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ECONOMIC DEVELOPMENT AND CHILD NUTRITION IN NEPAL

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TABLE OF CONTENTS

Page

Page

Page

LIST OF TABLES

Table Page

Appendix Table Page

LIST OF FIGURES

Figure Page

ABSTRACT

Thapa, Ganesh. Ph.D., Purdue University, December 2015. Economic Development and Child Nutrition in Nepal. Major Professor: Dr. Gerald Shively.

Child malnutrition rates in Nepal are among the highest in the world. Government and non-governmental agencies are actively seeking various pathways that might be useful to improve child nutrition outcomes in Nepal, fill gaps in understanding surrounding nutrition drivers, and shorten the time required to attain the Millennium Development Goals. This dissertation includes three essays that use a range of data, including nationally representative data on the growth of children nutrition below five years of age, to identify potential pathways for improving child nutrition in Nepal.

Essay 1 focuses on food prices. The analysis seeks to explain price movements and price variances in local markets. Since a majority of Nepalese households are net-buyers of food, food prices can be expected to influence nutrition outcomes among Nepalese children. A panel GARCH approach is used. Results suggest that rice prices in regional markets and wheat prices in border markets tend to strongly influence rice and wheat prices in local markets, respectively. The density of roads and bridges, and agricultural production, not unexpectedly, are negatively correlated with local food prices and price variances. Higher fuel prices are associated with higher local rice prices.

Essay 2 uses a series of multilevel (hierarchical) regression models to identify the factors correlated with child height-for-age and weight-for-height z-scores. The essay also assesses what factors account for the observed improvements in average outcomes between 2011 and 2006. Various factors observed at the child, mother, household, cluster, and district levels are found to be associated with child nutrition outcomes. The observed improvement in average height-for-age Z-score between 2011 and 2006 is explained largely by mother and district level variables while the observed improvement in average weight-for-height Z-scores between 2011 and 2006 seems more closely tracked by variables observed at the cluster and district levels.

Essay 3 studies the association between district-level infrastructure and district-average child nutrition outcomes in Nepal. A dose response function, and instrumental variable and spatial econometric techniques are used. Results suggest that roads and road quality matter for short- and long-term nutrition outcomes for children below five years. Significant spatial spillover effects of roads on long-term child nutrition outcomes is found.

Based on findings of these three essays, several policies that are likely to reduce food prices and variances, and improve child nutrition outcomes in Nepal are proposed. These include improving the connections between local and regional markets by improving road quality, extending the road network and constructing bridges, and formulating and implementing policies to increase cereal production. Policies targeted towards improving nutrition outcomes of twins, increasing mother's education level, promoting family planning, encouraging mothers to deliver babies in health facilities, avoiding smoke-producing fuels will help to improve the nutrition outcomes of children below age of five.

CHAPTER 1. INTRODUCTION

Nepal has some of the worst child nutrition statistics in the world. Overall, about 41% of children less than five years of age are stunted (a measure of chronic malnutrition) and 12% are wasted (a measure of acute malnutrition) (NDHS 2011). Unless the current child nutrition situation of the country is improved and the nutritional well-being of the Nepalese people is secured, the country is unlikely to develop quickly. This dissertation includes three essays that are directly or indirectly related to improving child nutrition outcomes in Nepal. Essay 1 (Chapter 2) and Essay 3 (Chapter 4) utilize food price and infrastructure (strategic roads) data, respectively, at the district-level as its unit of analysis. Essay 2 (Chapter 3) utilizes a complex set of household survey datasets with children under age five as the unit of analysis. Although the research objectives are overlapping somewhat, each chapter is considered as an independent essay and contains its own conclusions and policy implications.

What factors influence food prices and variances in Nepal? The answer to this question is important to current policy debates in Nepal, where high food prices and poorly functioning markets pose a serious challenge to the overall economy. In the present context, developing a better understanding of the determinants and behavior of food prices is important for three reasons. First, although Nepal is an agricultural country and more than 83% of Nepalese households depend on agriculture for their livelihoods (CBS 2013), the majority of agricultural households are net buyers of food (WFP/NDRI

2008; CBS 2011). On average, a Nepalese household spends approximately 60 per cent of its total budget on food. This share is even higher among poor households (WFP/NDRI 2008). High and variable food prices are therefore a concern because a slight increase in price can reduce household purchasing power and compromise food consumption. This can undermine efforts to reduce malnutrition rates. Second, high food prices are detrimental to peace and security in Nepal, especially in the wake of the Nepalese civil war which disrupted most rural development in Nepal for more than a decade and ended only in 2006. Third, in the aftermath of devastating earthquakes that struck in April and May of 2015, and at the stage of recent promulgation of a new constitution, high food prices may severely affect the earthquake recovery process and implementation of the new constitution. In recognition of the overall importance of food prices to human nutrition, peace and economic development in Nepal, Essay 1 concentrates on explaining the determinants of local food prices and price variances at the district-level. Monthly retail coarse rice and wheat flour prices from 2002 to 2010 are used. These data represent average transactions in thirty-seven districts (twenty-eight local markets, eight regional markets, and one central market) and seven Nepal-Indian border markets. By employing panel GARCH models, I assess the importance of a set of policy variables, including roads, bridges, agricultural production, and fuel prices, on food prices and food price variances are assessed. The analysis accounts for connections and price transmission along the food marketing chain. Results suggest that rice prices in regional markets and wheat prices in border markets are correlated with both price levels and price variances in local markets. Road density, bridge density and exchange rates are negatively correlated with price levels for rice. Road density and wheat production (1000

MT) are negatively correlated with price levels for wheat. Higher fuel prices are positively correlated with local price levels of rice. Rice production (1000 MT), road density, monthly fuel price (Rs/liter) and monthly exchange rate are negatively correlated with local price variance for rice. Road density and monthly fuel prices are negatively correlated with local price variance for wheat. Threshold effects are found for both rice and wheat, suggesting asymmetric effects of price shocks on price volatilities. Evidence does not support a hypothesis of short-and long-run market integration.

What factors explain observed patterns of child nutrition in Nepal? Essay 2 answers this question by investigating a broad set of determinants of child malnutrition using a series of hierarchical regression models. The hierarchy includes: district, clusters within districts, households within clusters, and children within households. Data from various sources are used. These include the Nepal DHS, NLSS and data on NDVI, rainfall, agricultural production and storage, transportation, and health infrastructure. Eight models are estimated that include variables observed at different levels (child, mother, household, cluster, and district). The first objective is to identify factors or variables that are strongly correlated with child nutrition outcomes in Nepal. The second objective is to assess what factors might account for the observed improvements in average outcomes between 2011 and 2006. The strong statistical evidence of improvements in Z-scores over time is largely explained by changes occurring in higher level variables, underscoring the importance of policy-driven changes occurring at cluster and district levels. Factors such as twin status, mother's employment status, ethnicity, whether a mother smokes or not, mother's education, total children ever born in the family, place of delivery, use of smoke-producing fuels, percentage of households with a bank account, food deficit status of a district, and presence of pediatrician in district hospital are found to be strongly correlated with long-term nutrition outcomes. Similarly, factors such as season of birth, twin status, presence of diarrhea and fever, mother working on farm, mean crop yield (kg/ha), district food deficit, percentage of households producing eggs, public food storage capacity, roads, vacant posts of doctors, zonal hospital, and number of private hospitals in a district are found to be strongly correlated with short-term nutrition outcomes.

