a say in finances, and to an increase in mothers' own-health status, due both to increased income availability for health inputs and to increases in health seeking behavior (Smith and Haddad 1999, Christaensen and Alderman 2004)

While virtually all studies discussed here measure maternal education, they approach its measurement in different ways. The simplest and most obvious approach is mother's years of education, as intuitively, more education raises a mother's social status and human capital, and thus her ability to care for her children. Studies using this approach have generated mixed results. One cross-country, multilevel study finds that the total years of maternal education has a significant, negative, and large effect on probability of stunting (Harttgen and Misselhorn 2006). Another finds a significant effect along with binary completion variables which suggest a fairly linear benefit from education (Alderman and Christiaensen 2004). In contrast, Alderman, Hoogeveen, and Rossi find a somewhat ambiguous effect. They measured education of both parents and found mother's education to have significance at a 5% confidence level in only one specification, with weak or no significance in others (Harttgen and Misselhorn 2006, Alderman and Christiaensen 2004, Alderman Hoogeveen and Rossi 2005). The weak effect found in the latter study suggests what may, somewhat counterintuitively, be a serious and fundamental problem with the use of years of education as an indicator of human capital and status: educational quality is not captured in this measure, and may vary a great deal across communities, while using years as an indicator implicitly assumes that a year of education has a standardized effect. Instead of years, many studies use variables measuring some combination of maternal literacy and grade segments, e.g. primary school, which a mother has completed. While this measure does not control for heterogeneities in educational quality, it does allow different levels of education to produce different coefficient estimates. This allows for more specific policy recommendations, as it differentiates between attainment levels in a way continuous years cannot. When' years of schooling' is used as the indicator for education, the coefficient estimate will, by construction, apply equally to any year, but with this completion measure, it is possible to distinguish the impact of different segments of schooling. Completion binaries obviously have drawbacks, most notably a distinct lack of granularity when compared to years of schooling, but they are widely used, and studies measuring education in this manner have found significant impacts on nutritional outcomes (Shrestha 2007, Garrett and Ruel 1999, Smith, Ruel, and Ndiaye 2004, Alderman, Hoogeveen and Rossi 2005). Using this measure in a multilevel model of Nepal, similar to the one employed here, Shrestha (2007) finds a spillover effect from maternal education: in communities where more women are educated, he finds that children are less likely to be stunted, even if their own mothers are not educated. Simply measuring maternal literacy is also helpful, because it captures the efficacy of education.

Finally, some studies, particularly cross-country studies with aggregated data, use female enrollment rates in secondary education as an indicator of women's status. This approach is a conceptually strong indicator of women's social status, but due to aggregation, it has a less clear proximate effect on the nutritional outcomes of individual children in individual households through maternal human capital accumulation effects, making it less useful for this analysis, except perhaps as a control variable for socio-cultural gender norms (Smith and Haddad 1999; Haddad et al. 2002).

A substantial literature on the immediate determinants of childhood malnutrition also exists, though it is primarily the province of clinical disciplines rather than social sciences. The health-oriented nature of the DHS means that the data necessary to measure the effects of these immediate determinants in the context of underlying and basic determinants is present in the dataset. It is important, however, to use caution when interpreting their effects, as many immediate determinants are avenues through which basic and underlying determinants affect nutritional status. Acute disease symptoms, such as diarrhea and fevers, are associated with malnutrition, as they place demands on a body's physical resources and make it more difficult to retain nutrition, and the direct measurement of these acute conditions by the DHS allows their explicit inclusion (Pelletier et al. 1995). Maternal characteristics, such as BMI, height, anemia status, and general nutritional status during pregnancy play a large role in the determination of children's nutrition, due to the key role natal and peri-natal health plays in early childhood development (Black et al. 2013) Care practices, especially feeding choices, also play a direct role in determining nutritional status. There is strong evidence that following the World Health Organization's recommendation of exclusive breastfeeding for the first six months of a child's life, and breastfeeding augmented by other foods until a child reaches two years of age, is the optimal feeding strategy for assuring proper nutrition and development (Saha et al. 2008, Black et al. 2013) The vast majority of children are breastfed in Nepal, however, so implementing this immediate determinant in the statistical model may be unproductive (Shrestha 2007). Including these immediate variables as well as the underlying variables which they mediate may generate ambiguous findings, but this can be handled with varied specifications and testing, which will ultimately create a better understanding of how these diverse factors work together to determine nutritional status.

Implementing indicators of the determinants Smith and Haddad term 'basic determinant' is difficult in a single-country household oriented context, as they apply this framework to a broad multi-country model which benefits from the availability of straightforward aggregate data on incomes and governance, an advantage the more specific approach lacks (Smith and Haddad 1999). A somewhat modified version of the basic determinant concept remains useful, however, due largely to the use of multilevel modeling in this study. While the advantages of multilevel modeling, the structure of the dataset, and their interaction will be discussed at length in chapter 3 and 4, some basic features are relevant here. Taken together, the community-level data in the NLSS dataset, combined with the level-sensitive format of the multilevel models, allows communities to show varied impacts of indicators of 'basic' factors such as wealth, infrastructure, and agricultural productivity. This provides a perspective on these factors which may in fact be more instructive than the aggregate approach used by Smith and Haddad, among others.

The literature on the determinants of childhood malnutrition offers evidence for a variety of factors' importance in childhood nutritional status. For the most part, extant literature focuses on what Smith and Haddad consider 'underlying determinants,' that is, levels of factors that affect household decisions that in turn determine 'immediate determinants' of malnutrition, such nutritional intake and health status (Smith and Haddad 1999). The combination of modeling technique and data used in this thesis makes it possible to implement components from all levels of Smith and Haddad's framework. The mathematical and conceptual rationale for this implementation is discussed in Chapters 3 and 4.

CHAPTER 3. EMPIRICAL STRATEGY

This study uses data from the 2006 and 2011 Nepal DHS surveys, combined with district-level variables from Nepal's National Living Standards Survey. Using these data I develop hierarchical models of nutritional outcomes as measured by height-for-age Z-scores (HAZ), to identify variables correlated with HAZ. In the service of improving the targeting of interventions and increasing the efficacy of policy, this approach has several advantages when compared to classical regression analysis on the DHS data alone. Past analyses of malnutrition, in Nepal and across the world, have relied on DHS data due to the rigor of its sampling, its national representativeness and the detail of its household level information. However, because the survey's priority is the collection of health-related information, it does not provide data necessary to assess the role of economic conditions and agricultural characteristics in influencing nutritional outcomes. The addition of NLSS data, which include detailed economic, agricultural and infrastructural variables, allow one to explicitly model the role these factors play in childhood nutrition.

The use of hierarchical modeling improves statistical precision and validity, compared to OLS regression, due both to its technical advantage in modeling phenomena with certain characteristics present in this case, and to the conceptual appropriateness of approaching this problem through a hierarchical framework. Hierarchical models allow variables which apply to members of some unit, in this case a district, to occur only once per unit in a regression, giving a more accurate standard error than in a classical OLS regression. Classical OLS regression assumes that observations are independent, but this assumption does not hold for data clustered in groups. In such a setting, OLS standard errors will be estimated incorrectly, which can lead to incorrect statistical inference.

For this project, using district fixed-effects estimation would be a more logical choice than using simple OLS, but a district fixed-effects model would still lack useful features of a multilevel model. Inter-district variance could be captured by the district-sensitive intercept and by the between-group variance term, but that would be the extent of the model's ability to examine variance. Fixed effects estimation is a substantial improvement over OLS, but there is no way to partition the between-group variance term in order to determine what characteristics of districts drive their intercepts. In contrast, a multilevel model may produce inferences similar to those derived from a fixed-effects model of the same data, but when group-level predictors are introduced, the multilevel approach gives a more complete impression of the phenomena driving inter-district variance, rather than simply reporting arbitrary differences in district-level outcomes.

This multilevel structure also allows the cluster intercepts to vary across the dataset, along with the standard errors and the slopes of explanatory variables defined at a given cluster level. Taken together, these technical features mean that coefficient estimates from a hierarchical model are more reliable than those generated by classical regression for the same model, given hierarchically nested data. (Gelman and Hill 2007, Misselhorn and Harttgen 2006) Furthermore, they provide conceptually useful information that OLS and fixed-effects estimation do not: in addition to producing more reliable coefficient estimates, they generate detailed information about variances at different levels, and they generate clear estimates of the sources of cluster-level variance.

Gelman and Hill characterize the general form of hierarchical models with varying slopes, intercepts, and higher-level predictors using the following equation:

$$Y_i = \alpha_{j[i]} + \beta_{j[i]} x_i + e_i \text{ for } i = 1, \ldots, I \tag{1}$$

where α_{ji} is the intercept and β is a vector of coefficients for the explanatory variable vector x_i, and N means that the function is normally distributed. Subscript i refers to the subjects that display the dependent variable, in our case children, as in classical regression, but the model departs from that framework with its second index j, which applies to the whole model, giving different slopes and intercepts for higher-level clusters. The second-level intercepts and slopes are given by the equations

$$\alpha_j = \gamma_0^{\alpha} + \gamma_{jk}^{\alpha} u_{jk} + e_j^{\alpha} \text{ for } j = 1, \ldots, J, k = 1, \ldots, K \tag{2}$$

$$\beta_j = \gamma_0^{\beta} + \gamma_{jk}^{\beta} u_{jk} + e_j^{\beta} \text{ for } j = 1, \ldots, J, k = 1, \ldots, K, \tag{3}$$

where γ_{jk}^{α} and γ_{jk}^{β} are vectors of coefficients for *j* clusters and *k* explanatory variables u_{jk}, γ_0's are intercepts, and the expanded variance terms allow variance at multiple levels (Gelman and Hill, 2007). This form allows a great deal of flexibility at the cluster level, and can be extended to the desired number of nested levels, by making γ's dependent on higher levels with another index structure and another combination of slopes, intercepts, and error terms arranged in this form.

Equations 2 and 3 can also be rewritten, with Equation 1 unchanged, to generate different models which still take advantage of multilevel features. Estimating a model using only equations 1 and 2 without any variables at the group level is possible, and produces a model in which each group has its own random intercept, all of which are associated with the second-level error term, while coefficient values are generated only for the household effects, which are interpreted as point estimates, as in an OLS regression. Such a model is equivalent to a group random-effects model estimated using the maximum likelihood estimator rather than OLS, and in Stata, such a model can be estimated using either the mixed command or the xtreg command with the mle and random options. Equation 4 expresses the form of the random intercept model from a multilevel perspective:

$$Y_i = \alpha_{j[i]} + \beta_i x_i + e_i \text{ for i} = 1, \ldots, \text{I} \tag{4a}$$

$$\alpha_j = \gamma_{0[j]}^{\alpha} + e_j^{\alpha} \tag{4b}$$

Including the γ_{jk}^{α} term in Equation 2 produces a very different model, in which that expression, generated from data presumably connected to dependent variable observations at the group, rather than the individual, level, is allowed to shift $\alpha_{j[i]}$ in Equation 1 through its addition to γ_0^{α}, the random intercept, in Equation 2. Models taking this form are referred to by a variety of names in the literature, but here, they are referred to as ‘random slope’ or ‘group level predictor’ models. The general form of a group level predictor model is expressed in Equation 5.

$$Y_i = \alpha_{j[i]} + \beta_i x_i + e_i \text{ for } i = 1, \dots, I \tag{6a}$$

$$\alpha_j = \gamma_0^\alpha + \gamma_{jk}^\alpha u_{jk} + e_j^\alpha \text{ for } j = 1, \dots, J, k = 1, \dots, K \tag{6b}$$

Finally, combining equations 1 and 3 produces a model in which some number of the variables in x_i are also included at the second level, to generate a random coefficient for each x within each group. This changes the original β value from Equation 1, denoted by γ_0^β in Equation 3, by the same amount within each district, so that each district will have its own total coefficient on each variable modeled with a random coefficient, though the β generated for a given variable in the first level fixed portion of the model will be the starting value from which individual districts diverge by varying amounts. The general form of the random coefficient structure is given by Equation 6.

$$Y_i = \alpha_{j[i]} + \beta_{j[i]} x_i + e_i \text{ for } i = 1, \dots, I \tag{6a}$$

$$\beta_j = \gamma_0^\beta + \gamma_{jk}^\beta u_{jk} + e_j^\beta \text{ for } j = 1, \dots, J, k = 1, \dots, K \tag{6b}$$

A wide variety of alternative components can be used to construct multilevel models, but given the purpose of this analysis and the data upon which it is based, these components, combined in various ways, compose the varied multilevel models discussed elsewhere.

Conceptually, applying this technique to the problem of malnutrition in Nepal makes sense based on the dataset used and on the levels at which variables considered important in the literature occur. The NLSS variables, which measure factors absent from the DHS data and from many other studies, are aggregated at the district level, as are several variables included in the DHS. While it is true that many of these variables would be most accurate if they could be correctly assigned at the household level, the DHS and NLSS variables were collected separately, and from different samples of households, so they cannot be matched. In this context, the option of using aggregated data to gain some insight into inter-district variance is much more attractive than avoiding certain questions due to perceived data constraints, and hierarchical modeling provides that option.

As discussed in Chapter 2, several important indicators of availability or incidence of underlying determinants of malnutrition are subject to unobserved between-cluster heterogeneities, making it difficult to accurately determine the role they play in overall between-district variance. The difficulties associated with measuring the effects of education illustrate this issue well. Educational attainments, when measured in either years of schooling or completion rates, and healthcare access, measured either in terms of distance to health facilities or incidence of facilities in a pre-defined geographic area, are both very important determinants which appear frequently in the literature and are particularly vulnerable to this service quality concern. That is, these indicators measure the presence of a service, but they are not sensitive to the quality of the service provided. A multilevel model can help account for these heterogeneities in quality, however, because the effect of these variables may be allowed to vary at the district level, so that attendance at a good school, common to members of a community but not to different communities, could contribute more strongly to a district's random variance from the mean of zero than attendance at a bad school. This is implemented by including the same explanatory at multiple levels, assigning a shift in that variable's estimated coefficient value for each district, generating a 'random coefficients' model. While allowing slopes and intercepts to be assigned at the clinic or school level would provide a more accurate estimate of the effect of education or other similarly heterogeneous determinants, the data do not allow it, and indeed it seems somewhat unreasonable to ask for any household survey to provide such a level of data resolution. The fact that each level of a multilevel model generates its own error term is also beneficial when dealing with known cases of unobserved heterogeneity, because the error terms capture the degree of unobserved heterogeneity at each level, along with other sources of error, of course. This means that in addition to partitioning between-district variance, the model generates estimates of what has been left out at each level, whether that is explicit measures of quality or simply factors not included in the model (Shrestha 2007).

To estimate the model, I implement the form specified in equations 2 and 3, which allows both slopes and intercepts to vary by district, conditional on district-level independent variable levels and coefficient estimates. The vast majority of the first-level, that is, household or child level, variables come from the DHS, and the vast majority of the second-level, that is, district level, variables come from the processed NLSS. The household level variables function in the same way as independent variables in a classical regression model, with some included as explanatory variables of specific interest and others included primarily as controls on those variables, so they can be implemented and interpreted on their own. The higher level variables help define the intercept, which helps determine the predictions of the model, and they may modify the slopes of child-level variables in certain cases, but these effects flow downward: the first-level DHS regression is ultimately modified, but it is nevertheless comprehensible as a classical regression.

The conceptual model proposed by Smith and Haddad (1999) is a helpful basis for thinking about the multilevel model, as their model can fit into a multilevel specification. They formalize this conceptual model with a set of equations built around a household utility function in which a household maximizes the utility of children, a caregiver, denoted by the index M, and some number of other adults with different weights determined by their status. Their household utility function is reproduced as Equation 7:

$$W(U^M_{m,}, U^1_{ad}, \dots, U^1_{ch}, \dots, U^J_{ch}; \beta \quad \beta = \left(\beta^M_m, \beta^1_{ad}, \dots, \beta^d_{ad}\right) \tag{7}$$

Where the U's in Equation 7 refer to the utility functions of individual members of households, and are assumed to take the structure expressed in Equation 8.

$$U^i = U(N, F, X_0, T_L) \quad i = 1, \dots, n = 1 + D + J. \tag{8}$$

In Equation 8, the arguments N, F, X_0, and T_l refer to nutritional status, food consumption, nonfood consumption, and leisure time respectively. Nutritional status is a function of a vector of arguments expressed in Equation 9:

$$N^i_{ch} = N\left(F^i, C^i, X^i_N; \xi^i, \Omega_{HEnv}, \Omega_{Food}, \Omega_{NEnv}\right) \quad i = i, \dots, J \tag{9}$$

Equation (9) states that the nutritional status of child *i* is a function of that child's food consumption (*F*), care (C), nonfood consumption of good N (X_N), and her genetic endowment influencing health (*ξ*), all of which are measured at the household level in the dataset used in this analysis. Equation 9 also includes three community-level arguments:

health environment ($\Omega_{\boldsymbol{HEnv}}$), which includes access to sanitation, clean water, and health services, food availability ($\Omega_{\boldsymbol{Food}}$), which is distinct from a child's observed food consumption, though they are related, and natural environment ($\Omega_{\boldsymbol{NEnv}}$), which includes factors such as agricultural potential, weather, and access to natural resources. A multilevel mixed model of childhood malnutrition is, essentially, an estimation of the unspecified function denoted by N in Equation 9. Fitting a multilevel mixed model which includes the arguments Smith and Haddad mention estimates the roles of these factors in determining nutritional status, accounting for the hierarchy of household and community arguments.