Can improvements in infrastructure help lead to improvements in nutrition outcomes? This question is very important for policy makers and development agencies in Nepal because many parts of the country are geographically and economically isolated. Essay 3 answers this question by estimating the causal impact of roads on child nutrition outcomes using a dose response function and an instrumental variable approach. This essay also employs a spatial econometric approach to estimate the spatial externality effects of roads on nutrition outcomes. Unweighted district average HAZ and WHZ for 2006 and 2011 are used as indicators of child nutrition outcomes. Annual time series data on total length (km) of earthen, gravel and black pitched roads are used as treatments. A quality-adjusted index of road density is calculated and used for the final analysis. The dose-response function indicates that road infrastructure improves short-term and long-term nutrition outcomes for children below age 5. Long-term nutrition outcomes are more responsive to road infrastructure at later stages of child growth than at earlier stages and vice-versa in the case of short-term child nutrition outcomes. Observed local changes in the road network over time are clearly associated with improvements in short-term nutrition outcomes. A higher proportion of all-season roads in a district is found to significantly improve the long-term nutrition outcomes for children under three years.

All three essays make original contributions to the existing literature on food prices and variances, child nutrition, and infrastructure. The first essay incorporates data on rainfall and transportation (roads, bridges, fuel prices) as well as remotely-sensed data on vegetation, and is the first study to use these data and a rigorous econometric approach to empirically examine food prices and variances. The second essay is the first study I know of that uses comprehensive data and a multi-level empirical approach incorporating spatial effects to study the determinants of child nutrition. The third essay is the first study conducted globally to examine an association between transport infrastructure and child nutrition outcomes, and to estimate the spillover effects of roads on child nutrition outcomes.

CHAPTER 2. DETERMINANTS OF FOOD PRICES AND FOOD PRICE VARIANCE IN NEPAL

2.1. Introduction

Despite Nepal's heavy reliance on agriculture, the sector's performance has been disappointing over the past two decades. For example, Nepal's average cereal yield was 2,570 kg/ha in 2013, lower than Bangladesh (4,384), India (2,975), Sri Lanka (4,799), and Pakistan (2,930) (WB 2013). Although the country derives 35% of its gross domestic product (GDP) from agriculture (NMOF 2011) and 66% of Nepal's population depends on agriculture for its livelihood (CBS 2011), the government has not invested heavily in the development of the sector.[1] The Terai produces a food surplus in most years, but distribution of this surplus to food deficit districts of the hilly and mountainous regions of the country is problematic, and in the wake of the 2015 earthquakes, movement of foodstuffs will continue to be problematic. Even before the quakes, problems with food

[1]Nepal has invested more as a share of its national budget than India and Pakistan, but less than Bangladesh, and about the same as Srilanka. Agriculture's share of Nepal's national budget was 2.45% (2007/08), 3.12% (2010/11), 4.1% (2012/13) and 3.8% (2013/14) (GON 2014); for India, it was 2.67% (2007/08), 2.35% (2010/11), 2.49% (2012/13) and 2.76% (2013/14); for Bangladesh, it was 8.52% (2007/08), 5.86% (2010/11), 5.1% (2012/13) and 6.48% (2013/14); for Pakistan, it was 0.83% (2007/08), 0.92% (2010/11), 0.49% (2012/13) and 0.57% (2013/14); for Srilanka, it was 4.80% (2007/08), 4.12% (2010/11), 3.48% (2012/13) and 3.08% (2013/14). Sources: Ministry of Finance and national budget speeches of respective countries.

distribution were widespread and the cost of transportation were high, a situation often attributed to the harsh topography and isolation of food-deficit regions (NAPMDD 2010; NMOAD 2012). As a result of these challenges, a majority of the rural population, especially those who are net-buyers of food, struggle to meet their consumption needs (CBS 2011). This is reflected in Nepal's disappointing child malnutrition statistics. Approximately 48% of children less than five years of age are stunted (a measure of chronic malnutrition) and 12% are wasted (a measure of acute malnutrition) (NDHS 2011).[2] The stunting rate is even higher (about 60%) in the mountain region (NDHS 2011). Figures 1 and 2 shows the district-wise distributions of Z-scores in the country. These figures reveal that child malnutrition rates are high in all districts. However stunting is worst in the mountainous and hilly districts, the regions where high food prices and high food price variability are also observed. Figures 3 and 4 highlight these patterns and underscore the considerable heterogeneity in market performance observed in Nepal. Elsewhere, food prices have been linked to nutritional consequences (Bouis 2008; Hadley et al. 2012), and also linked to various social and non-nutritional outcomes (ACF 2009; Hadley et al. 2012), including social unrest (Bellemare 2014). Higher food prices were found to be detrimental to short-term child nutrition outcomes (weight-for-height) in Cote d'Ivoire (Thomas et al. 1992), increases in the prices of plantain and sugar were found to negatively affect short-term child nutrition outcomes in rural Ghana (Lavy et al. 1996), and a study from Kenya found negative impacts of food price

[2] Child nutrition outcomes are measured by comparing anthropometric data such as height-for-age and weight-for-height Z-scores for children under five against the WHO standard (WHO, 1995)

increases on child health (Grace et al. 2014). Figure 5 displays bivariate plots between district average WHZ and real coarse rice price in food surplus and deficit districts of Nepal. Although a small positive correlation between retail coarse rice prices and short-term child nutrition outcomes is observed in food surplus districts of Nepal, a large negative correlation between retail coarse rice prices and short-term child nutrition outcomes is observed in food deficit districts. As Deaton (1989) argues, increases in food prices reduce purchasing power in food deficit households. This compromises not only the consumption of high quality/nutritious food required for pregnant woman and children but also nutrition-sensitive basic needs such as health care and education (FAO et al. 2011).