Smith and Haddad explore the determination of the individual components of Equation 6 further, and including components of their nested equations improves the precision of the analysis when the data permits it. In Equation 10, they formalize the care received by child *i* as some function of the caregiver's time allocation to an individual child from Equation 7 (T_c^i), the caregivers own food consumption (N_m), the caregiver's educational attainment (E^M), and cultural factors relevant to caregiving, such as modal gender roles and the relative social status of men and women ($\Omega_{\boldsymbol{C}}$). The caregiver's nutritional status is, in turn, a function of consumption, genetics, and community factors, as shown in Equation 8. This equation is essentially a restatement of Equation 9 with a different dependent variable, though it includes ψ, which represents the cultural factors which determine intra-household distribution of power and resources.

$$C^i = C\left(T_c^i, N_m;\ E^M, \Omega_C\right) \quad i = 1, \dots, J \tag{10}$$

$$N_m = N(F^M, C^M, X_N^M;\ \xi^M, \Omega_{HEnv}, \Omega_{Food}, \Omega_{NEnv}, \psi) \tag{11}$$

When all of these equations are substituted into Equation 6**,** they yield the reduced-form Equation 12, in which the maximization of Equation 6 determines the nutritional status of child *i* subject to equations 8, 9, 10, and 11.

$$N_{ch}^{i*}(\psi, \xi^1, \dots, \xi^J, \xi^M, \Omega_{HEnv}, \Omega_{Food}, \Omega_{NEnv}, \Omega_C, E^M, P, I) \quad i = 1, \dots, J \tag{12}$$

This reduced form equation includes components of each of the previous equations, as well as P, a vector of prices of consumption goods, and *I*, the household's income. This reduced form equation is the equation this project seeks to estimate, and the hierarchy of its right-hand side variables translates comfortably into a hierarchical mixed model specification. Despite the detail of the dataset used in this analysis, it is not possible to explicitly include all of the factors included in Smith and Haddad's formalized conceptual model, but the dataset does allow the inclusion of a large proportion of these components, and between hierarchical error terms and the use of proxy variables, it is possible to capture some of the effects of other factors implicitly.

Treating the general form of the multilevel model expressed in equations (1) through (3) as the functional form for the reduced form equation expressed in equation (12) generates a set of equations which can be used to estimate a multilevel model. Equations (13a)-(13c) specify the multilevel mixed model with predictors using the variables and notation proposed by Smith and Haddad (1999), and this formal specification represents the core model of malnutrition used in this analysis.

$$HAZ_i = \ a_{j[i]} + \ \beta_{j[i]}x_i + e_i \quad i = 1, \dots, I \tag{13a}$$

$$\beta = F^i, C^i, X_N^i, \xi^M, T_c^i, F^M, C^M, X_N^M, E^M, I, P, \psi$$

$$\alpha_j = \ \gamma_0^\alpha + \gamma_{jk}^\alpha u_{jk} + e_j^\alpha \text{ for } j = 1, \dots, J, k = 1, \dots, K \tag{13b}$$

$$\beta_j = \gamma_0^\beta + \gamma_{jk}^\beta u_{jk} + \ e_j^\beta \text{ for } j = 1, \dots, J, k = 1, \dots, K \tag{13c}$$

$$\gamma = \ \Omega_{HEnv}, \Omega_{Food}, \Omega_{NEnv}, \Omega_C$$

A child's HAZ is thus a function of variables which occur at both community and household levels, and the variables presented by Smith and Haddad are organized into different levels of the model using the notation presented in equations 1-3.

In Smith and Haddad's empirical model, country level rates of underweight, measured as the national proportion of children under five years of age displaying a weight-for-age z-score (WAZ), of -2 or below, are explained by a combination of underlying and basic determinants. The underlying determinants include proportion of the population with access to safe water, female secondary school enrollment rates, the ratio of female life expectancy to male life expectancy, and per-capita dietary energy supply (DES), used as measures of health environment, maternal education, gender equity, and food supply, respectively, following a conceptual model similar to the one outlined in Equation 13. The basic determinants are per capita income and an index of democratic governance, treated as measures of economic development and political freedom. The country-specific dataset used in this analysis includes a variety of plausible analogues for each of these variables except for the democracy index, making a translation of Smith and Haddad's multicountry model possible. This translation is reasonable because it makes it possible to compare and contrast the relative importance of the determinants included in both models in explaining two different but related questions, and because it serves as a helpful illustration of some features of multilevel models useful in measuring childhood malnutrition in these data.

Because Smith and Haddad are interested in explaining between-country differences in aggregate rates of underweight prevalence, their unit of analysis is the individual country, so all of their independent variables occur at the country level. By contrast, the Nepal dataset, in which the unit of analysis is the individual child, includes information on several determinants that occur at the household level, but are treated as aggregates in Smith and Haddad. The multilevel specification allows a model to include these household variables alongside variables which are aggregated at the district level, either because the household data lacks a legitimate indicator of the factor of interest or because the factor of interest is thought to be determined at the community level, and to affect households and children indirectly.

NLSS variables are not directly matched to the dependent variables, which occur at a lower level than the NLSS variables, so it is important to interpret them carefully, accounting for the way the data were gathered and the way they have been aggregated in the dataset. District level variables can influence the child-level dependent variables, but when interpreting their variance coefficients, it would be incorrect to infer direct marginal effects – the effects are not that direct, for multiple reasons. Most clearly, this interpretation ignores the fact that the independent variable in question is a mean, so an increase of the same magnitude in one household's income will have at most a small effect on the variable in the regression, and due to the processing of the original NLSS data, discussed in detail in Chapter 4, this aggregation issue affects all of the NLSS variables. Furthermore, without additional information, it is difficult to be sufficiently sure of the direction of causation to make clear, policy-relevant statements about the coefficient estimate of this NLSS variables, as well as several others, though there are several, for example infrastructure, health, facility, and market access variables, for which this is a less serious concern. Even if teasing out some kind of impact of economic variables on Z-scores is infeasible, the NLSS variables retain substantial values as controls on community characteristics, and the multilevel structure of the model enhances their utility on this front.

The interpretation of district-level results is further complicated by the fact that numerical estimates are measures of properties which differ fundamentally from those estimated for the household-level fixed effects component of the model. The household component generates standard point estimates with confidence intervals, which can be interpreted easily as marginal effects of changes in certain characteristics, but the district-level variance estimates are random effects centered around zero, so they represent the between-district variance associated with a given variable. As discussed previously in this section, this is useful because it adds a level of insight beyond detecting between-district variance to control the fixed effects component, instead providing some evidence of the sources of between-district variances, and their relative weights. The inclusion of these group-level predictors serves a function more similar to that of control variables than of traditional point estimates, but the partitioning of the between-district variance is an important feature of multilevel models, and understanding its limitations and correct interpretation is necessary to use the technique properly.

CHAPTER 4. DATA

4.1 Data Sources and Structure

This analysis uses a dataset constructed from components of two other datasets: the Nepal Demographic and Health Survey (DHS), and the Nepal Living Standards Survey (NLSS). The DHS is the core of the dataset, as it includes the anthropometric data that provide the dependent variable in econometric analyses. The survey was designed and executed by personnel from Nepal's Ministry of Health and Population, New ERA, a Nepali research organization, and ICF International, a US consulting firm. To create the survey's nationally representative sample, the survey designers divided the country into fifteen 'domains,' sections of the country uniquely identified by the combination of their ecological zone, Mountain, Hill, or Terai, and development region, Eastern, Central, Western, Mid-western, and Far-western. Due to their very low populations, the Western, Mid-western, and Far-western mountain domains were then combined into one region, bringing the total number down to 13. These were further divided into rural and urban areas to create 25 strata, as the combined mountain districts have only rural areas. Within these strata, samples were selected through a two-stage process in which enumeration areas were chosen to provide an adequate sample size for both urban and rural areas, and then weighted due to the oversampling of urban areas caused by this approach (DHS 2011).

The DHS collects detailed health information about children and their parents, and includes certain health-relevant household characteristics, such as water treatment options, parental education levels, and involvement with public health agents and institutions. In the DHS data, the child is the unit of analysis, and the dataset used in this study includes both the 2006 and 2011 rounds of the DHS, which include 5,237 and 2,335 observations, respectively, for a total of 7,572 observations.

The NLSS focuses on household level data, primarily regarding economic activity, agriculture, food, and infrastructure. It was collected in 2004, and again in 2010. Like the DHS, it is a nationally representative survey, though it used six strata rather than the twenty-five used in the DHS. The NLSS was sampled using a process similar to the two-stage process used in the DHS, with 334 primary sampling units (PSU's), and 12 households per PSU. Population densities differ greatly between districts, so certain areas are much more PSU-dense than others, and consequently have more households in the NLSS than other, less populated, districts (Central Bureau of Statistics, 2004).

To create the merged DHS/NLSS dataset, NLSS data were summarized and then matched to the DHS data. The 2004 NLSS were matched to the 2006 DHS, and the 2010 NLSS data were matched with 2011 DHS data. It was not possible to match specific DHS children to NLSS households, and indeed there was no guarantee that all DHS children were part of NLSS households. To give the data a form more appropriate for multilevel modeling, the NLSS data were also pre-processed to provide district level averages for variables of interest. The data were collapsed into 75 districts for each year, and matched to children by district–year combinations.

When discussing the features of the population included in this dataset, it is important to keep the different levels at which variables occur in mind. District-level variables contain information about community characteristics, so while it is possible to say something about the nutrition effect of living in a wealthier, more connected, more productive, or more hygienic community may have on a child's z-scores, it is imperative that this distinction is understood. The coefficient estimates for district-level variables cannot be used to make causal statements in the way they might be used in a classical regression, where all variables occur at the same level, because they are not matched to the unit of measurement at which the dependent variables occur. For example, it cannot be said that a child's household had x level of income and that consequently, that child had a z-score characterized by $y = \beta x$, where y is the z-score, as income is measured as a district-level mean, based on an aggregation of households. District-level random intercepts and random slopes do play a role in determining the predictions of multilevel models using these data, and their inclusion can point to the sources of estimated variance, but the coefficient estimates for these variables will vary between districts, because they are based on variance estimates centered around the variance estimate at the overall dependent variable mean, which is zero.

The combined DHS-NLSS dataset allows models drawing on it to formalize all of Smith and Haddad's determinant levels and to model all of the factors which they, and others discussed above, consider important. It includes data on a wide array of potential determinants, and allows many of these determinants to be modeled in a variety of ways. The diversity of options allows the detailed analysis of multiple types of specification within the multilevel framework.

4.2 Dependent Variable Features

Height-for-age is a measure of stunting, which occurs when a child was unable to access adequate nutrition for a prolonged period of time further in the past. The z-scores represent the magnitude of a child's anthropometric distance from the reference population, as the Z-score is the child's number of standard deviations from the median. While a negative standard deviation is technically incoherent, negative z-scores are used to describe distances below the median of the reference population, which is the metric of interest when analyzing malnutrition.

As Figure 3 shows, the distribution of HAZ in these data is approximately normal. In practical terms, this distribution shows us that the average child is, in Z-score terms, very close to being stunted, and the distribution as a whole gives a sense of the number of children who are stunted, and the severity of that stunting. While it cannot be observed visually from Figure 3, it is worth noting that the Z-scores improved by a statistically significant amount between 2006 and 2011. The HAZ distributions also had slightly different shapes in each year.

Using HAZ rather than binary variables indicating stunting makes sense for a variety of reasons, and allows the use of certain analytical techniques that would be more difficult in limited dependent variable models using indicators. Z-scores capture depth of stunting or wasting as well as its presence or non-presence, so once coefficient values of independent variables are fitted, models using these continuous variables will allow prediction not only of whether or not a child would be classified as stunted or wasted, but also how serious that condition would be. Use of a continuous dependent variable also makes estimation and interpretation somewhat simpler in the context of a multilevel model, as the use of limited dependent models introduce complications which do not occur when using estimation techniques appropriate for predicting z-scores (Wagstaff, van Doorslaer, and Watanabe, 2003).

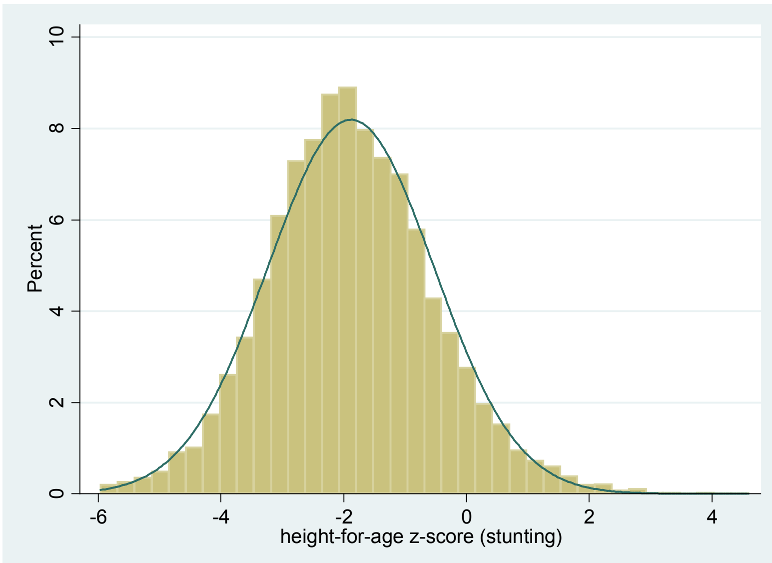

Figure 3. Height-for-age Z-Scores (2006 and 2011) with Normal Distribution.

4.3 Explanatory Variable Considerations

Due both to the multilevel structure of the model and to the varied priorities of the surveys which comprise the dataset, it is useful to think of independent variables as members of their source datasets. For the most part, DHS variables occur at either the child or household level, so they appear in the ‘standard’ part of the hierarchical model, the general form of which is expressed in Equation 1, though they can appear a second time in the group component of a model including random coefficients, as in Equation 6. As discussed above, these variables generally measure dimensions or determinants of health status, though some, notably the wealth index and educational attainment variables, can be interpreted clearly and profitably as social and economic variables. NLSS variables are measured at the district level, so for the purposes of multivariate hierarchical modeling, they appear in the group level equations, the general form of which is given by equations 2 and 3. Like the DHS variables, these variables measure a wide selection of factors, but for the purposes of this study, the most important variables are agricultural, demographic, and health variables, processed as various descriptive statistics at different levels of aggregation, as discussed above. Tables 1 and 2 summarize the child and household level variables, while Tables 3 and 4 summarize district level variables. Household variables come from the DHS, and while for the most part, district variables come from the NLSS, some – *marginal* and *femaleratio* – come from census data (Central Bureau of Statistics 2007, Department of Education 2014). *Marginal* is applied to districts in both years, as it is based on 2001 data processed many years later, and while this is not optimal, it captures historical ethnic settlement patterns. *Femaleratio* is constructed using 2007 data for 2006 observations, as 2006 data are not available, and 2011 data for 2011.

In the interest of parsimony, the variables modeled at the household level are expected to affect children's nutritional status in fairly direct and straightforward ways. Child's age, and squared age, are included as controls, and the use of months, rather than years, makes it possible to pinpoint specific periods where a child may, all other things being equal, be more vulnerable. Breastfeeding is an obvious immediate determinant of malnutrition, because it is a direct source of food for children for which data are actually available, but its specification in this model is somewhat unintuitive given the long-term nature of HAZ, due to data constraints. A substantial number (n=939) of the children in the 2011 DHS are listed as having breastfed, but not breastfeeding currently, without any indication of how long they were breastfed. It would be possible to estimate models using length of breastfeeding without these children, but this would remove almost half of the 2011 sample. From a nutritional standpoint, however, length of breastfeeding is only one of several important components in the utility of breastfeeding: initiation of breastfeeding and both the timing and the content of a child's supplemental diet towards the end of breastfeeding matters as well (WHO 2001). While the DHS does include information on these measures, they have many missing values, so I use the combination of a 'still breastfeeding' binary variable, an interaction between this variable and months of breastfeeding, and the squared interaction term, to capture breastfeeding length for the majority of children (59.3% overall) who are still breastfed. This functional form is used to capture the expected nonlinearity in the effects of breastfeeding, based on the WHO's recommendation of changing children's diet after two years of age. This approach has serious drawbacks, most notably that it does not estimate the effects of breastfeeding for the ~40% of children who are no longer breastfed. It is possible to generate months and months-squared variables for the children who are no longer breastfed, but coding the 939 children for whom no direct measure of breastfeeding length is available presents serious problems for this measure, if the full sample is to be maintained.

The importance of maternal education is discussed throughout the literature, and is measured here as a child's mother's years of schooling. Education is expected to improve nutritional outcomes through a variety of mechanisms, discussed in Chapter 2. Mother's BMI is included as a measurement of mother's health, though it may also capture elements of household food access, and is also expected to have a positive impact on HAZ. Wealth is measured with the asset index discussed in Chapter 2, and sanitation is measured using a binary indicator, *watertreat*, that takes a value of 1 if the household does anything to purify their drinking water, which is also expected to have a positive coefficient. The binary indicator for year = 2011 is included as a control for unexplained changes in HAZ between years. Household altitude is included as a measure of remoteness and associated characteristics, with the intuition being that higher altitude households should be more vulnerable to certain shocks and less connected to certain resources which would be helpful in maintaining good nutrition, so I expect a negative coefficient. Finally, I include an indicator variable that takes a value of 1 if a child's mother is a member of the marginalized Dalit caste.

The district level variables are much less straightforward than the household variables. District level variables were chosen for their ability to measure some aspect of the community factors discussed in Chapter 3, particularly in Equation 13, so they fall into specific categories. Food supply is measured as the percentage of NLSS respondents who viewed their food consumption within the last month as inadequate, a measure which admittedly lacks the explanatory power of the DES measure employed by Smith and Haddad. This variable has several problems, most notably the time horizon, given that the dependent variable measures a child's long-term nutrition. Furthermore, regardless of a district's proportion of households reporting a food shortfall, an individual child either will or will not have an adequate amount of food to eat. This somewhat undermines the appropriateness of this variable as a measure of community-level food supply. The validity of surveyed food shortage as a measure of food supply thus depends on the assumptions that in a given month, the proportion of households declaring a shortage of food is determined at least partially by factors which affect all households in a district, such as weather, soil, and price level, and that a substantial proportion of these unobserved factors are stable over time, so that *foodshort* will capture a wide array of factors which are plausibly determined at the district level and also affect long-term nutrition. A more direct variable would be preferred, especially given the intuitive importance of long-term food supply in the process this analysis seeks to describe, but alternative measures in the dataset are also problematic, so despite efforts to find or generate a better alternative, this measure appears to be the best available.

The dataset also includes *commercial*, the proportion of NLSS households in a district reporting selling some amount of their agricultural output. This is included as a measure of market access, as all other things being equal, districts in which more people sell their goods can be expected to have more accessible markets, which can improve food security. Using NLSS data on food consumption and FAO food price indices for Nepal, I also generate *foodsupply*, the mean value of consumed food per household for a given district (in 2006 rupees). Finally, the dataset includes data on the proportions of households using irrigation and improved seeds, *irrigation* and *impseed* respectively, and on the average weight of chemical fertilizer use in kilograms, *fertkg*, also on a per household basis. All of these are expected to capture more specific elements of the food economy than *foodshort*, and are analyzed in Chapter 5.

I use median distance to the nearest hospital, in minutes by foot, as an indicator of healthcare access. While hospital access is only one dimension of healthcare, it indicates the presence of a variety of other important healthcare related factors. I also include variables calculated in the same way as *foodshort*, as proportions of NLSS respondents giving a certain response to service and standard of living questions. These variables are *healthshort* and *healthsvc*, which correspond to proportion of households reporting inadequate healthcare and proportion of households reporting that government health service is bad. These variables have the same advantages and disadvantages as *foodshort*, but determining their appropriateness is, to a large degree, best determined by comparing their relative impact on fitted models.

Finally, I include several social, cultural, and demographic measures. I use percentage of a district's population belonging to marginalized ethnic or caste groups, from census data, as an explanatory variable, expecting that districts where more marginalized citizens reside will be affected by certain historical factors which cause that demographic composition, and by deficits in access to services and resources. Also using census data, I use the ratio of female students to total students in a district, as a measure of gender equity. From the NLSS, I generate the proportion of households in a district owning radios as an indicator of an average resident's access to outside messages which may influence social norms relevant in childhood nutrition.

For the most part, these variables are standardized, so that instead of the independent variables used in the regressions corresponding to the units in which the original variable is measured, they are measured in standard deviations. This makes it easier to compare the effects of independent variables measured in different kinds of units, and it gives the household level intercept a more meaningful interpretation, because with standardized variables, zero values correspond to the mean, which will always have some meaning, as opposed to the somewhat arbitrary meanings of zero values in the default units. Some variables are not standardized in this way, however – binary variables are not, because the mean value, which will fall between zero and one, is not a permissible value for binary variables. The wealth index is not standardized either, for similar reasons – it can only take integer values between one and five, so the mean, approximately 2.6, is not meaningful. Instead, I use the given value's difference from three, the median allowable value, so that the variable will capture the difference from a central value while maintaining a meaningful marginal interpretation. Standard deviations are not as meaningful for this index.

Table 1: Child and Household Characteristics by Wealth Index Quintile

Wealth Index Quintile	Poorest	Poorer	Middle	Richer	Richest
HAZ	-2.25	-2.05	-1.87	-1.59	-1.25
(standard deviation)	1.32	1.28	1.34	1.30	1.29
Child's age (months)	30	30	30	29	31
(standard deviation)	17	17	17	17	17
Child is breastfeeding (0/1)	59.13%	61.00%	60.35%	61.30%	53.63%
(standard deviation)	0.49	0.49	0.49	0.49	0.50
Months breastfeeding if still=1	12.20	13.14	12.25	12.07	10.32
(standard deviation)	14.65	15.01	14.69	14.00	13.46
Mothers years of education	1.00	1.73	2.49	4.05	7.03
(standard deviation)	2.29	2.87	3.42	4.02	4.02
Mother's BMI	20.24	19.94	20.28	20.68	22.34
(standard deviation)	2.19	2.31	2.45	2.93	3.41
Anything done to treat water	2.93%	4.99%	8.45%	13.49%	39.75%
(standard deviation)	0.17	0.22	0.28	0.34	0.49
Altitude	1243.61	801.19	684.51	611.43	557.48
(standard deviation)	793.45	831.48	829.25	708.76	669.23
Mother is a Dalit	25.69%	17.19%	14.36%	11.64%	6.44%
(standard deviation)	0.44	0.38	0.35	0.32	0.25
N	2219	1582	1372	1297	1102

Table 3: District Characteristics by Ecological Zone

Ecological Zone	Mountain	Hill	Terai
HAZ	-2.32	-1.87	-1.77
(standard deviation)	0.41	0.35	0.35
Mean share of income from ag.	55.98%	54.42%	47.88%
(standard deviation)	0.19	0.17	0.09
Total food consumption value (2006 rupees)	41534.29	38927.97	37983.31
(standard deviation)	9225.48	7583.62	3724.10
Mean fertilizer usage (kg)	44.87	86.01	183.88
(standard deviation)	60.77	115.70	76.67
Ratio of female students to total students	47.51%	49.24%	46.34%
(standard deviation)	0.04	0.02	0.03
Median distance to hospital on foot (minutes)	449.78	299.63	130.70
(standard deviation)	452.96	305.65	73.96
% Village Dev. Committees Open Defecation Free	7.67%	14.53%	6.29%
(standard deviation)	0.13	0.26	0.18
Mean district-level % of households with given characteristic			
Food shortage in past month	35.57%	26.84%	26.84%
(standard deviation)	0.24	0.13	0.11
Selling some amount of produced food (Commercial)	37.59%	41.58%	60.49%
(standard deviation)	0.23	0.18	0.11
Using improved seeds	16.34%	24.03%	36.37%
(standard deviation)	0.11	0.16	0.19
Belonging to marginalized ethnic/caste group	35.46%	43.25%	61.88%
(standard deviation)	0.21	0.16	0.15
Owning a radio	60.99%	64.71%	49.63%
(standard deviation)	0.12	0.10	0.14
Reporting insufficient healthcare	41.55%	27.42%	23.06%
(standard deviation)	0.23	0.15	0.07
Describing govt. health service as 'bad'	34.08%	21.73%	18.28%
(standard deviation)	0.20	0.13	0.05
N	1235	2997	3340

CHAPTER 5. RESULTS AND DISCUSSION

5.1 Random Intercept and Adapted Model

Results for a random intercept model are presented in Table 5. Three models are reported. Model 5a is a null model, which includes no explanatory variables, and thus acts as a summary of variance at different levels. Model 5b is a random intercept model, which includes explanatory variables at the child level, but only a random intercept at the district level. Model 5c is a random slope model, and includes child level predictors, a random intercept, and district level explanatory variables. Maternal education, wealth, and sanitation are treated as household-level effects, in contrast to the way they are implemented in Smith and Haddad's model. While aggregate indicators of these factors at the district level may have some explanatory power, the levels of these variables in a given child's household are intuitively more interesting as predictors of malnutrition. The random intercepts associated with this model, 5b, are summarized at the subregion level in Figure 4. These intercepts are, for the most part, fairly close to zero, though even those close to zero have similar magnitudes to a one quintile shift in the wealth index, based on the coefficient estimated in Model 5b. As the ends of the boxplots demonstrate, there is substantial variance in the intercept both within and across subregions. Specifically, the Western Terai seems to differ substantially from other subregions, because the average intercept value, denoted by the tick mark within the shaded area of its boxplot, is relatively far from those of other subregions.

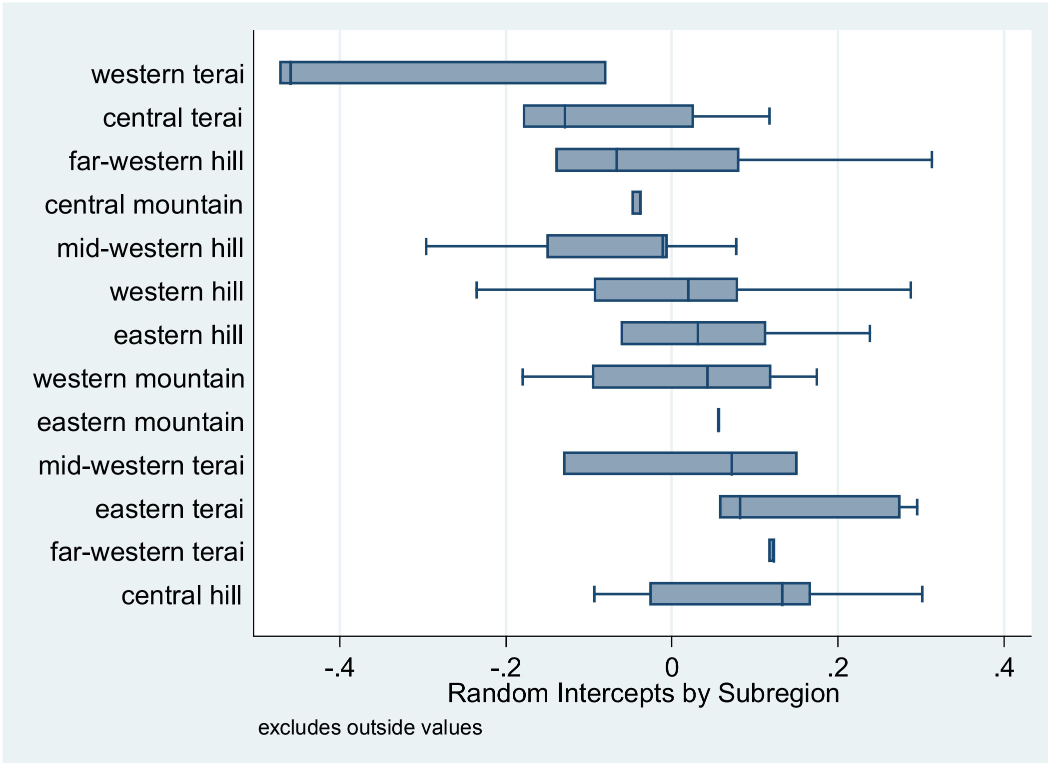

Figure 4 – Random Intercepts by Subregion (no second level variables)

Equation 13 gives the general form of this multilevel model, and I fit a variety of models including varying numbers of the components included in this general specification. In this section, I focus on the random intercept specification, in which explanatory variables only occur at the child level. In section 5.2, I discuss several alternative specifications which act as robustness checks. These include three alternative specifications of the random intercept model, two using smaller units as second level variables, rather than district, and one using a random coefficient model. I also respecify the model in three levels, using household as an intermediate level. In section 5.3, I discuss several random slope specification, introduced in more detail in the section itself. Finally in section 5.4, I discuss the results from all of these models together.

Women's relative status, Ω_C in Equation 13, can be measured at both the household and community level in these data, using either a given mother's decision-making power with regard to her own healthcare or the proportion of a district's schoolchildren who are girls. Arguments exist for either measure, and for their concurrent inclusion. A mother's control over her own healthcare suggests a certain level of empowerment, as well as the absence of a potential constraint on her health status, which is an important determinant of the child's nutritional status. Since these effects occur at the household level, it is easier to detect and interpret an effect for a given child. At the same time, community gender norms will affect mothers both in their households and in the community at large, and somewhat counterintuitively, the fact that *femaleratio* does not help explain a second component of malnutrition works in its favor as an indicator of gender equity. *Healthdecision* has at least two potential effects that are expected to have the same sign in a regression, and decomposing those effects to explicitly model the impact of increased gender equity is difficult. In contrast, all that is required for *femaleratio* to be a valid measure of community gender equity norms is that we make the reasonable assumption that being born a girl is random, and that at the aggregated district level, girls' being underrepresented in schools is primarily the result of some form of gender-based bias against them. *Femaleratio* is the preferred indicator due to this endogeneity concern, though both alternatives are analyzed together and separately. Likelihood ratio tests indicate that adding either variable to the household and random-intercept model changes the model significantly, however, and that adding either variable to a model including the other also significantly improves the likelihood.

As Model 5c shows, the determinant measures adapted from Smith and Haddad's model are statistically significant, with the expected signs and large estimated coefficients on the fixed effects variables. In Table 5, the significance of the random effects component is determined by a variety of LR tests, against different alternatives, which creates a summary of the results which may be somewhat confusing. This ambiguity arises from the variance in the random slopes shown in Figure 4. In the default Stata output, variance terms, along with their standard errors and 95% confidence intervals, are reported for each random effect, including the intercepts associated with each level of the model. These variance terms express the variances of each random component, and applying a conventional t-test to these variances can determine the statistical significance of between-district variance in random slopes or intercepts. Failure to reject the null hypothesis of zero variance based on these components means that one cannot be confident that the coefficient in question varies between districts, but this does not imply that the inclusion of the variable associated with the coefficient fails to change the distribution of the model in a statistically significant way. The significance of the inclusion of an additional random component can be tested, however, with the likelihood ratio test, by applying the test to the estimates from two models that are the same except for the inclusion of the variable to be tested (Rabe-Hesketh and Skrondal 2008, StataCorp 2013). Most of the models estimated and discussed here include several variance components, so there are many possible specifications which can be compared to a given model in the nested likelihood ratio test. To accurately represent this feature of likelihood ratio testing with these models, multiple likelihood ratio test statistics are reported along with their p values in several tables. This approach is somewhat unconventional, but it provides a complete impression of the significance of a given model compared to the possible smaller models which can be constructed from its variance components, so that its significance is clearer in context.

The results summarized in Table 5 represent a set of models with interpretable results, but the null model, which separates the total dependent variable variance into between-child and between-district components, reflects results that are interesting independent of the predictions of the models. In the null model, the variance term on the district constant, which represents the variance of the second-level error term, accounts for a very small proportion of the total variance, which is the residual variance plus the second-level error variance. In practical terms, this means that while HAZ does vary between districts, it does not vary by a large amount between districts, so understanding between-district variance can only go so far in understanding overall malnutrition. Since a major benefit of the multilevel approach is its ability to focus on between-district dependent variable variance, these findings somewhat weaken the argument for the multilevel approach. This emphasis on between-group variance is, of course, not the only benefit of multilevel modeling, but it is an important one.