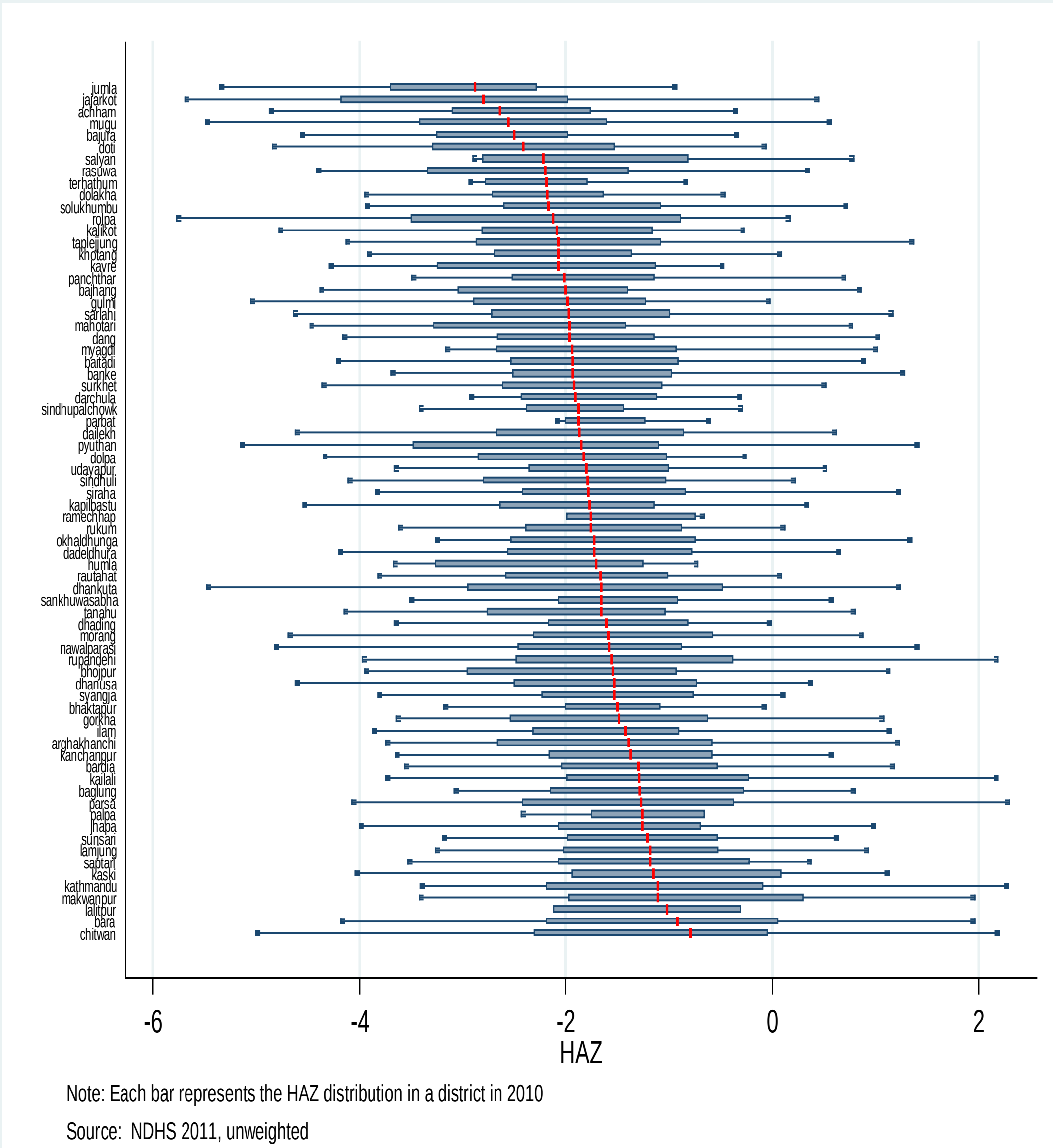


Figure 1. HAZ Distribution by District in 2010

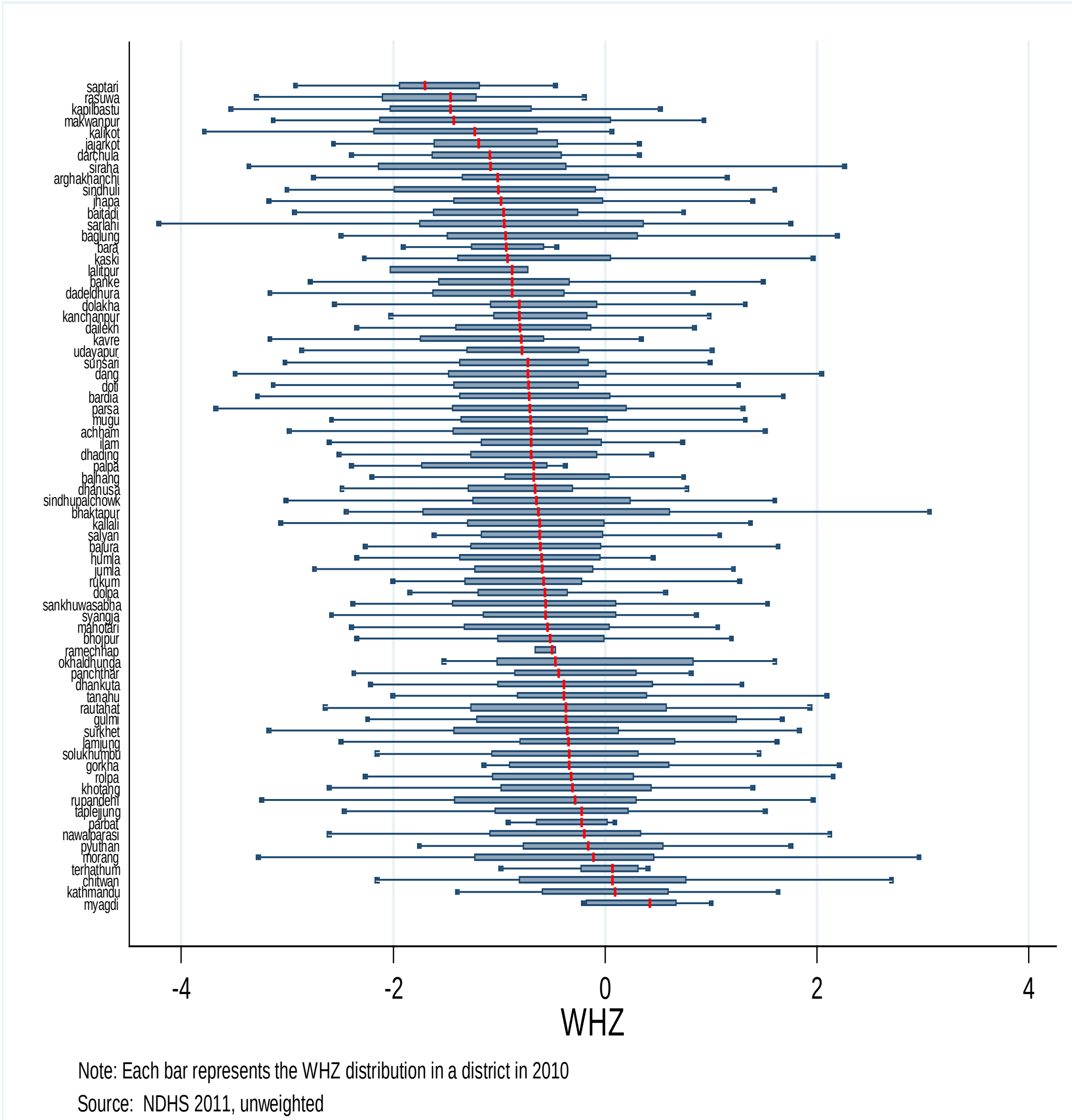


Figure 2. WHZ Distribution by District in 2010

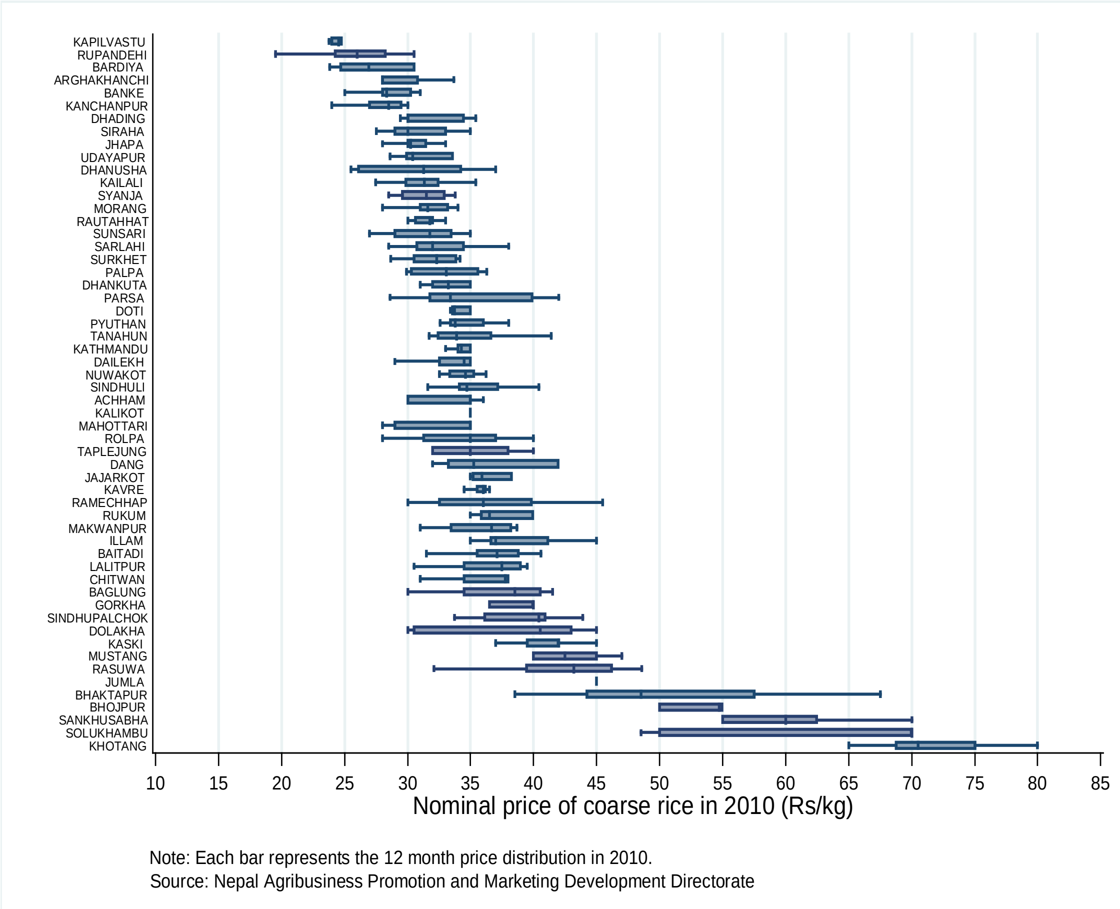


Figure 3. Nominal Price of Coarse Rice by District (2010)

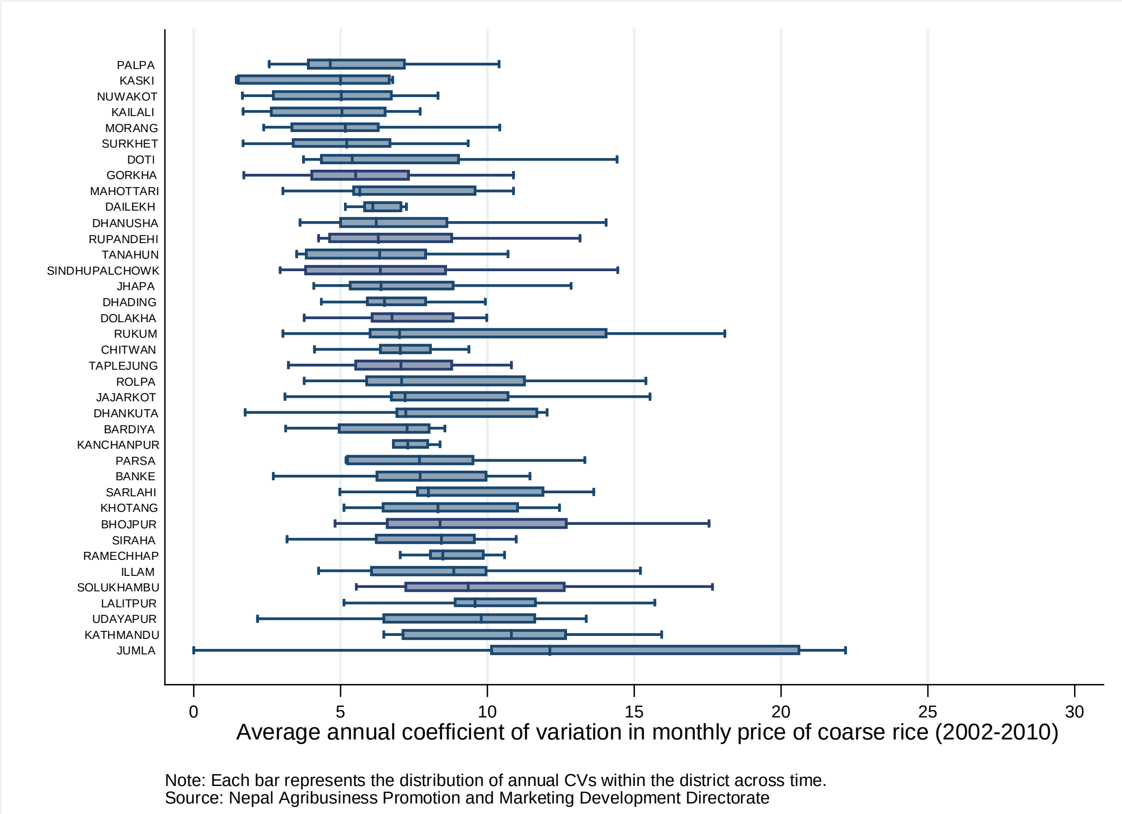


Figure 4. Variation in Real Price of Coarse Rice, by District (2002-2010)

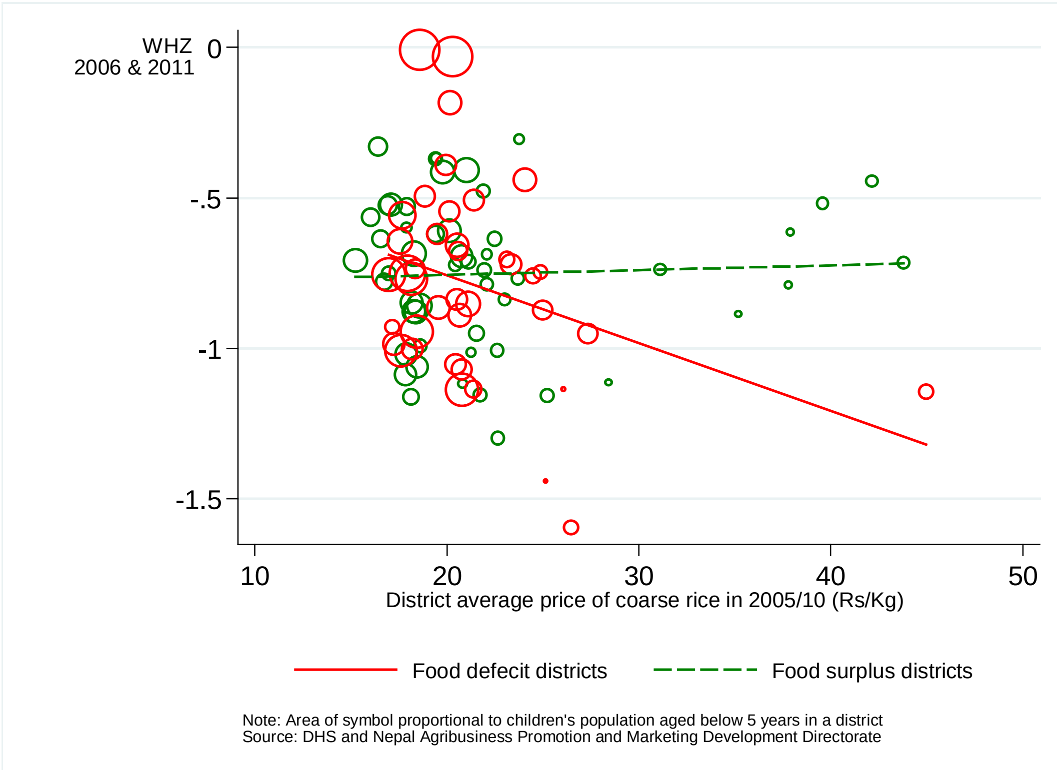


Figure 5. District Average WHZ and Price of Real Coarse Rice in Food Surplus and Deficit Districts

Food price variability is also of concern in Nepal, as elsewhere. Large unexpected price fluctuations have been identified as a major threat to food security in developing countries, especially when there is a lack of dietary diversification (FAO 2010a). Although potatoes and barley are considered staples in the hilly and mountainous areas of Nepal, places that are generally unsuitable for rice production, the main staple food in most parts of Nepal, and for most Nepalese, is rice. Wheat flour is considered by many Nepalese consumers to be a close but imperfect substitute for all grades of rice, and prices of these food items (including potatoes) have positive and statistically significant pairwise correlations (Table 1). Pan et al. (2009) argue that price uncertainty is likely to reduce the caloric intake of rural Nepalese households. Anriquez et al. (2013) from their cross-country study found that food price spikes affected nutritional status in Bangladesh, Guatemala, Nepal, Cambodia, Tajikstan, Vietnam, Kenya and Malawi. As indicated by Figure 6, higher price variability (as measured by the coefficient of variation in coarse rice) is negatively correlated with both HAZ and WHZ in Nepal, the later strongly so.