Table 5: Summary of Basic Models

HAZ	5a -- Null Model Coefficient (Std. Err.)	5b -- Random Intercept Model Coefficient (Std. Err.)	5c -- District Predictor Model Coefficient (Std. Err.)
Age		-0.194***	-0.191***
(months, standardized)	--	(0.0608)	(0.0607)
Age squared		0.145***	0.146***
(months, standardized)	--	(0.0421)	(0.0421)
Still breastfeeding		0.885***	0.889***
(0/1 indicator)	--	(0.2381)	(0.2376)
Breastfeeding duration if still=1		-0.538***	-0.537***
(months, standardized)	--	(0.1264)	(0.1261)
Duration squared		0.141***	0.140***
(months, standardized)	--	(0.0351)	(0.035)
Mother's education		0.182***	0.183***
(years, standardized)	--	(0.017)	(0.017)
Mother's BMI		0.115***	0.115***
(index, standardized)	--	(0.0146)	(0.0146)
Wealth Index Quintile	--	0.107***	0.105***
(difference from md. value of 3)		(0.0133)	(0.0137)
Water purification	--	0.076	0.072
(indicator, 1=something done)		(0.04831)	(0.0483)
Year indicator	--	0.153***	0.158***
(0=2006, 1=2011)		(0.0302)	(0.0361)
Altitude			
(meters above sea lv.,		-0.185***	-0.196***
standardized)	--	(0.0267)	(0.0285)
Mother is a Dalit		-0.149***	-0.158***
(0=no, 1=yes)	--	(0.0379)	(0.0381)
	-1.918***	-2.677***	-2.672***
Constant	(.0429)	(0.138)	(0.1382)
Variance Component and Fit Statistics			
	1.717***	1.337***	1.328***
Residual Variance	(.02811)	(0.0219)	(0.0218)
	0.112***	0.041***	0.034***
District Variance	(.0224)	(0.0095)	(0.0096)
			0.008
Food shortage	--	--	(0.0058)
			0.012*
Female ratio	--	--	(0.0064)
Total Variance	1.829	1.378	1.362
Level 1 R-squared	--	0.221	0.227
Level 2 R-squared	--	0.636	0.696
Overall R-squared	--	0.247	0.255
Log-Likelihood	-12794.689	11831.530	11820.893
AIC	--	23693.060	23675.790
BIC	25616.160	23796.970	23793.550
LR test value (p value)		1926.31*** (.0000)	8.13*** (.0044)
Intraclass correlation	.061	.03	.025
N	7533	7533	7533

Note: Standard errors in parentheses

5.2 Robustness Checks

The DHS includes two alternative community denominations, wards, a political unit defined by the government of Nepal, and DHS primary sampling unit. There are several times as many of each of these groups as there are districts, at 372 wards and 399 PSU's in total. Multilevel models using these variables as the second-level groups can act as a check on the robustness of the low between-district variance, as these smaller districts will vary more, and because it is possible that some idiosyncrasy of the potentially over-aggregated district grouping understates the true variance between communities. If the variance in these more variable models is still small, this is evidence that HAZ varies by a limited amount between districts. Table 6 summarizes the results of these alternative specifications. Models 6a and 6c are null two-level models, using PSU and ward as the second-level unit, respectively, and Models 6b and 6d add fixed predictors to these null models. The results of these models suggest that between-community variance does seem to be unimportant relative to between-child or between-household variance, because at most, between-community variance accounts for approximately 11% of total variance. This is a larger proportion than what is observed in the district null model in Table 5, but the fact remains that the vast majority of HAZ variance occurs between children. Furthermore, in both alternative group specifications, the inclusion of the household-level variables explains the majority of the between-community variance, and when these variables are included, the variances are fairly close to the between-district variance, though they do remain somewhat larger.

The model estimated to generate the output summarized by Model 5c utilize group-level predictors, that is, variables which are the same for every member of a group in a given year. In a group level predictor model, these variables affect the dependent variable by shifting their district's intercept, in the form specified by the combination of equations 13a and 13b, while the β's estimated in the first-level portion remain fixed point estimates. In a random coefficient model, which combines equations 13a and 13c, the β's are shifted by the addition of some coefficient for each district, if the x associated with a given β is included at both the first and second level of the model. This specification is helpful because it allows the identification of variables assumed to have fixed effects which in fact differ across groups, which makes it possible to incorporate some otherwise unobserved heterogeneity into predictions. It can act as an additional test on the robustness of the predictive models in Table 5 by testing the implicit hypothesis that the household level coefficients are fixed across communities, and by testing the overall predictive impact of controlling for these potential sources of variation.

A random coefficient generally does not come with a clear narrative in the same way that a group level predictor does, as in many cases, a wide variety of unobserved heterogeneities could modify the effect of a variable across districts. Even without a clear story, the clarification these models provide is a useful feature of multilevel models. With variables for which unobserved heterogeneities are expected and understood – years of education, for example – random coefficient significance can be interpreted to an extent, as a control for expected heterogeneities such as teacher quality or access to materials, in the education example. Because this analysis is chiefly concerned with the ways in which community characteristics do or do not influence childhood nutrition, the random-slope models are most important. The random coefficient models are interesting, but ultimately, they can only act as evidence for the absence or presence of heterogeneity in household level effects. While they do identify a source of between-district variance, that variance is not explained: these models tell us that the coefficient on, for example, wealth index changes between districts, but they do not give any indication of why they might vary. In contrast, reductions in district intercept variance due to the addition of specific district-level predictors is at least associated with the factor or factors measured by that predictor. When an interpretation of random coefficient variance is readily available or where a plausible random slope variable is unavailable, it can be reasonable to use a random coefficient along with a random slope in this context, but their inclusion here is as a robustness check.

In the fixed household specification employed here, several variables display significant random coefficient variance when included at both the household and district levels. Age, maternal education, wealth index, the year 2011 indicator variable, altitude, and the Dalit indicator are all significantly different from zero at the 95% confidence interval according to nested likelihood ratio testing. This suggests that allowing these coefficients to vary between districts changes the model significantly. Some of these variables make more sense than others as random coefficients – it is quite difficult to come up with a story for a variable age effect between districts, for example, though years of education varying in its effect across district can be associated with a variety of potential unobserved factors. The significance of age drops below accepted levels when it is modeled along with other, more legitimate, random slopes, leaving wealth index, education, altitude, *Dalit*, and year as random slopes, each of which makes some intuitive sense as a random slope. Education has perhaps the most intuitive interpretation, as education quality can very easily vary across communities, for a variety of reasons.

Variance in the effect of wealth could capture different price levels or preferences across communities, a varying *Dalit* effect could reflect different levels of marginalization across communities, and a varying year effect can be seen as a clarification of the already unexplained change over time controlled by the inclusion of the fixed year effect at the first level. Altitude is less intuitively reasonable as a random coefficient, but it could reflect different levels of adaptation to harsh terrain, a difference in the level of biophysical characteristics which usually correlate with altitude, or simply act as a correction for an undetected nonlinearity in the effect of altitude, given the great diversity in altitude levels across Nepal.

Tables 7a and 7b summarize several random coefficient models. Models 7a-7e each contain an additional fixed component variable, chosen from those discussed in the previous paragraph, so that Model 7a includes only one random coefficient, for mother's education, and 7e includes random coefficients for all five of these variables. In many of these models, the variance between district coefficients is not significant. This means that the coefficient estimates cannot be treated as an indication of genuine coefficient heterogeneity, even if the inclusion of the random coefficient term significantly changes the model, based on likelihood ratio testing. In either possible variance significance outcome, however, these random coefficient models yield useful results: if coefficients vary significantly between groups, this provides useful information about heterogeneity, and if they do not, this reinforces the validity of the fixed component. The primary finding among the results summarized in Tables 7a and 7b is the combined likelihood ratio significance and variance component significance of the year indicator variable, because though this variable is included in this analysis as a control variable, this information can improve its precision in that specific capacity.

The child-level specification in all of these models simplifies the true hierarchical structure of the data by treating many effects that occur at the household level as though they occur at the child level. This is done because many children do not have any siblings under age 5, so differentiating household and child effects is meaningless in many cases, as the observed child is often the only one to whom a household effect value can be applied. While many of these single children have siblings, those siblings may be over five years old, and thus fall outside the population of interest.

A subsample of children with siblings does exist in the dataset, however, identified by common mother identification numbers. Out of the 7,572 children included in the dataset, 4,061 have one or more siblings also in the dataset, as well as non-missing values for all the independent variables used in the fitted models. Using common household identifiers as an intermediate level can provide additional context to the two level models, because models specified in this way measure the household variance component, and apply household characteristics in a more appropriate manner. Measuring the share of variance occurring between households adds context to the results presented for Model 5a, the two-level null model, in which the vast majority of the variance occurs between children: if a large proportion of this variance shifts to the households when they are included, initial findings regarding these variance components may become suspect. These models can thus provide feedback on the variance component shares in the original models, and on the utility of the household level coefficients in those models.

Table 8 presents the results of two-level models, like those in Table 5, fit to the sibling subsample, and Tables 9a and 9b present the estimates and descriptive statistics of several specifications of this three-level model for that same subsample. Models 8a and 9a are null models, models 8b and 9b are random intercept models with child-specific predictors, models 8c and 9c are random intercept models with child and household predictors, and models 8d and 9d are random slope models with child and household predictors, as well as the random slopes adapted from Smith and Haddad, used in Model 5c.This sub-sample's HAZ variance is very close to the full sample's (1.82 compared with 1.828) though the mean is lower (significantly so according to a simple bivariate regression of HAZ on a binary variable taking a value of one for a child with one or more siblings in the dataset). This difference in mean is explained by the negative impact of increasing the number of children in a household, however, as controlling for dependency ratio and additional children born to a child's mother to that bivariate regression reduces the coefficient estimate on the binary variable by a large enough amount that it is no longer statistically different from zero. These control variables will, all things being equal, rise when a child has more siblings, and they are negatively correlated with HAZ, so it seems that the apparent difference in the sample means is explained by the fact that the children with siblings in the DHS come from larger families. Based on the similarities between the sibling subsample and the overall sample, it is appropriate to compare and contrast the results of regressions which exploit the option of adding a household level to the child – district models with those base models, but the degree to which this subsample differs from the survey sample almost certainly reduces the representativeness of the sample, and thus the generalizability of regression estimates. Models including the household level are informative in their own right and provide context for the child/district models, but because of this generalizability issue, the three-level household model is not the preferred specification.

The results are striking, starting in the null model. In the null model, the addition of the household level moves a substantial proportion of the overall variance from the child level to the household level – variance between households accounts for approximately 19% of dependent variable variance, and group variance, encompassing both between-household and between-district variance, accounts for approximately 24% of total variance. This result differs substantially from the variance estimates generated by fitting a two-level model to this subsample, which results in an estimate of 6% of variance occurring between groups. Between-district variance is very similar between the two models, but the addition of the household level moves variance naively attributed to children to a more informative, and theoretically defensible, level.

Adding child-level independent variables produces another striking result, not detectable in the two-level models. The inclusion of these variables actually *increases* the between-household variance, while decreasing between-district, overall, and between-child variance, the latter of which occurs by construction. Such a result is impossible in OLS, and while this behavior is not expected in a multilevel model, it is a valid outcome, and it provides useful information about relationships within the data. Increasing between-group variance conditional on the inclusion of lower level predictors suggests that the null model variance estimates were naively conservative, due to unobserved correlation between lower level predictors and higher level errors (Gelman and Hill 2009). The null model misses some variation between households because it estimates inappropriately high intercepts for households with higher levels of independent variables. Likewise, conditioning intercept estimates on this new information yields more varied intercepts, and thus a higher variance estimate and a higher proportion of total variance from between-household variance. By this logic, the relative sizes of the variance components in Model 9b are more credible than their counterparts in Model 9a. That being said, computing R-squared based on comparisons with Model 9b does not provide the information R-squared is supposed to provide, that is, the proportion of total variance explained by a set of independent variables. Some overall variance, approximately 16%, is explained by these child-level independent variables, so using the district, child, and household variances as null variance in R-squared computations is clearly inappropriate. At the same time, computing household-level R-squared values based on the null models makes no sense, because for a model that displays a substantial reduction in variance compared to Model 9b, the R-squared could easily be negative. The R-squared values using Model 9a as the null for overall, child, and district R-squared, and the values using Model 9b as the null for household R-squared are preferred because the inclusion of the child variables changes between-child variance both by explaining some and by shifting some to the household level. This means that the household variance in Model 9b is more likely to be the true between-household variance, though using these variance estimates as the null model for the other R-squared computations is clearly incorrect, as parts of their variances are explained by the inclusion of child variables. This interpretation suffers from the fact that it conveniently prefers higher R-squared estimates. So as to avoid the appearance of bias, I report R-squared using each set of variance estimates as the null values.

The household level variables also improve the fit of the model, though their coefficients must be evaluated differently in this random effects specification than in the original specification, which treated them as fixed. Taken together, the likelihood ratio test suggests that their inclusion changes the model's likelihood significantly, but several coefficients do not vary significantly between districts, and the multilevel model's random effects components do not allow for analogs to the t-tests automatically performed on the fixed-effects versions of these coefficients. Comparing the descriptive statistics of Models 8b, Model 5b fit to the sibling subsample where N=4,061 rather than 7,533, and 9c allows us to determine which version of this child and household model best fits the data.

Adding district level predictors to the third level of Model 9c makes it possible to decompose the variance explained by these predictors into household and child components, in addition to simply improving the predictive power of the model. The three-level model with district level predictors, Model 9d, does display a significantly higher likelihood than Model 9c, but only at the 90% confidence level ($p = .0916$). By other descriptive statistics, it is also a marginal improvement, but because this exercise is, at its core, a robustness check exploring a subset of the data, the results generated by this model are still useful. As one would expect, this model estimates a lower level of district intercept variance than the child and household predictor model, due to the inclusion of the random slopes, but this reduction is much smaller than the reduction observed in its two-level counterpart, because in that specification, the original specification of the fixed effects component explained the majority of between district variance. Given this information, this particular district level specification does a better job of partitioning the sources of between district variance, because the district-level r-squared improvement achieved by including these variables, compared to simply including the combined household and child variables, was smaller in the two-level model than in Model 9d.

The additional partitioning of variance into households yields some interesting insights, but overall, it does not change the predictive power of the model significantly, given the same set of independent variables. As in the original models, the majority of the variance in the dependent variable occurs between children and a very small proportion of the variance occurs between districts, and the stability of this general breakdown with the addition of the household level suggests that the general narrative suggested by the original model is reasonable. These three-level models do suggest that multilevel models can help organize these data by partitioning large components of the variance into smaller denominations, as the household variance is both substantial and explicable by variables discussed in the literature and in Chapter 3, but overall, the more appropriate three-level model does not substantially alter the predictions of the two-level model, or their power.

Table 6: Alternative Community Unit Random Intercept Models

HAZ	Model 6a Coefficient (Standard Error)	Model 6b Coefficient (Standard Error)	Model 6c Coefficient (Standard Error)	Model 6d Coefficient (Standard Error)
Age (months, standardized)	--	-0.0410*** (0.0118)	--	-0.0404*** (0.0118)
Age squared (months, standardized)	--	0.0005*** (0.0001)	--	0.0005*** (0.0001)
Still breastfeeding (0/1 indicator)	--	0.8982*** (0.2371)	--	0.9107*** (0.2382)
Breastfeeding duration if still=1 (months, standardized)	--	-0.5472*** (0.1258)	--	-0.5526*** (0.1264)
Duration squared (months, standardized)	--	0.1410*** (0.035)	--	0.1432*** (0.035)
Mother's education (years, standardized)	--	0.1801*** (0.0172)	--	0.1768*** (0.0171)
Mother's BMI (index, standardized)	--	0.1147*** (0.0146)	--	0.1170*** (0.0146)
Wealth Index Quintile (difference from md. value of 3)	--	0.0932*** (0.014)	--	0.1009*** (0.0134)
Water purification (indicator, 1=something done)	--	0.0730 (0.0492)	--	0.0942* (0.0485)
Year indicator (0=2006, 1=2011)	--	0.1658*** (0.0368)	--	0.1647*** (0.0344)
Altitude (meters above sea lv., standardized)	--	-0.1562*** (0.0242)	--	-0.1737*** (0.0229)
Mother is a Dalit (0=no, 1=yes)	--	-0.1559*** (0.0397)	--	-0.1525*** (0.0391)
Constant	-1.8532*** (0.0281)	-1.9227*** (0.3563)	-1.7995*** (0.0282)	-1.9233*** (0.3577)
Variance Component and Fit Statistics				
Residual Variance	1.6257 (0.0272)	1.2981 (0.0217)	1.6561 (0.0276)	1.3148 (0.0219)
Random Intercept Variance	0.1980*** (0.0215)	0.0838*** (0.0118)	0.1792*** (0.0213)	0.0614*** (0.0097)
Total Variance	1.8237	1.3818	1.8353	1.3762
Level 1 R-squared	--	0.2016	--	0.2061
Level 2 R-squared	--	0.5770	--	0.6575
Overall R-squared	--	0.2423	--	0.2501
Log-Likelihood	-12736.76	-11817.76	-12782.37	-11832.49
AIC	25479.52	23665.51	25570.74	23694.99
BIC	25500.30	23769.42	25591.52	23798.89
ICC	0.1086	0.0606	0.0977	0.0446
N	7533	7533	7533	7533

Note: Standard errors in parentheses

Table 7a: Random Coefficient Models, Fixed Component

HAZ	Model 7a Coefficient (Std. Err.)	Model 7b Coefficient (Std. Err.)	Model 7c Coefficient (Std. Err.)	Model 7d Coefficient (Std. Err.)	Model 7e Coefficient (Std. Err.)
Age (months)	-0.1933*** (0.0608)	-0.1938*** (0.06071)	-0.1952*** (0.0606)	-0.1945*** (0.0606)	-0.1944*** (0.0606)
Age squared	0.1448*** (0.0421)	0.1451*** (0.0421)	0.1465*** (0.042)	0.1464*** (0.042)	0.1469*** (0.042)
Still breastfeeding (0/1)	0.8883*** (0.238)	0.8904*** (0.2386)	0.8823*** (0.237)	0.8834*** (0.2373)	0.8851*** (0.2372)
Months breastfeeding if still=1	-0.5394*** (0.1263)	-0.5411*** (0.1261)	-0.5362*** (0.126)	-0.5366*** (0.126)	-0.5371*** (0.1259)
Months squared	0.1412*** (0.035)	0.1416*** (0.035)	0.1398*** (0.035)	0.1399*** (0.03495)	0.1401*** (0.03492)
Mother's years of education	0.1814*** (0.0195)	0.1803*** (0.0188)	0.1817*** (0.0187)	0.1798*** (0.01867)	0.1819*** (0.0185)
Mother's BMI	0.1147*** (0.0146)	0.1127*** (0.0146)	0.1132*** (0.0146)	0.1124*** (0.0146)	0.1126*** (0.0146)
Wealth Index Quintile	0.1077*** (0.0133)	0.1045*** (0.0161)	0.1044*** (0.0161)	0.1041*** (0.0156)	0.1047*** (0.0155)
Something done to purify water (0/1)	0.0773 (0.0486)	0.0708 (0.0489)	0.0738 (0.0488)	0.0735 (0.0488)	0.0738 (0.04885)
Year = 2011 (0/1)	0.1546*** (0.0303)	0.1523*** (0.0304)	0.1498*** (0.0305)	0.1535*** (0.0307)	0.1588*** (0.0386)
Altitude	-0.1820*** (0.0268)	-0.1786*** (0.0271)	-0.1811*** (0.0273)	-0.1711*** (0.0331)	-0.1656*** (0.0329)
Mother is a Dalit (0/1)	-0.1510*** (0.038)	-0.1533*** (0.0381)	-0.1316*** (0.0458)	-0.1321*** (0.0456)	-0.1321*** (0.0453)
Constant	-2.6782*** (0.138)	-2.6824*** (0.1379)	-2.6797*** (0.1378)	-2.6815*** (0.1379)	-2.6856*** (0.1378)
N	7533	7533	7533	7533	7533

Note: Standard errors in parentheses

Table 7b – Random Coefficient Model, Random Components

Random Coefficient Variances:	7a Coefficient: (Std. Err.)	7b Coefficient: (Std. Err.)	7c Coefficient: (Std. Err.)	7d Coefficient: (Std. Err.)	7e Coefficient: (Std. Err.)
	1.33***	1.33***	1.32***	1.32***	1.31***
Residual Variance:	(0.0219)	(0.0219)	(0.0219)	(0.0219)	(0.0218)
	0.04***	0.041***	0.041***	0.032***	0.032***
District Variance:	(0.009)	(0.01)	(0.01)	(0.01)	(0.011)
Mother's education	0.005	0.004	0.003	0.003	0.003
(years, standardized)	(0.0031)	(0.0031)	(0.003)	(0.0029)	(0.0029)
Wealth Index Quintile (difference from md. value of		0.0046**	0.0046**	0.0035	0.003
3)	--	(0.0022)	(0.0022)	(0.0021)	(0.002)
Mother is a Dalit			0.030	0.029	0.027
(0=no, 1=yes)	--	--	(0.0203)	(0.0201)	(0.0201)
Altitude (meters above sea lv.,				0.024*	0.022*
standardized)	--	--	--	(0.0131)	(0.0131)
Year indicator					0.032**
(0=2006, 1=2011)	--	--	--	--	(0.0151)
Total Variance:	1.373	1.368	1.364	1.353	1.346
Level 1 R-squared:	0.224	0.227	0.229	0.231	0.234
Level 2 R-squared:	0.642	0.637	0.639	0.713	0.719
Overall R-squared:	0.249	0.252	0.254	0.261	0.264
Log-Likelihood:	-11829.3	-11824.8	-11822.9	-11820.1	-11815.4
AIC:	23690.54	23683.69	23681.69	23678.19	23670.87
BIC:	23801.37	23801.45	23806.38	23809.8	23809.41
	4.53**	8.85**			9.32***
LR test statistic (p value):	(.0333)	(.0029)	4** (.0456)	5.5** (.019)	(.0023)
Intraclass correlation:	.0293	.0296	.0296	.0236	.0232
N:	7533	7533	7533	7533	7533

Note: Standard errors in parentheses

Table 8: District Random Intercept Models for Sibling Subsample

HAZ	8a: Null Model Coefficient (Std. Error)	8b: Child model Coefficient (Std. Error)	8c: Household Model Coefficient (Std. Error)	8d: District Predictors Coefficient (Std. Error)
Age (months, standardized)	--	-0.2081*** (0.0769)	-0.1835*** (0.0744)	-0.1796*** (0.07411)
Age squared (months, standardized)	--	0.1788*** (0.054`)	0.1687*** (0.0522)	0.1687*** (0.0521)
Still breastfeeding (0/1 indicator)	--	0.8958*** (0.303)	0.9291*** (0.2931)	0.9359*** (0.2923)
Breastfeeding duration if still=1 (months, standardized)	--	-0.5551*** (0.1635)	-0.5566*** (0.1579)	-0.5572*** (0.1576)
Duration squared (months, standardized)	--	0.1834*** (0.0508)	0.1645*** (0.0491)	0.1648*** (0.049)
Mother's education (years, standardized)	--	0.1901*** (0.0434)	0.1123*** (0.0426)	0.1139** (0.0482)
Mother's BMI (index, standardized)	--	--	0.1157*** (0.021)	0.1125*** (0.021)
Wealth Index Quintile (difference from md. value of 3)	--	--	0.0937*** (0.0181)	0.0953*** (0.0182)
Water purification (indicator, 1=something done)	--	--	0.1057*** (0.074)	0.1056*** (0.074)
Year indicator (0=2006, 1=2011)	--	--	-0.1927*** (0.0329)	-0.1942*** (0.0349)
Altitude (meters above sea lv., standardized)	--	--	-0.2004*** (0.0507)	-0.2086*** (0.0509)
Mother is a Dalit (0=no, 1=yes)	--	--	0.1840*** (0.0242)	0.1805*** (0.0243)
Constant:	-2.9435*** (0.04577)	-2.9435*** (0.18)	-2.7808*** (0.172)	-2.7772*** (0.1723)
District Variance:	0.1103 (0.0252)	0.1049 (0.023)	0.0472	0.0385
Residual Variance:	1.7178 (0.0385)	1.4290 (0.032)	1.3354	1.3259
Total Variance:	1.8281	1.5339	1.3825	1.3644
Level 1 R-squared:	--	0.1681	0.2226	0.2281
Level 2 R-squared:	--	0.0495	0.5726	0.6509
Overall R-squared:	--	0.1610	0.2437	0.2537
Log-Likelihood:	-6912.091	-6541.895	-6386.238	-6382.041
AIC:	13830.18	13101.79	12802.48	12798.08
BIC:	13849.11	13158.57	12897.11	12905.34
LR test statistic (p value):		740.39 (0)	311.31 (0)	8.39 (.0151)
ICC:	0.0604	0.0684	0.0341	0.0282
N:	4061	4061	4061	4061

Table 9a: Child and Household Characteristics, 3-Level Model

HAZ	9a: Null Model Coefficient (Std. Error)	9b: Child Model Coefficient (Std. Error)	9c: Household Model Coefficient (Std. Error)	9d: District Predictors Coefficient (Std. Error)
Age (months, standardized)	--	-0.2353*** (0.0714)	-0.2336*** (0.0708)	-0.2318*** (0.0708)
Age squared (months, standardized)	--	0.1968*** (0.0502)	0.1944*** (0.0497)	0.1941*** (0.0497)
Still breastfeeding (0/1 indicator)	--	0.8263*** (0.2801)	0.8431*** (0.2776)	0.8466*** (0.2775)
Breastfeeding duration if still=1 (months, standardized)	--	-0.5357*** (0.1507)	-0.5470*** (0.1493)	-0.5472*** (0.1493)
Duration squared (months, standardized)	--	0.1632*** (0.0469)	0.1677*** (0.0466)	0.1680*** (0.0466)
Year = 2011 Indicator (1=2011, 0=2006)	--	0.1871*** (0.0488)	0.1806*** (0.0494)	0.1947*** (0.0551)
Constant:	-1.9600*** (0.0456)	-2.9080*** (0.1662)	-2.9314*** (0.1645)	-2.9226*** (0.1648)
Residual Variance:	1.3804 (0.0412)	0.9692 (0.029)	0.9432	0.9434 (0.0292)
Household Variance:	0.3451 (0.0374)	0.4716 (0.0336)	0.3271	0.3312 (0.0503)
District Variance:	0.1004 (0.0249)	0.0911 (0.0226)	0.0856	0.0714 (0.0216)
Total Variance:	1.8259	1.5320	1.3559	1.3460
Mother's BMI (Index value, std.)	--	--	0.0468 (0.0295)	0.0467 (0.0293)
Wealth Index: (distance from md.)	--	--	0.0233 (0.0177)	0.0200 (0.0176)
Sanitation: (0/1 indicator for water treatment)	--	--	0.0000 (0)	0.0000 (0)
Altitude: (MASL, std.)	--	--	0.0063 (0.0412)	0.0000 (0)
Mother is a Dalit (0/1 indicator)	--	--	0.0525 (0.0793)	0.0446 (0.0792)
Mother's Education (years, standardized)	--	--	0.0788** (0.0341)	0.0775** (0.0338)
N:	4061	4061	4061	4061

Note: Standard errors in parentheses

Table 9b: District Characteristics and Descriptive Statistics, 3-Level Model

HAZ:	9a: Null Model Coefficient (Std. Error)	9b: Child model: Coefficient (Std. Error)	9c: Household Model Coefficient (Std. Error)		9d: District Predictors Coefficient (Std. Error)	
Foodshort	--	--	0.0211 (.0182)		0.0211 (.0182)	
Femaleratio	--	--	0.0051 (.0093)		0.0051 (.0093)	
R^2 Base Model	--	Null:	Null:	Child:	Null:	Child:
Level 1 R-squared	--	.2979	0.3167	0.0269	0.3166	0.0267
Level 2 R-squared	--	-0.3666	0.0521	0.3064	0.0403	0.2978
Level 3 R-squared	--	--	0.1474	0.0603	0.2891	0.2165
Overall R-squared	--	0.1610	0.2574	0.1149	0.2628	0.1214
Log-Likelihood	-6892.80	-6405.73	-6397.39		-6395.00	
AIC	13730.07	12831.47	12826.78		12826.00	
BIC	13755.31	12894.56	12927.73		12939.57	
LR test statistic (p value)		910.6 (0)	16.69 (.0105)		4.78 (.0916)	
ICC, District	0.055	0.0595	0.0631		0.053	
ICC, Household	0.244	0.3673	0.3044		0.2991	
N	4061	4061	4061		4061	

Note: Standard errors in parentheses

5.3 Group Predictor Models

While between-community variation accounts for a small proportion of variation in HAZ, determining the relative importance of the specific factors into which that variance can be partitioned still provides useful information. Equation 13 identifies several community level factors which can be most appropriately modeled as group level predictors: health environment, natural environment, food, and cultural factors. The sources used in compiling this dataset do not include much data on characteristics of natural environment, so while it is a legitimate determinant of malnutrition, it is not pursued here. There are sufficient data to include these other components as district characteristics, however. To evaluate the roles of these determinants, I start by estimating a general model extending Model 5c, the model adapted from Smith and Haddad. I then estimate groups of nested models for each of these determinant categories, and finally estimate a model including the most robust indicators of each determinant group, given the constraint on the number of possible second-level predictors.

The NLSS includes several items which can be used to construct measures of community-level health environment, as does the DHS, but ultimately, median distance to the nearest hospital on foot, *hospital*, was selected as the measure of interest. This measure benefits from a clear interpretation and conceptual appropriateness as a factor which is connected to some set of district characteristics, rather than an aggregation of more idiosyncratic factors. *Femaleratio* is used as a measure of district gender equity norms. When hospital distance is included in the model, food shortage loses its significance, as the model including both hospital distance and food shortage is not significantly different from the model including only hospital distance. The model estimated using all four variables for comparison does not converge, so while modelling food shortage in this model would be preferable, it is omitted, though given other tests, there is evidence that it would not be helpful. The role of district ethnic and caste composition is also examined through *marginal*, which measures the proportion of a district's population that belongs to a marginalized group. This is meant to capture otherwise unobserved social and historical factors associated with ethnic makeup, and is assumed to be distinct from *femaleratio*. Tables 10a and 10b summarize this general model. These tables include three random slope models, using different combinations of *femaleratio*, *marginal*, and *hospital* to generate a general specification which draws on diverse categories of predictors. According to the likelihood ratio test, R-squared values, and AIC, Model 10b, which includes *marginal* and *hospital* at the district level, is a substantial improvement over model 10a, which includes only *hospital*. Adding *femaleratio* in Model 10c improves the model by a negligible amount, leading to an insignificant LR test result and a higher AIC, as the penalization from the additional variable easily overcomes the modest improvement in the log-likelihood. This suggests that, when one controls for *marginal* and *hospital*, *femaleratio* is superfluous.

The limited number of level two units used in this analysis (75) makes it difficult to include a large numbers of second-level predictors, so the analysis of multiple dimensions of community-level determinants of malnutrition requires separate models, rather than the normal approach of adding new variables of interest to a base model as in the general models summarized in tables 10a and 10b. To supplement this general model, I report results from several models that expand on the general factors of interest measured with single representative variables in this model: agriculture, socio-cultural factors, and health environment.

These agriculture models are reported in tables 11a through 11d. These tables include two sets of random slope models focused on district-level agricultural characteristics. Models 11a through 11c, presented in tables 11a and 11b, combine input variables (*fertkg* and *impseed*) with *foodshort* and *totalfood*, the 2006 rupee value of food consumption, while models 11d-11g, in tables 11c-11d, replace *totalfood* and *foodshort* with *commercial* and *agincshr*, while keeping the input variables. Intuitively, food supply should be an important determinant of children's nutritional status in a given district, but it is far from the only important factor: a large supply of inaccessible or non-nutritious food will not ensure sufficient nutrition, nor will a highly variable food supply with a seemingly adequate mean value. To a certain extent, the *foodshort* measure used in many of the models already discussed solves these problems, as it measures individuals' assessments of their food supply so that variations in access and supply are accounted for, though the measure does have the drawbacks discussed in Chapter 4. This makes it a convenient measure for the general models, but due to its convenient generality, it tells only a very general story. To compare the different features of district-level food and agricultural economies for which data are available, more specific variables, corresponding to more objective measures, are necessary. To this end, I estimate several models using yield, total food consumption in 2006 rupees, agricultural income as a proportion of total income, ratio of consumption from food produced by a household to its total food consumption, percentage of households reporting selling any amount of their produced crops, and input usage variables, all in mean and median terms at the household level, averaged over all observed households in each district. Many of these variables overlap – *totalfood* and *yield* both measure food supply, and the ratio variables measure subtly different features of households' interactions with food markets, to capture both diversification, and thus vulnerability, and the health of district-level food markets, but sufficiently important differences exist between these related variables to merit the analysis of alternatives.