A range of studies from Nepal and elsewhere demonstrate how poor consumers are adversely affected by a rise in food prices (e.g. Von Braun 2008; Bouis 2008; Andreyeva et al. 2010; Alem and Soderbom 2011; Hawkes 2012). UNOCHA (2008) indicates that about 4.4 million people in Nepal are at risk from rising food prices. Given the widespread recognition of the importance of food prices to nutritional outcomes in developing countries, it is somewhat surprising that relatively little attention has been devoted to the study of agricultural markets and prices in Nepal. To date, most studies (e.g. WFP/FAO 2007; Agostinucci and Loseby 2008; WFP/NDRI 2008; FAO 2010b) have been descriptive in nature. A small number of studies (Sanogo 2008; Sanogo and Amadou 2010; Shrestha 2013) have employed econometric techniques, but most have not focused on understanding how agricultural prices are determined in Nepal. Moreover, they all use relatively short price series and a limited set of covariates, making it difficult to draw strong inference from the results. To formulate appropriate and accurate national agricultural policies in Nepal, especially as earthquake reconstruction unfolds in coming years, work with a longer and more comprehensive price series seems warranted. In recognition of the overall importance of food prices to human nutrition and economic development in Nepal, as well as the large empirical gap in existing research, the primary research goal in this essay is to use monthly agricultural price data and time-series econometric techniques to study the factors influencing the means and variances of rice and wheat prices in Nepal.

Table 1. Correlation Matrix among Monthly Retail Prices of Staple Foods in Nepal (2002-2010)

	Coarse Rice	Medium Rice	Fine Rice	Wheat Flour	Red Potato	White Potato
Coarse Rice	1					
Medium Rice	0.9314*	1				
Fine Rice	0.7466*	0.8394*	1			
Wheat Flour	0.8572*	0.8162*	0.6555*	1		
Red Potato	0.4371*	0.4749*	0.4458*	0.3730*	1	
White Potato	0.4368*	0.4910*	0.4381*	0.3890*	0.8842*	1

Note: *significance at 1% level, monthly retail prices of 20 districts (Bhojpur, Dhankuta, Doti, Illam, Jumla, Kaski, Kathmandu, Nuwakot, Palpa, Ramechhap, Rolpa, Banke, Chitwan, Dhanusa, Jhapa, Kailali, Morang, Parsa, Rupandehi and Surkhet) are used

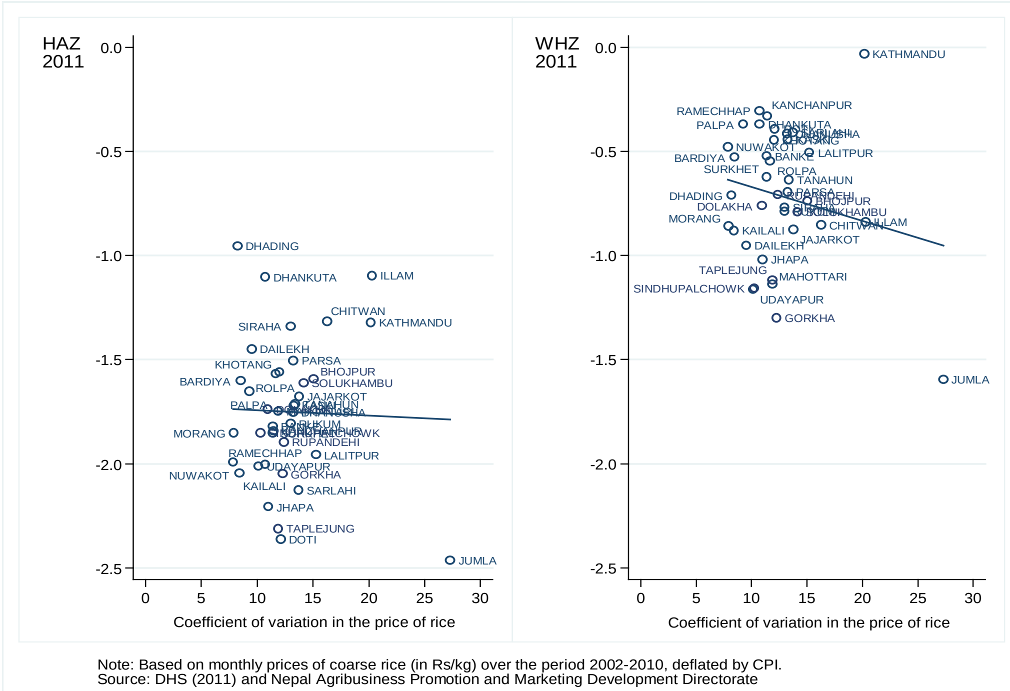


Figure 6. Coefficient of Variation in the Price of Rice and Average WHZ and HAZ in 2011

2.2. Background

Nepal emerged from civil war in 2006, and nearly a decade later was only able to promulgate a new constitution, just after a few months when disaster struck, in the form of twin earthquakes in April and May of 2015. Even before the earthquakes, government instability hampered reforms and there was growing public frustration towards the government (Lawoti 2014). Out-migration has been substantial over the past decade, with many thousands of productive youth leaving the country each year to seek employment in India and the Middle East. The hazardous nature of this work, much of which is concentrated in the construction industry, has resulted in loss of life, debt entrapment and social suffering (Donini et al. 2013). Although personal remittances contributed about

30% of Nepal’s GDP in 2013 (WB 2013), this remittance boom has resulted in a trade deficit and high inflation, and has increased the country’s reliance on food purchases. Pre-quake, the country appeared to be stuck in a low equilibrium growth trap (Kruse and Sapkota 2013).

Given the current situation, a first concern regarding food prices is that any sharp increase in food prices could be detrimental to the implementation of new constitution, peace, security and overall economic performance (WFP/NDRI 2008). Kharas (2011) argues that unexpected changes in food prices create turbulence in markets and politics, and undermine social stability.

A second and related reason why high and variable food prices are of concern is that high price variability has been shown to have a negative effect on household welfare indicators (FAO et al. 2011; Cummings 2012; Dawe and Timmer 2012; Bellemare et al. 2013; Akter et al. 2014). For net-seller households, of course, higher food prices are potentially beneficial, since they are likely to result in higher household incomes. The majority of agricultural households in Nepal, however, are net-buyers of food (WFP/NDRI 2008; CBS 2011). On average, a Nepalese household spends approximately 60 per cent of its total budget on food. This share is even higher among poor households (WFP/NDRI 2008). For the vast majority of Nepalese households, who have little or no savings, a slight increase in price can reduce household purchasing power and compromise food consumption (Timmer 1989).