To eliminate the necessity of some specifications, each of these variables was tested for significance via a likelihood ratio test of a model containing one variable at a time against the random intercept model. The majority of these variables were significant at the 90% confidence interval or higher, though yield was not (p=.1048). Testing combinations of the input variables – fertilizer usage, percentage of households using improved seeds, percentage using irrigation, and percentage receiving agricultural advice from the government – also revealed that the inclusion of the advice and irrigation variables does not change the model significantly, compared to alternatives.

While a variety of potential specifications were estimated using these agriculture variables, many were uninformative or failed to converge. A subset of these models are summarized in Tables 11a-11b. These results suggest that commercialization and input usage can partition a substantial proportion of the between-district variance remaining in the random intercept model into combinations of district level coefficients and variable values, and that including other variables along with these factors does little to nothing to improve the model. This is somewhat surprising, given the indirect pathways through which these variables may effect nutritional status. Taken together, the input variables and commercialization do capture important dimensions of both food supply and market access. The significance of these variables compared to the more direct measures tested along with them suggests that at least in this context, the variables calculated as proportions may be more informative than the variables calculated as descriptive statistics. Based on the significance and fit statistics in Tables 11a-11d, fertilizer usage and commercialization are the most important agricultural indicators of nutrition outcomes among those analyzed here.

The dataset includes fewer variables measuring healthcare than agriculture, but there is enough information to control for factors that are not explicitly observed in the hospital variable used in the general model. Table 12 presents three random slope models employing these controls. To control for the perceived quality of healthcare availability, I include measures generated from the NLSS service and consumption section similar to *foodshort*. These are *healthshort*, the proportion of households reporting that they see their healthcare as inadequate, and *healthsvc*, the proportion of households reporting that they view government health services in their area as bad. These measures are very similar conceptually, and bivariate regressions, in both the complete dataset and in a collapsed version wherein observations are district-year combinations rather than children, reveal that they are highly correlated. Consequently, they are not included together, as that would introduce an obvious colinearity. Because there is no clear reason to prefer one to the other as a measure of community-level healthcare quality, however, both are regressed along with hospital distance, as alternative measures to control for otherwise-unobserved variations in community-level healthcare quality. These health regressions are summarized in Table 12. Neither of the quality controls changes the model significantly according to the results of the likelihood ratio test, and the variance terms on each model are very close to zero when regressed along with hospital distance. In regressions not summarized here, however, including health shortage as a variance component along with the household variables does produce a significant change in the model, and its variance component is significant. This suggests that *hospital* and *healthshort* are, to some extent, measuring the same factors, rather than complementary factors as initially expected.

Several district-level indicators of sociocultural and demographic factors have been discussed in the context of previous models, both as district predictors and random coefficients, but in addition to these variables, Tables 13a and 13b include models using percentages of households in a given district with radios. Radio ownership prevalence is included as a measure of access to messages from outside the community designed to change cultural norms, an intervention which has been used successfully in the past in Nepal (Sharan and Valente 2002). As in the models summarized in Table 10, *marginal* plays a large role in these models, but the addition of the other variables changes the model significantly as well, though the case for the effect of radio prevalence is somewhat dubious. The multiple likelihood ratio tests executed for the addition of each variable are informative here. The models including *radio* do display significant changes in log likelihood compared to the models I summarize in Tables 10a and 10b, but as the likelihood ratio test results show, the models including *radio* are not significantly different from simpler models including either *marginal* and *femaleratio* or all three other variables, where radio is included in a model one variance component larger.

Tables 14a and 14b summarize the preferred random slope models. These models include the variables that have the strongest effects in the families of predictor-type models. Model 14a is the preferred specification, because it is more parsimonious without losing explanatory power, based on its AIC value relative to Model 14b. Model 14b includes *fertilizer* in addition to the other 14a variables to observe the impact of including all of the district-level predictors that appear to improve predictions, based on the models in Tables 11 through 13. Model 14b is not significantly different from 14a, supporting its status as the preferred specification. This model partitions the overwhelming majority of between-district variance into specific sources of heterogeneity, and a higher proportion of overall variance than the other models summarized in this chapter.

Table 10a: General Specification Fixed Component

HAZ	10a Coefficient (Std. Err.)	10b Coefficient (Std. Err.)	10c Coefficient (Std. Err.)
Age	-0.194***	-0.193***	-0.192***
(months, standardized)	(0.0607)	(0.0607)	(0.0607)
Age squared	0.148***	0.148***	0.147***
(months, standardized)	(0.0421)	(0.0421)	(0.0421)
Still breastfeeding	0.883***	0.884***	0.888***
(0/1 indicator)	(0.238)	(0.238)	(0.238)
Breastfeeding duration if still=1	-0.533***	-0.534***	-0.537***
(months, standardized)	(0.1261	(0.1261)	(0.1261)
Duration squared	0.140***	0.140***	0.141***
(months, standardized)	(0.035)	(0.035)	(0.035)
Mother's education	0.184***	0.183***	0.183***
(years, standardized)	(0.017)	(0.017)	(0.017)
Mother's BMI	0.116***	0.116***	0.115***
(index, standardized)	(0.0146)	(0.0146)	(0.0146)
Wealth Index Quintile	0.106***	0.108***	0.108***
(difference from md. value of 3)	(0.0133)	(0.0133)	(0.0133)
Water purification	0.069	0.067	0.069
(indicator, 1=something done)	(0.0483)	(0.0482)	(0.0482)
Year indicator	0.166***	0.165***	0.146***
(0=2006, 1=2011)	(0.0355)	(0.0352)	(0.036)
Altitude	-0.178***	-0.179***	-0.189***
(meters above sea lv., standardized)	(0.027)	(0.0263)	(0.0267)
Mother is a Dalit	-0.145***	-0.142***	-0.146***
(0=no, 1=yes)	(0.038)	(0.0379)	(0.0379)
	-2.679***	-2.682***	-2.671***
Constant	(0.137)	(0.1372)	(0.1373)
N	7533	7533	7533

Note: Standard errors in parentheses

Table 10b: General Specification Variance Component and Fit Statistics

HAZ	10a Coefficient (Std. Err.)	10b Coefficient (Std. Err.)	10c Coefficient (Std. Err.)
	1.328***	1.329***	1.328***
Residual Variance	(0.0218)	(0.0218)	(0.0218)
	0.036***	0.006***	0.006***
District Variance	(0.0094)	(0.0091)	(0.0093)
Female Ratio			0.007
(%, standardized)	--	--	(0.0101)
Hospital Distance	0.028**	0.026**	0.016
(md. distance in mins, standardized)	(0.0117)	(0.0109)	(0.0136)
Marginal		0.032**	0.027***
(%, standardized)	--	(0.014)	(0.0064)
Total Variance	1.364	1.335	1.335
Level 1 R-squared	.227	0.226	0.226
Level 2 R-squared	0.680	0.943	0.943
Overall R-squared	0.254	0.270	0.270
Log-Likelihood	-11820.710	-11817.875	-11817.139
AIC	23673.410	23669.750	23670.280
BIC	23784.250	23787.510	23794.960
LR test statistic (p value)	21.65*** (.0000)	20.89*** (.0000)	1.47 (.2248)
LR test statistic (p value)*		5.66** (.0173)	
Intraclass correlation	.0276	.0048	.0048
N	7533	7533	7533

Note: Standard errors in parentheses

Table 11a: Agricultural Variable Models, Fixed Component

HAZ	11a Coefficient (Std. Err.)	11b Coefficient (Std. Err.)	11c Coefficient (Std. Err.)
Age	-0.196***	-0.196***	-0.195***
(months, standardized)	(0.0608)	(0.0607)	(0.0607)
Age squared	0.149***	0.149***	0.148***
(months, standardized)	(0.0421)	(0.0421)	(0.0421)
Still breastfeeding	0.872***	0.875***	0.877***
(0/1 indicator)	(0.238)	(0.238)	(0.238)
Breastfeeding duration if still=1	-0.530***	-0.531***	-0.532***
(months, standardized)	(0.1263)	(0.1263)	(0.1263)
Duration squared	0.139***	0.140***	0.140***
(months, standardized)	(0.035)	(0.035)	(0.035)
Mother's education	0.182***	0.183***	0.183***
(years, standardized)	(0.017)	(0.017)	(0.017)
Mother's BMI	0.116***	0.116***	0.116***
(index, standardized)	(0.0146)	(0.0146)	(0.0146)
Wealth Index Quintile	0.106***	0.107***	0.108***
(difference from md. value of 3)	(0.0133)	(0.0133)	(0.0133)
Water purification	0.074	0.070	0.070
(indicator, 1=something done)	(0.0483)	(0.0483)	(0.0483)
Year indicator	0.157***	0.142***	0.144***
(0=2006, 1=2011)	(0.0332)	(0.0338)	(0.0342)
Altitude	-0.187***	-0.177***	-0.177***
(meters above sea lv., standardized)	(0.0269)	(0.0268)	(0.0269)
Mother is a Dalit	-0.154***	-0.152***	-0.152***
(0=no, 1=yes)	(0.038)	(0.038)	(0.038)
	-2.666***	-2.671***	-2.672***
Constant	(0.1381)	(0.138)	(0.138)
N	7533	7533	7533

Note: Standard errors in parentheses

Table 11b: Agricultural Variables, Random Component and Descriptive Statistics

HAZ	11a Coefficient (Std. Err.)	11b Coefficient (Std. Err.)	11c Coefficient (Std. Err.)
Improved seed prevalence	0.012*	0.011*	0.011*
(%, standardized)	(0.0063)	(0.0061)	(0.0061)
Fertilizer use		0.006	0.005
(mn. kg, standardized)	--	(0.0052)	(0.0051)
Total food			0.002
(mn. 2006 rupees, standardized)	--	--	(0.005)
Total Variance	1.368	1.365	1.364
Level 1 R-squared	0.224	0.224	0.225
Level 2 R-squared	0.681	0.701	0.707
Overall R-squared	0.252	0.254	0.254
Log-Likelihood	-11827.010	-11824.800	-11824.750
AIC	23686.010	23683.610	23685.500
BIC	23796.850	23801.370	23810.190
LR test statistic (p value)	9.05*** (.0026)	4.41** (.0358)	.1 (.7469)
LR test statistic (p value)*	--	7.87*** (.0050)	3.89** (.0487)
LR test statistic (p value)*	--	--	6.67*** (.0098)
Intraclass correlation	.0262	.0246	.0241
N	7533	7533	7533

Note: Standard errors in parentheses

Table 11c: Alternative Agriculture Specifications, Fixed Component:

HAZ	11d Coefficient (Std. Err.)	11f Coefficient (Std. Err.)	11g Coefficient (Std. Err.)	11h Coefficient (Std. Err.)
Age	-0.1948***	-0.1961***	-0.1961***	-0.1961***
(months, standardized)	(0.06071)	(0.0607)	(0.0607)	(0.0607)
Age squared	0.1475***	0.1491***	0.1493***	0.1493***
(months, standardized)	(0.0421)	(0.0421)	(0.0421)	(0.0421)
Still breastfeeding	0.8794***	0.8720***	0.8730***	0.8730***
(0/1 indicator)	(0.2377)	(0.2377)	(0.2377)	(0.2377)
Breastfeeding duration if still=1	-0.5339***	-0.5296***	-0.5297***	-0.5297***
(months, standardized)	(0.1262)	(0.1262)	(0.1262)	(0.1262)
Duration squared	0.1399***	0.1388***	0.1392***	0.1392***
(months, standardized)	(0.035)	(0.035)	(0.035)	(0.035)
Mother's education	0.1810***	0.1813***	0.1822***	0.1822***
(years, standardized)	(0.017)	(0.017)	(0.017)	(0.017)
Mother's BMI	0.1144***	0.1150***	0.1146***	0.1146***
(index, standardized)	(0.0146)	(0.0146)	(0.0146)	(0.0146)
Wealth Index Quintile (difference from md.	0.1039***	0.1040***	0.1053***	0.1053***
value of 3)	(0.0133)	(0.0133)	(0.0133)	(0.0133)
Water purification (indicator, 1=something	0.0730	0.0720	0.0684	0.0684
done)	(0.0483)	(0.0482)	(0.0483)	(0.0483)
Year indicator	0.1325***	0.1394***	0.1276***	0.1276***
(0=2006, 1=2011)	(0.0343)	(0.0358)	(0.0362)	(0.0362)
Altitude (meters above sea lv.,	-0.1908***	-0.1920***	-0.1830***	-0.1830***
standardized)	(0.0274)	(0.0273)	(0.0272)	(0.0272)
Mother is a Dalit	-0.1559***	-0.1580***	-0.1556***	-0.1556***
(0=no, 1=yes)	(0.0381)	(0.0381)	(0.0381)	(0.0381)
	-2.6520***	-2.6486***	-2.6541***	-2.6541***
Constant	(0.1382)	(0.1382)	(0.138)	(0.138)
N	7533	7533	7533	7533

Note: Standard errors in parentheses

Table 11d: Alternative Agricultural Specifications, Variance Component and Fit Statistics

HAZ	11d: Coefficient (Std. Err.)	11f Coefficient (Std. Err.)	11g Coefficient (Std. Err.)	11h Coefficient (Std. Err.)
Residual Variance	1.3296 (0.0219)	1.3288 (0.0218)	1.3282 (0.0218)	1.3282 (0.0218)
District Variance	0.0285 (0.0092)	0.0257 (0.0096)	0.0244 (0.0093)	0.0243 (0.0093)
Commercial	0.0283 (0.0115)	0.0240 (0.0117)	0.0211 (0.0109)	0.0209 (0.0109)
Fertilizer use (std. mean kgs)			0.0044 (0.0057)	0.0044 (0.0057)
Improved seed prevalence		0.0061 (0.0057)	0.0061 (0.0046)	0.0061 (0.0046)
Agricultural income share				0.0003 (0)
Total Variance	1.3581	1.3545	1.3526	1.3524
Level 1 R-squared	0.2255	0.2260	0.2263	0.2264
Level 2 R-squared	0.7466	0.7710	0.7832	0.7839
Overall R-squared	0.2575	0.2595	0.2605	0.2606
Log-Likelihood	-11823.56	-11822.64	-11821.08	-11821.07
AIC	23679.13	23679.28	23678.15	23680.15
BIC	23789.96	23797.04	23802.84	23811.76
LR test statistic (p value)	15.94 (.0001)	1.85 (1.741)	3.13 (.0771)	0 (.9491)
LR test statistic (p value)*		8.73 (.0031)	1.85 (.1739)	
LR test statistic (p value)*			7.45 (.0063)	
Intraclass correlation	.021	.019	.018	.018
N	7533	7533	7533	7533

Note: Standard errors in parentheses

Table 12: Health Variables

HAZ	9a Coefficient (Std. Err.)	9b Coefficient (Std. Err.)	9c Coefficient (Std. Err.)
Age (months)	-0.1935*** (0.0607)	-0.1935*** (0.0607)	-0.1935*** (0.0607)
Age squared	0.1477*** (0.0421)	0.1477*** (0.0421)	0.1477*** (0.0421)
Still breastfeeding (0/1)	0.8829*** (0.2376)	0.8829*** (0.2376)	0.8829*** (0.2376)
Months breastfeeding if still=1	-0.5333*** (0.1261)	-0.5333*** (0.1261)	-0.5333*** (0.1261)
Months squared	0.1397*** (0.03498)	0.1397*** (0.03498)	0.1397*** (0.03498)
Mother's years of education	0.1844*** (0.017)	0.1844*** (0.017)	0.1844*** (0.017)
Mother's BMI	0.1160*** (0.0146)	0.1160*** (0.0146)	0.1160*** (0.0146)
Wealth Index Quintile	0.1064*** (0.01335)	0.1064*** (0.01335)	0.1064*** (0.01335)
Something done to purify water (0/1)	0.0690 (0.0483)	0.0690 (0.0483)	0.0690 (0.0483)
Year = 2011 (0/1)	0.1655*** (0.0355)	0.1655*** (0.0355)	0.1655*** (0.0355)
Altitude	-0.1784*** (0.027)	-0.1784*** (0.027)	-0.1784*** (0.027)
Mother is a Dalit (0/1)	-0.1448*** (0.038)	-0.1448*** (0.038)	-0.1448*** (0.038)
Constant	-2.6791*** (0.1379)	-2.6791*** (0.1379)	-2.6791*** (0.1379)
Variance Component and Fit Statistics			
Residual Variance	1.3279 (0.0218)	1.3279 (0.0218)	1.3279 (0.0218)
District Variance	0.0359 (0.0094)	0.0359 (0.0094)	0.0359 (0.0094)
Hospital distance	0.0276 (0.0119)	0.0276 (0.0119)	0.0276 (0.0119)
Health shortage	--	0 (0)	--
Health service	--	--	0 (0)
Total Variance	1.3638	1.3638	1.3638
Level 1 R-squared	0.2265	0.2265	0.2265
Level 2 R-squared	0.6802	0.6802	0.6802
Overall R-squared	0.2544	0.2544	0.2544
Log-Likelihood	-11820.71	-11820.71	-11820.71
AIC	23673.41	23675.41	23675.41
BIC	23784.25	23793.17	23793.17
LR test statistic (p value)	21.65 (.0000)	0 (1)	0 (1)
N	7533	7533	7533