As argued in the introduction, there is a high degree of spatial variation in prices in Nepal. For the same agricultural commodity, price differentials across markets are quite high. As an example, in 2004 the average monthly prices of coarse rice and wheat flour in

Surkhet, which is relatively well connected to other markets, were Rs 16 and Rs 15, respectively. In contrast, in the same year prices in Humla, one of the most remote districts of Nepal, were Rs 31 and Rs 85, respectively, or approximately 109% and 470% higher (NAPMDD 2004). Although linkages between agricultural markets in Nepal are imperfect, they had been improving over time in conjunction with improvements in market infrastructure, at least prior to the 2015 earthquakes. Post-quake development efforts will need to focus on rebuilding transport and market infrastructure and reestablishing confidence and economic activity. To date, the literature lacks a complete assessment of price determination and food market integration in Nepal. One goal of the analysis presented below is to test hypothesis regarding the importance of a set of policy variables, such as roads, bridges, agricultural production, and fuel prices, on food prices and food price variance, while at the same time accounting for connections and price transmission along the food marketing chain. In Nepal, this supply chain extends from border markets to regional, central and local markets. The following sections briefly review the conceptual framework for the analysis and the potential role of key variables in influencing food prices.

2.2.1. Local markets

I define *local markets* as those small and locally important trading centers that are located (mainly) in food deficit districts of the country. These markets receive inflows of foods via border and regional markets. Local food prices are expected to depend on local supply, and to be influenced through trade by prices in regional, central and border markets. I begin with 28 local markets for which a fairly complete time series of data on prices is available (Table 2 and Figure 7). These markets are typical, but not nationally representative. They represent food deficit districts, have poor child nutrition outcomes, or both. As shown in Figure 8, these are the districts that lies in the upper part of the map where the flow of commodities ends. For three selected local markets, Figures 9-11 display how border (panel A), regional (panel B), and central (panel C) market prices are correlated with the local market price. The time trends in these local, regional, border, and central market prices are displayed in panel D of each figure.

2.2.2. Regional markets

Regional markets are those located in districts with high production potential, storage facilities, and direct links with border markets in India. All of the regional markets are located in the Terai (Figure 7). Their role in providing spatial and temporal arbitrage mean they can be expected to play an important role in stabilizing food prices in the entire country through stock flows and imports from India (Action Aid Nepal 2006). The Terai is highly suitable for cereal production compared with the hilly and mountainous regions. Regional markets supply foods mainly to food deficit districts that fall within their marketing network. One might reasonably expect supply shocks affecting regional markets to be quietly transmitted to local markets. For example, as figures 9B to 11B illustrate, coarse rice prices in the local markets Mahottari and Kaski are positively correlated with prices in their corresponding regional markets.

Table 2. Local Market and Associated Regional and Border Market

Local market	Regional market	Border market
Bardiya	Kailali	Paliya
Bhojpur	Morang	Jogbani
Dailekh	Banke	Rupedihya
Dhading	Chitwan	Raxaul
Dhankuta	Morang	Jogbani
Dhanusha	Siraha	Sonabarsha
Dolakha	Chitwan	Raxaul
Doti	Kailali	Paliya
Gorkha	Chitwan	Raxaul
Illam	Jhapa	Naxalbadi
Jajarkot	Banke	Rupedihya
Jumla	Banke	Rupedihya
Kanchanpur	Kailali	Paliya
Kaski	Chitwan	Raxaul
Khotang	Siraha	Sonabarsha
Mahottari	Siraha	Sonabarsha
Nuwakot	Chitwan	Raxaul
Palpa	Rupandehi	Nautanawa
Ramechhap	Chitwan	Raxaul
Rolpa	Rupandehi	Nautanawa
Rukum	Rupandehi	Nautanawa
Sarlahi	Parsa	Raxaul
Sindhupalchowk	Chitwan	Raxaul
Solukhambu	Siraha	Sonabarsha
Surkhet	Banke	Rupedihya
Tanahun	Chitwan	Raxaul
Taplejung	Jhapa	Naxalbadi
Udaypur	Siraha	Sonabarsha