Note: Standard errors in parentheses

Table 13a: Social, Cultural, and Demographic Factors, Fixed Components

HAZ	13a Coefficient (Standard Error)	13b Coefficient (Standard Error)	13c Coefficient (Standard Error)	13d Coefficient (Standard Error)
Age	-0.193***	-0.191***	-0.190***	-0.192***
(months, standardized)	(0.0608)	(0.0607)	(0.0607)	(0.0606)
Age squared	0.145	0.145	0.145	0.146***
(months, standardized)	(0.0421)	(0.0421)	(0.0421)	(0.042)
Still breastfeeding	0.889***	0.894***	0.896***	0.890***
(0/1 indicator)	(0.2380)	(0.2377)	(0.2376)	(0.2374)
Breastfeeding duration if still=1	-0.540***	-0.542***	-0.543***	-0.539***
(months, standardized)	(0.1264)	(0.1262)	(0.1261)	(0.126)
Duration squared	0.142***	0.142***	0.142***	0.141***
(months, standardized)	(0.0351)	(0.035)	(0.035)	(0.035)
Mother's education	0.181***	0.181***	0.183***	0.183***
(years, standardized)	(0.0169)	(0.017)	(0.017)	(0.017)
Mother's BMI	0.115***	0.114***	0.115***	0.115***
(index, standardized)	(0.0146)	(0.0146)	(0.0146)	(0.0146)
Wealth Index Quintile (difference from md. value	0.108***	0.106***	0.105***	0.104***
of 3)	(0.0132)	(0.0133)	(0.0133)	(0.0133)
Water purification (indicator, 1=something	0.074	0.072	0.072	0.075
done)	(0.0482)	(0.0482)	(0.0482)	(0.0482)
Year indicator	0.152***	0.128***	0.132***	0.131***
(0=2006, 1=2011)	(0.0301)	(0.034)	(0.0347)	(0.0348)
Altitude (meters above sea lv.,	-0.183***	-0.201***	-0.195***	-0.197***
standardized)	(0.0258)	(0.027)	(0.0268)	(0.0268)
Mother is a Dalit	-0.146***	-0.154***	-0.156***	-0.137***
(0=no, 1=yes)	(0.0378)	(0.0379)	(0.0379)	(0.0452)
	-2.682***	-2.663***	-2.667***	-2.667***
Constant	(0.1373)	(0.1375)	(0.1376)	(0.1374)
N	7533	7533	7533	7533

Note: Standard errors in parentheses

Table 13b: Variance Component and Fit Statistics

HAZ	13a Coefficient (Standard Error)	13b Coefficient (Standard Error)	13c Coefficient (Standard Error)	13d Coefficient (Standard Error)
District Variance	0.010 (0.0088)	0.009 (0.0103)	0.008 (0.01)	0.007 (0.0095)
Total Variance	1.347	1.340	1.338	1.334
Marginal (%, standardized)	0.032** (0.0134)	0.026* (0.0139)	0.024* (0.0133)	0.024* (0.013)
Femaleratio (%, standardized)	--	0.015** (0.0067)	0.009 (0.0061)	0.009 (0.0061)
Radio (%, standardized)	--	--	0.009 (0.0075)	0.009 (0.0075)
Dalit (0/1 indicator)	--	--	--	0.028 (0.0191)
Level 1 R-squared	0.221	0.225	0.225	0.227
Level 2 R-squared	0.915	0.917	0.926	0.934
Overall R-squared	0.264	0.267	0.268	0.271
Log-Likelihood	-11828.320	-11820.960	-11819.780	-11817.840
AIC	23688.640	23675.930	23675.560	23673.680
BIC	23799.470	23793.690	23800.240	23805.290
LR test statistic (p value)	6.42** (.0112)	14.71*** (.0001)	2.37 (.1238)	3.88 (.0489)
LR test statistic (p value)	--	4.13** (.0421)	5.08** (.0243)	2.26 (.1325)
LR test statistic (p value)	--	--	3.78* (.0518)	4.82** (.0281)
LR test statistic (p value)	--	--	--	4.05** (.0442)
Intraclass correlation	.0071	.0069	.0062	.0056
N	7533	7533	7533	7533

Note: Standard errors in parentheses

Table 14a: Preferred Specifications, Fixed Component

HAZ	14a Coefficient (Std. Err.)	14b Coefficient (Std. Err.)
Age	-0.193***	-0.191***
(months, standardized)	(0.0607)	(0.0607)
Age squared	0.147***	0.146***
(months, standardized)	(0.0421)	(0.0421)
Still breastfeeding	0.886***	0.893***
(0/1 indicator)	(0.2375)	(0.2375)
Breastfeeding duration if still=1	-0.536***	-0.539***
(months, standardized)	(0.1261)	(0.1261)
Duration squared	0.140***	0.142***
(months, standardized)	(0.035)	(0.035)
Mother's education	0.182***	0.183***
(years, standardized)	(0.017)	(0.017)
Mother's BMI	0.115***	0.114***
(index, standardized)	(0.0146)	(0.0146)
Wealth Index Quintile	0.107***	0.108***
(difference from md. value of 3)	(0.0133)	(0.0133)
Water purification	0.068***	0.066***
(indicator, 1=something done)	(0.0482)	(0.0482)
Year indicator	0.142***	0.127***
(0=2006, 1=2011)	(0.0365)	(0.0368)
Altitude	-0.191***	-0.186***
(meters above sea lv., standardized)	(0.0267)	(0.0266)
Mother is a Dalit	-0.148***	-0.147***
(0=no, 1=yes)	(0.038)	(0.038)
	-2.667***	-2.672***
Constant	(0.1374)	(0.1374)
N	7533	7533

Note: Standard errors in parentheses

Table 14b: Preferred Specification, Random Component and Descriptive Statistics

	14a	14b
HAZ	Coefficient (Std. Err.)	Coefficient (Std. Err.)
	1.328***	1.328***
Residual Variance	(0.0218)	(0.0218)
	0.004	0.003
District Variance	(0.0087)	(0.0081)
Total Variance	1.332	1.331
Marginal	0.025*	0.024*
(%, standardized)	(0.0132)	(0.0122)
Femaleratio	0.006	0.007
(%, standardized)	(0.0062)	(0.0062)
Commercial	0.007	0.007
(%, standardized)	(0.0095)	(0.009)
Hospital distance	0.012	0.009
(md. distance in mins., standardized)	(0.0093)	(0.008)
Fertilizer usage		0.004
(mean kg., standardized)		(0.0044)
Level 1 R-squared	0.226	0.227
Level 2 R-squared	0.965	0.974
Overall R-squared	0.272	0.273
Log-Likelihood	-11816.73	-11815.47
AIC	23671.47	23670.94
BIC	23803.08	23809.48
LR test statistic (p value)	7.95** (.0471)	2.52 (.1121)
LR test statistic (p value)	10.54*** (.0052)	--
LR test statistic (p value)	4.47** (.0344)	--
Intraclass correlation	.0029	.0022
N	7533	7533

Note: Standard errors in parentheses

5.4 Discussion

All of the household level variables, with the exception of water treatment, display significant and, on a standard deviation basis, reasonably large coefficient estimates. The wealth index provides a useful metric for comparing coefficient levels, because given its construction, it makes more sense to center it around three, the median value on the 1 – 5 scale, than to standardize it, as standard deviations are substantially less useful for a variable measured this way. From this perspective, mother's health and education appear to be very important – a one standard deviation increase in mother's BMI has a stronger effect on HAZ than an increase in wealth index, and a one standard deviation increase in mother's education has almost twice the effect of a one quintile increase in wealth index. Altitude has a similarly strong negative effect, suggesting that children living in very high areas will, all other things being equal, be much shorter for their age, so that remoteness has a strong, negative association with long-term nutritional outcomes.

The structure of the combined coefficients of breastfeeding and age are also interesting, and they are somewhat counterintuitive given the unwieldy reasoning behind their specification, discussed in Chapter 4. Manipulating the function generated by a combination of *agemos*, *agemossq*, *bfstill*, *stillmonths*, and *stillsq* multiplied by their coefficients reveals some interesting results, as taken together, they constitute two twice-differentiable functions, because many children take zeroes for the breastfeeding variables given the issues discussed previously. These functions, and their first derivatives, are presented in Equations 14 and 15, under the assumption that all other variables are held equal. The coefficients in these equations differ from those presented in the results tables because in the regression that generated them, the unit is months, rather than standard deviations of months, because I am explicitly interested in the marginal effects of age, rather than in easily comparable coefficients.

$$(HAZ \mid bfstill{=}0) = -.04132(agemos) + .000499(agemos^2) \tag{14a}$$

$$\left(\frac{d(HAZ)}{d(agemos)} \mid bfstill{=}0\right) = -.04132 + .000998(agemos) \tag{14b}$$

$$\begin{gathered}(HAZ \mid bfstill{=}1) = .8847(bfstill) - .04132(agemos) + .000499(agemos^2) \\ -.05343(agemos) + .000673(agemos^2)\end{gathered} \tag{15a}$$

$$\left(\frac{d(HAZ)}{d(agemos)} \mid bfstill{=}1\right) = -.04132 + .000998(agemos) - .05343 + 0.001346(agemos) \tag{15b}$$

The first-derivative of the *bfstill* function, with respect to child's age, is negative for the first 40 months, so the marginal effect of continuing to breastfeed is estimated to be negative for that whole period, which directly contradicts extant natural science research on breastfeeding, and so it is reasonable to diagnose this finding as a statistical anomaly. Until twenty-four months of age, however, the sum of the breastfeeding function remains positive, as the very large constant value of the *bfstill* indicator variable balances the marginal negative effect of *stillmonths* until that point, as shown in Figure 5. This result is more consistent with the natural sciences' understanding of breastfeeding, as it suggests that prolonged breastfeeding, which may be correlated with a lack of knowledge leading to other suboptimal childcare decisions, is associated with worse nutritional outcomes for children. Taken together, these variables serve primarily to reinforce the literature's emphasis on the importance of good maternal health and education for child nutrition, but the strong effects of altitude and breastfeeding practice are also interesting.

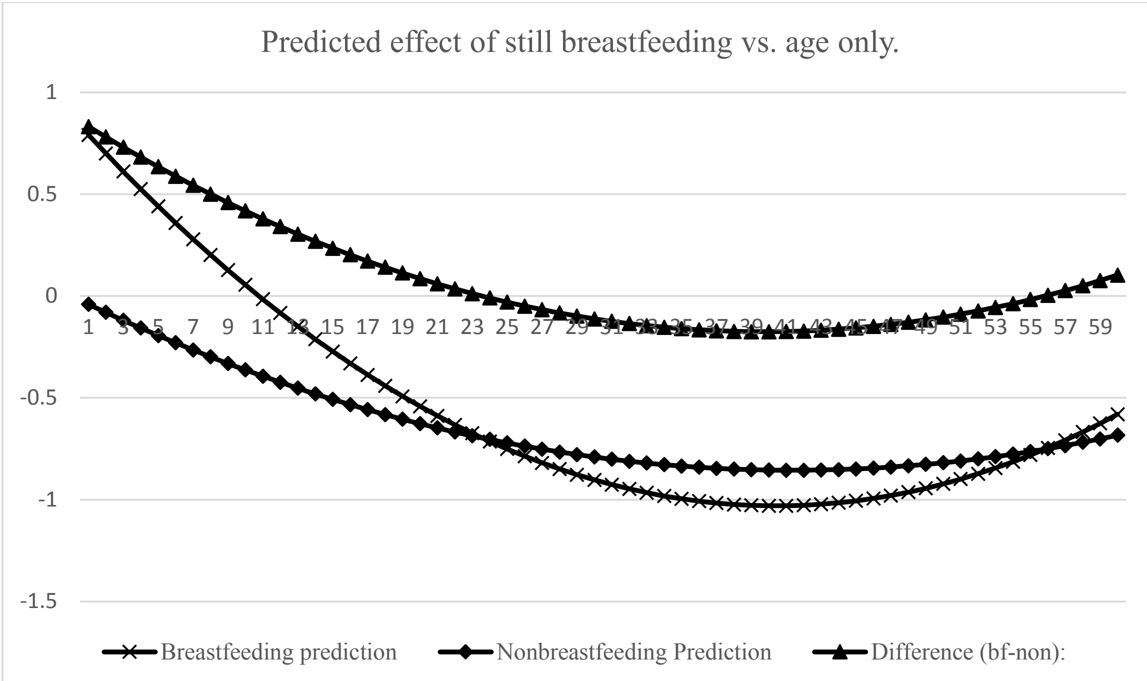

Figure 5 – Predicted Effect of Still Breastfeeding vs. Age Only

Regression Model 5c, the multilevel specification of Smith and Haddad's empirical model, allows for worthwhile comparisons of their empirical approach and the one employed here. The models obviously differ greatly in meaningful ways – dependent variable measurement, the level at which the dependent variable occurs, and the units between which variance is to be examined – but the similarities and differences between their analysis and this more focused analysis can still be instructive. The variables which have direct equivalents in the Nepal model are significant with reasonably strong coefficients, as discussed above, but they leave a majority of the between-child variance unexplained. While this is expected given the massively higher level of granularity in the units of observation here, it underscores the importance of analyzing malnutrition at the appropriate level: aggregates tell one coherent story, while more detailed data suggests that it is difficult to explain more than a fairly small proportion of the observed variation, even with a more sensitive estimation technique.

The random coefficient models reported in Table 6 suggest that variance in the effects of household level variables plays a role in between-district variance in HAZ. However, without additional analysis and detailed data, there is no way to conclusively explain that variance, though this variance suggests the existence of certain effects. Coefficient variance may be a productive topic for future research, as it can be used to identify districts which behave in unexpected ways, but given the focus of this analysis, it serves primarily as a robustness check.

The regressions reported in Tables 10-13 support several conclusions. In general, the contribution of these theoretically supported determinants to goodness of fit and likelihood improvements supports the initial hypothesis that community characteristics play a detectable role in the determination of children’s nutritional status. Differences in the explanatory power of these groups of models is also instructive, however – intuitively, features of the community food economy should play a major role in nutrition, but compared to the models in Tables 10 and 13, the models in Table 11 do a poor job of explaining malnutrition. These results also show that including *marginal* as a district-level predictor substantially improves the power of a given model, as demonstrated by the very high second-level R-squared in Model 13a and the substantial improvement in the descriptive statistics of Model 10b compared to Model 10a, due to the addition of *marginal*. This is helpful because it enhances the predictive power of the models, but it lacks the explanatory power of some other variables, because the pathway through which the proportion of marginalized citizens could affect malnutrition is unclear, and because there is a strong possibility that this measure is capturing some number of unidentified confounders. The other variables which improve the models are, of course, not causally linked to malnutrition, but their relative specificity makes it much easier to develop a plausible interpretation of the observed associations.

The preferred models summarized in Table 14a and 14b includes the strongest indicators from each area, and are statistically distinct from each set of random slopes, according to multiple likelihood ratio tests. Model 14a partitions almost all of the district intercept variance in HAZ into variances in specific parameters, and it includes indicators of each category of district level factors discussed in Chapter 3. These measures vary in the significance of their coefficient variances, though this is not necessarily a problem, as a variable can quite plausibly improve the model with a similar coefficient for each district. This model is not a substantial improvement over Models 10c and 13c, but because it includes the full array of predictors and thus controls for a broader array of effects, it is preferred to the narrower models. The consistency of the first-level coefficients when district intercept variance has dropped to a very low level, due to the inclusion of district random slopes, reinforces the importance of these factors.

Taken together, these models suggest that heterogeneities in levels and relative importance of certain district characteristics can ‘compress’ district random-intercept variance in HAZ, but the low proportion of between-district variance in the null model, the majority of which is explained by even a parsimonious selection of household level variables, means that there is not much variance in the first place. That being said, the factors which were expected to play a role did improve the model, and many showed significant variance in their effects across districts, a behavior which would not be detected in a classical regression model. Data and computational constraints make a complete comparison difficult, but it appears that healthcare, cultural norms, and aspects of the food economy are, in some way, related to the majority of the intercept variance remaining after the inclusion of household variables in a multilevel random intercept model, consistent with the relevant theory. While these features make the models more reliable, they do not substantially improve the fit of the model or the relative importance of household characteristics, so although the multilevel approaches discussed here provides a benefit, it is limited.

CHAPTER 6. SUMMARY AND CONCLUSIONS

6.1 Summary

This thesis has analyzed the determinants of malnutrition in Nepali children using data occurring at individual, household and community levels. A variety of multilevel econometric models, designed to analyze these effects in a conceptually and technically appropriate manner, were reported. The multilevel approach was chosen for conceptual and technical reasons: based on intuition and on the literature, it seemed that characteristics of the communities in which children reside could provide useful context for their nutritional status, and given the structure of the dataset, as well as the drawbacks of using least squares estimators on data for which the independence assumption fails, using a technique that can handle measures at different levels appropriately was appealing.

Using the detailed data from the combined dataset, I fit a variety of models using accepted measures of factors considered important in the literature as independent variables. With only 75 district units in the dataset, fitting models with more than five district-level random effects was problematic, as it increased the chance of non-convergence, and because the ratio of predictors to groups drops very quickly, reducing the validity of the estimates even if convergence is achieved. This meant that the obvious approach of fitting a large model with many district factors of interest was not a viable option. Instead, I fitted initial general models based on the literature, and then models for each category of community factors expected to be important. The choice of variables used in these models followed the testing of a wide array of alternative variables in each category, a process not discussed here for the sake of brevity and due to the limited analytical value of those tests. This analysis showed that HAZ does not vary substantially between districts, though it does vary substantially between children. Robustness checks determined that denominating the two-level multilevel model on units with more observations did not produce substantially higher between-community variances. Replicating several two-level regressions in a three-level specification including the intermediate household level generated interesting results, but overall, it did very little to change the predictions of the model, compared to a two-level specification using the same subsample of the dataset. The limited impact of these alternative specifications suggests that the original specification is reasonable, because the confounding factors that these alternatives were designed to detect do not seem to be present.

Following these robustness checks, I estimated several models, differentiated by the district level predictors, to examine the importance of the different categories of different types of predictors. These models included a final general model, which was an improvement over the previous models in several ways: although some models displayed similarly good fits, fewer types of predictors were represented in those narrower models with AIC's and r-squared values similar to those of the preferred specification. In very broad terms, these models suggest that between-district variance is, to some extent, related to a diverse set of district-level characteristics, including variables measuring social, agricultural, and healthcare factors, and that many variables which one may expect to play an important role in district intercept heterogeneities do not.

Given these results, the primary finding of this analysis is that HAZ does not vary by much between districts, and that conventional child and household predictors of childhood malnutrition persist in their importance even when district factors are controlled in a multilevel modeling context. This finding does call into question the utility of the multilevel approach, but it remains appropriate for several reasons. First, the approach makes sense intuitively and pragmatically, given the data: it would have been impossible to measure the relationship between district characteristics and child level HAZ values without this estimation technique, and at the outset, it seemed that because children are nested within districts, the violation of independence would justify the multilevel approach. The multilevel modeling approach has also generated results which other approaches would not. It can improve the reliability of the fixed effects coefficients, can test for variations in coefficients as well as intercepts, and can be used to explore the partitioned variances discussed both as results and robustness checks on those results. These features did not generate novel insights into childhood malnutrition, but the fact that using this new approach generated results which more or less confirm past studies is a useful result, because this approach could very well have suggested that past studies using alternative empirical approaches miss important information. Furthermore, many of these results which remain unexplained are interesting topics for future research.

6.2 Policy Implications

This thesis presents a predictive model, so the policy implications apply to prediction of malnutrition, and thus to the targeting of nutrition-oriented interventions. The most relevant result in policy terms is the limited importance of district in this sample, which is a somewhat disappointing result from a policy perspective, because observing districts for targeting purposes is considerably easier than targeting on characteristics such as mother's education or household assets. At the same time, the three-level model employed as a robustness check does suggest that a nontrivial proportion of the overall variance occurs between households, and is misattributed to children in the two-level model, suggesting that at least some of this substantial between-child variance is misattributed, and occurs at a different level. These results do, however, reinforce the utility of many traditional predictors of malnutrition, suggesting that they are stronger predictors than the many district characteristics examined here, and some of these predictors are more easily observed than others. For example, the Dalit indicator variable and altitude have comparatively large coefficients, both larger in magnitude than the marginal effect of moving up a wealth index quintile. These results confirm conventional wisdom about social marginalization and physical remoteness negatively affecting households' ability to feed their children, and the wide variety of controlled factors, at multiple levels, enhances these findings. The relatively small estimated association between wealth and malnutrition is also interesting, although inferential work would be necessary to ascertain the relationship between wealth and nutrition in this context. This general pattern in the results does have one notable exception, however. The sanitation variable is significant in only a few regressions, and even then, only marginally so, at the 90% confidence level. The limited estimated effect of household sanitation suggests that it is relatively unimportant in determining long-term nutritional status when the other explanatory variables are held constant, but HAZ is one of many measures of nutritional status, so it would be inappropriate to interpret this result as cause for the dismissal of sanitation as a potential cause of malnutrition more generally.

The random slope results also include relevant information, though their interpretation requires more caution than the interpretation of fixed component coefficients or variance components at different levels. The ability of theoretically supported variables such as *hospital*, *commercial*, *fertkg,* and *impseed* to partition between-district variance while a large number of more obvious variables, such as *foodshort* and various measures of income, could not, suggests that these variables capture important district-level phenomena. The coefficients do vary substantially, so it would be inappropriate to numerically define the relationship between these variables and malnutrition at the national level, and the coefficients do, in fact, sometimes switch signs between districts, but even so, their ability to act as variance partitions more explicit than district random intercepts makes them worthy of attention in policy discussion.

6.3 Directions for Further Research

Several variables known to affect long-term malnutrition through children's health were omitted from this analysis, due primarily to limitations in the data, and including them would improve any research building on the approach discussed here. There is evidence that the indoor air pollution generated by burning of biomass and tobacco smoke can negatively affect children's nutritional status, and both of these sources of pollution are common in Nepal (Mishra and Retherford 2007, Kyu, Georgiades, and Boyle 2009). The DHS measures many important determinants of household air pollution, tracking parental smoking behavior, primary fuel, whether households use a separate room for cooking, type of stove, and ventilation of that stove, but the dataset lacks some information that may be very important in defining the air pollution – malnutrition relationship, most notably the intensity of biomass burning. Birth order is also recognized as an important determinant of malnutrition, due to its influence on intra-household distribution of resources and on parental care, but determining a child's birth order from the DHS data used here proved impossible, as the data only include the intervals between a child's birth and the birth of her previous and next siblings (Horton 1988). A more detailed approach to measuring breastfeeding behavior would also improve this analysis, particularly if such an approach were to include a careful measure of the exclusivity of breastfeeding, as in the context of Nepal, where breastfeeding is quite widespread, exposure to proper breastfeeding practices may be more important than simple exposure to breastfeeding (Kramer and Kakuma 2002)

This thesis raises a variety of questions for further research, due largely to the ways in which multilevel models partition variance. The between-district heterogeneities in the child and household variable coefficients raise the question of why these coefficients may vary, and answering this question will require more detailed household data. While the use of villages and wards as the second level unit confirmed that variance between these units was not substantially higher than variance between districts, analysis using district or village level predictors may also yield interesting and useful results, because as is shown in the three-level exercise, variance may increase when the model gains certain details. The inclusion of specific data on long-term food security would also be helpful, and would be more useful the more levels of the model it could be applied to. Finally, the significant change in HAZ between 2006 and 2011 is unexplained in this thesis, but understanding why this change occurred, a project which probably requires longitudinal data rather than the pooled cross-sectional data used here, may yield new and interesting knowledge about the dynamics of malnutrition in Nepal. While this multilevel framework does ultimately reinforce the existing understanding of the determinants of childhood malnutrition, the flexibility of the multilevel approach has a wide array of benefits that make it a worthwhile tool for future research into this question and related questions, as new data become available.

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APPENDIX

APPENDIX

Table 2: Child and Household Characteristics by Subregion

Subregion	Eastern Mountain	Central Mountain	Western Mountain	Eastern Hill	Central Hill	Western Hill	Mid-Western Hill	Far-Western Hill	Eastern Terai	Central Terai	Western Terai	Mid-Western Terai	Far-Western Terai
HAZ	-1.98	-2.05	-2.32	-1.77	-1.69	-1.75	-2.19	-2.19	-1.48	-1.94	-1.96	-1.73	-1.58
(standard deviation)	1.29	1.17	1.36	1.33	1.32	1.34	1.32	1.27	1.33	1.48	1.31	1.31	1.26
Child's age (months)	30.02	31.03	29.03	29.85	31.31	29.76	30.77	30.14	29.63	30.15	28.89	30.06	30.21
(standard deviation)	16.59	17.45	17.00	17.11	17.00	16.95	17.19	16.68	17.49	17.33	17.28	16.76	16.84
Child is breastfeeding (0/1)	54.50%	55.94%	60.53%	59.61%	51.87%	61.21%	60.54%	63.44%	56.73%	55.71%	62.14%	62.03%	66.73%
(standard deviation)	0.50	0.50	0.49	0.49	0.50	0.49	0.49	0.48	0.50	0.50	0.49	0.49	0.47
Months breastfeeding if still=1	10.63	11.13	11.77	11.75	10.18	12.75	13.09	13.87	10.59	10.96	12.42	13.37	15.06
(standard deviation)	13.44	14.07	14.00	13.80	13.46	14.73	15.38	15.26	13.59	14.07	14.69	14.98	15.65
Mothers years of education	3.54	2.26	1.15	3.50	3.36	4.89	2.38	1.66	3.32	1.81	3.11	2.70	3.20
(standard deviation)	3.80	3.43	2.69	3.88	4.23	3.93	3.67	3.15	4.02	3.33	4.06	3.56	3.93
Mother's BMI	21.45	21.37	20.07	21.10	21.77	21.47	20.52	19.89	20.37	19.71	20.68	20.07	19.97
(standard deviation)	2.76	2.36	1.92	2.70	2.95	2.89	2.15	1.92	3.20	2.72	2.90	2.47	2.54
Anything done to treat water	22.27%	7.69%	2.66%	21.35%	25.93%	23.05%	8.08%	6.84%	12.23%	3.13%	11.06%	6.60%	3.04%
(standard deviation)	0.42	0.27	0.16	0.41	0.44	0.42	0.27	0.25	0.33	0.17	0.31	0.25	0.17
Altitude	1542.17	1490.71	1962.44	1033.28	1206.28	1256.16	1264.65	1372.39	105.37	131.09	203.44	300.51	166.30
(standard deviation)	545.33	344.86	581.29	676.98	441.35	1231.02	397.13	384.18	63.70	195.35	592.53	235.97	22.38
Mother is a Dalit	12.80%	5.24%	23.72%	9.79%	6.22%	21.18%	21.39%	29.88%	22.12%	14.01%	12.40%	14.80%	15.02%
(standard deviation)	0.33	0.22	0.43	0.30	0.24	0.41	0.41	0.46	0.42	0.35	0.33	0.36	0.36
Household wealth index quintile	2.06	2.41	1.61	2.33	3.13	3.07	1.74	1.72	3.46	2.97	3.50	2.86	3.13
(standard deviation)	1.08	1.15	0.93	1.32	1.68	1.51	1.20	1.12	1.12	1.24	1.24	1.26	1.34

Table 4: District Characteristics by Subregion

Subregion:	Eastern Mountain	Central Mountain	Western Mountain	Eastern Hill	Central Hill	Western Hill	Mid-Western Hill	Far-Western Hill	Eastern Terai	Central Terai	Western Terai	Mid-Western Terai	Far-Western Terai
HAZ	-2.02	-2.06	-2.49	-1.78	-1.74	-1.74	-2.19	-2.16	-1.51	-1.93	-1.98	-1.72	-1.56
(standard deviation)	0.23	0.01	0.43	0.28	0.33	0.33	0.30	0.27	0.43	0.27	0.40	0.14	0.09
Mean share of income from ag.	65.68%	58.90%	52.20%	67.18%	47.80%	46.47%	59.97%	55.91%	44.23%	50.02%	46.50%	45.98%	54.47%
(standard deviation)	0.08	0.03	0.23	0.06	0.26	0.10	0.14	0.06	0.09	0.08	0.12	0.11	0.08
Total food consumption value (2006 rupees)	49675.81	39184.05	39796.91	40121.07	42002.68	41754.08	33649.24	31089.65	36535.53	40173.54	38170.67	36626.27	35691.50
(standard deviation)	3616.56	7804.08	9905.48	5187.23	9166.83	7852.09	3001.26	3113.99	2921.69	4354.72	4518.41	1739.24	2916.48
Mean fertilizer usage (kg)	82.23	132.82	7.28	60.01	195.91	41.08	81.08	22.90	160.17	236.77	177.26	124.20	157.51
(standard deviation)	64.04	46.55	12.15	50.93	190.48	26.46	82.05	12.59	49.86	101.02	43.13	30.71	17.04
Ratio of female students to total students	49.65%	50.09%	46.09%	50.30%	49.50%	50.05%	47.81%	46.78%	47.20%	43.83%	46.57%	49.08%	48.51%
(standard deviation)	0.01	0.00	0.04	0.01	0.01	0.00	0.02	0.02	0.03	0.03	0.03	0.01	0.00
Median distance to hospital on foot (minutes)	284.56	754.53	407.93	414.46	168.02	206.34	356.45	523.26	131.30	104.72	119.25	180.54	162.52
(standard deviation)	287.64	756.90	392.75	435.25	219.60	151.82	288.26	420.02	101.90	68.30	9.64	98.02	20.06
% Village Dev. Committees Open Defecation Free	4.95%	0.00%	10.79%	0.76%	4.48%	36.32%	10.00%	12.74%	3.57%	11.07%	1.98%	8.13%	0.00%
(standard deviation)	0.06	0.00	0.15	0.02	0.10	0.39	0.13	0.18	0.06	0.29	0.03	0.14	0.00
Mean district level % of households with given characteristic													
Food shortage in past month	25.94%	16.81%	44.08%	37.58%	14.71%	27.63%	30.51%	24.04%	35.58%	24.60%	22.37%	26.70%	19.75%
(standard deviation)	0.22	0.06	0.24	0.13	0.07	0.12	0.13	0.12	0.11	0.12	0.05	0.06	0.04
Selling some amount of produced food (Commercial)	55.71%	58.55%	25.87%	47.95%	51.03%	26.41%	47.03%	39.77%	67.71%	64.63%	57.88%	42.77%	58.40%
(standard deviation)	0.20	0.08	0.19	0.18	0.18	0.12	0.18	0.10	0.08	0.06	0.09	0.14	0.02
Using improved seeds	10.97%	25.13%	15.31%	12.81%	26.55%	33.54%	22.22%	17.85%	26.14%	33.99%	62.19%	38.25%	28.69%
(standard deviation)	0.15	0.08	0.09	0.08	0.14	0.19	0.13	0.12	0.08	0.22	0.11	0.12	0.13
Belonging to marginalized ethnic/caste group	65.20%	49.76%	22.25%	59.75%	41.16%	39.68%	41.67%	27.54%	58.98%	58.83%	64.78%	72.85%	58.97%
(standard deviation)	0.08	0.16	0.10	0.05	0.20	0.15	0.11	0.05	0.23	0.12	0.16	0.10	0.12

Table 4 continued

Owning a radio	61.83%	62.14%	60.39%	59.39%	67.99%	65.36%	69.28%	58.22%	50.89%	41.41%	49.71%	59.88%	59.76%
(standard deviation)	0.02	0.10	0.14	0.11	0.08	0.09	0.10	0.11	0.11	0.16	0.16	0.12	0.04
Reporting insufficient healthcare	37.96%	26.11%	47.26%	34.76%	19.16%	20.43%	39.20%	29.95%	27.31%	20.24%	25.01%	23.62%	18.59%
(standard deviation)	0.15	0.02	0.27	0.10	0.08	0.09	0.18	0.23	0.07	0.05	0.13	0.05	0.08
Describing govt. health service as 'bad'	20.22%	22.80%	41.63%	17.76%	15.79%	21.60%	34.10%	21.73%	17.01%	19.71%	22.20%	13.90%	17.15%
(standard deviation)	0.07	0.11	0.21	0.06	0.05	0.08	0.18	0.26	0.04	0.05	0.03	0.08	0.02
N	422	286	527	562	563	642	631	599	728	928	597	561	526