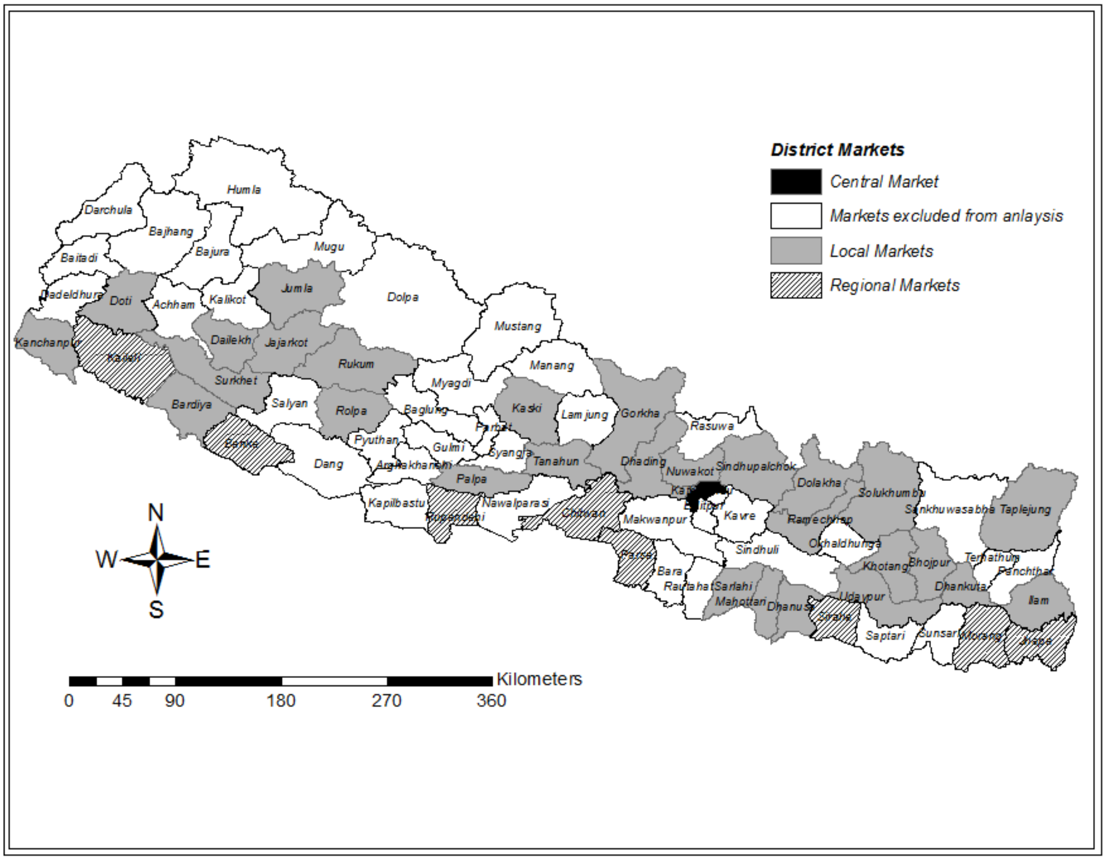


Figure 7. Markets Covered by the Analysis

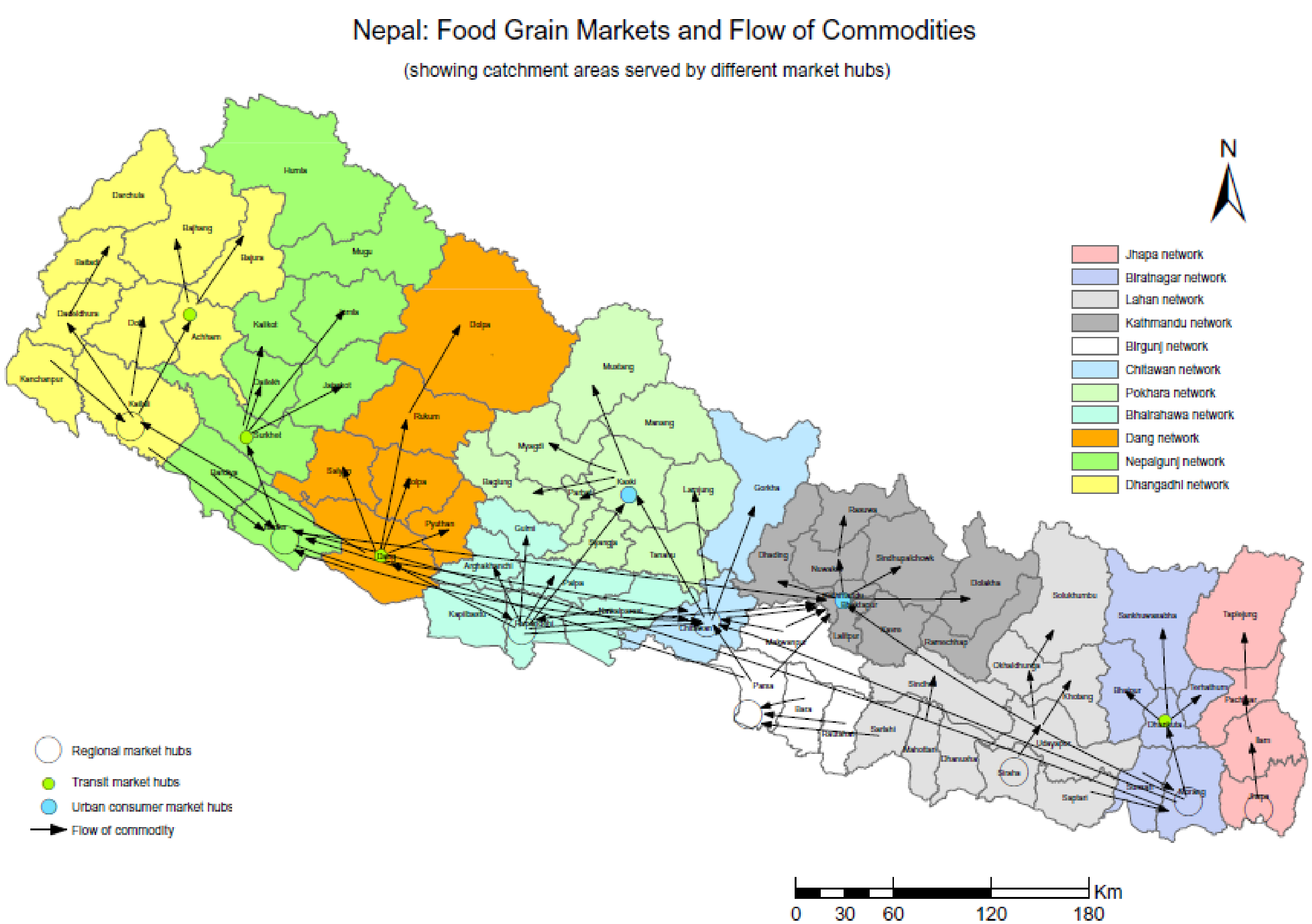


Figure 8. Food Grain Markets and Commodity Flows in Nepal (Source: WFP/FAO 2007)

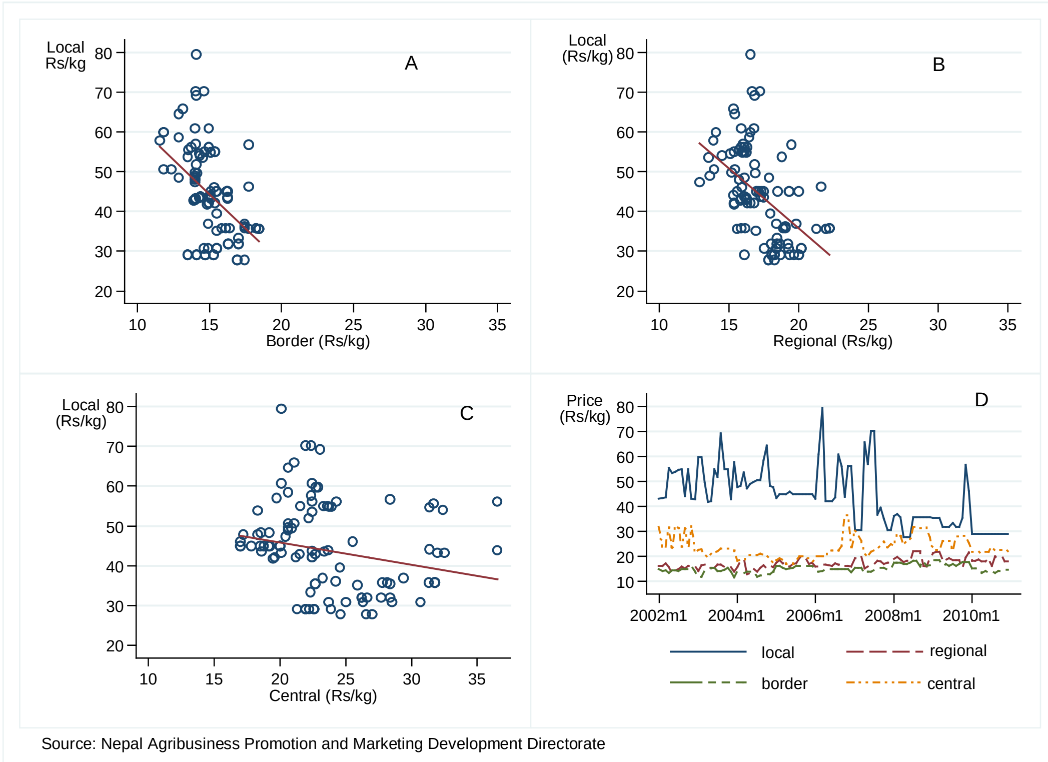


Figure 9. Monthly Real Coarse Rice Prices in Jumla and Companion Markets (2002-2010)

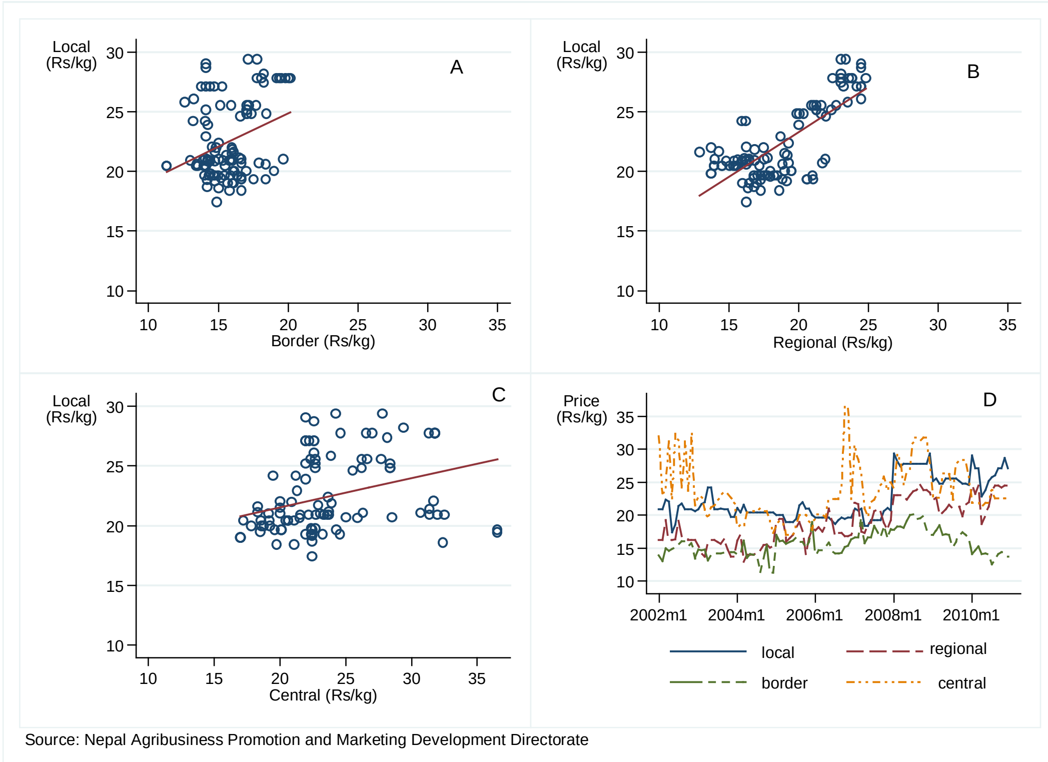
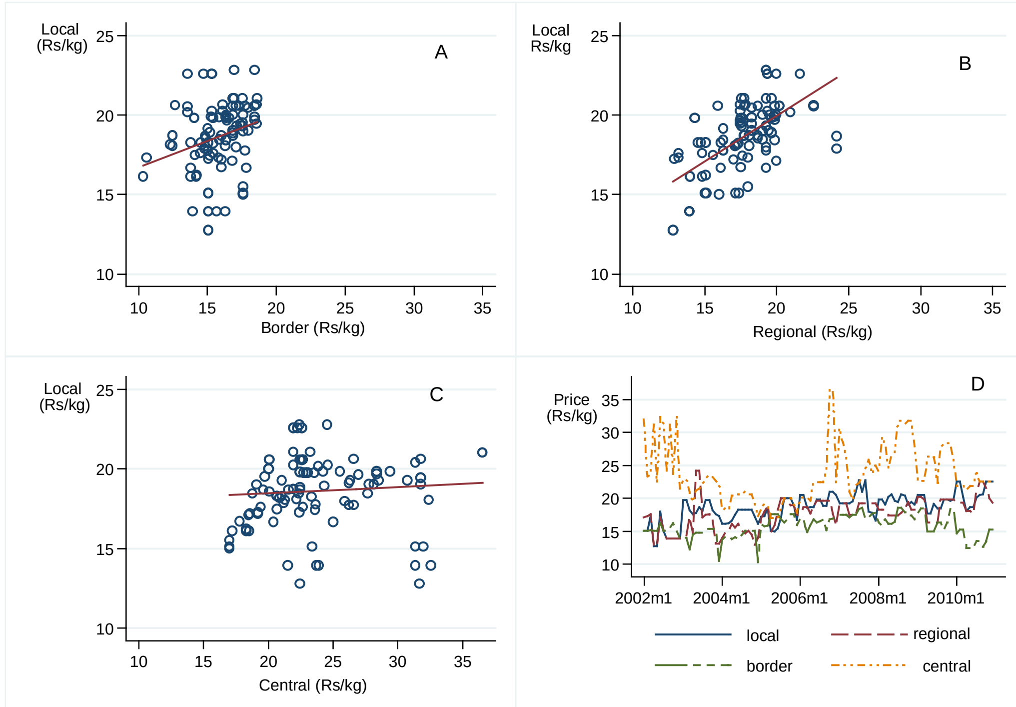


Figure 10. Monthly Real Coarse Rice Prices in Kaski and Companion Markets (2002-2010)



Source: Nepal Agribusiness Promotion and Marketing Development Directorate

Figure 11. Monthly Real Coarse Real Prices in Mahottari and Companion Markets (2002-2010)

2.2.3. The central market

I assume that Kathmandu serves as the *central market* for all local markets. Approximately 10% of Nepal's population lives in Kathmandu (NPHC 2011). According to WFP/FAO (2007), demand in Kathmandu largely determines the position of the national demand curve. Thus demand from the Kathmandu valley is expected to play an important role in influencing local prices at the margin. As figures 9C-11C show, coarse rice prices in Mahottari and Kaski are positively correlated with central market prices.

2.2.4. Border markets

Border markets connect Nepal with India. Nepal and India share an open and porous 1185 km border. Of the 30 customs offices in Nepal, 20 are located on the Indian border. In addition, 9 sub-customs offices are authorized to trade with India. All would-be traders must complete a customs transit and summary declaration form through which all imports are officially registered and subjected to customs duty and taxes (Ministry of Finance, Nepal). However, a high volume of Nepal's trade is informal and unregistered. As a result, officially recorded trade data can be misleading. Nevertheless, observed border prices should incorporate information regarding the total volume (both formal and informal) traded between India and Nepal. Prices in Nepal are usually higher than in border markets and are widely assumed to be influenced by Indian market prices. In fact, the NRB (2007) argues that food prices in Nepal are, in essence, determined by India, a conjecture that seems only partially plausible.[3] According to WFP/FAO (2007), the importation of low-quality coarse and medium rice varieties from India has resulted in a decline in domestic retail prices in Nepal. A cursory examination (see figures 9A-11A) shows that border market prices are positively correlated with local agricultural prices in Mahottari and Kaski but not in Jumla. The analysis described below incorporates border market prices in the measurement of local market price movements.

[3] I test this hypothesis below.

2.2.5. Transportation and fuel prices

The markets described above are connected, to varying degrees, by a road network. These road network are further supplemented by motorable bridges. Within the last decade, at least up to the time of the 2015 earthquakes, there was substantial improvement in the road network and bridge construction in Nepal. The government, with the support of foreign donors, made expansion of road connectivity and improvements in rural infrastructure a top priority. Of the total budget allocated for transportation development, roughly two-thirds came from foreign sources in recent years (DOR 2012). The World Bank (WB) and the Asian Development Bank (ADB) have been the main institutions supporting road network improvement and bridge construction projects in Nepal. Between 2003 and 2013, the country's total strategic road length increased 58%, from 16,018 km to 25,265 km. The length of black-pitched, gravel and earthen roads expanded 129%, 18%, and 47%, respectively over the same period (DOR 2013). In 2013-14, the GON allocated about 8% (Rs 51.15 billion) of its total budget to the transportation sector. The cost of road construction in hilly and mountainous regions is higher than in the Terai, largely due to harsh topography characterized by deep valleys, high ridges and low plains. Hundreds of glaciers feed rivers that flow down from the mountains to the plains. Such features make travel in many places difficult and risky, especially during the monsoon season. To provide year-round access, the road networks cannot function in absence of bridges that connect different linkages. In the past decades, the Terai was given priority for road and bridge construction. However, during the last few years, the Nepal government has prioritized road and bridge construction in hilly/mountainous regions.

In spite of the high priority of the government and concerned agencies in expanding the road network and bridges, most of the hilly and mountainous regions of the country are still not easily reached. Although the road network exist, they do not function during the monsoon season due to the lack of concrete bridges in many rivers. Most of the bridges constructed in the hilly and mountainous areas are either crude suspension bridges or unreliable wire bridges. At the time of writing, two districts (Humla and Dolpa) were not connected by road to remaining districts of the country and earthquake damage had hindered transport in many areas. There are many locations where several hours or days of road travel are required to reach the district headquarters (CBS 2011). In those places, imported goods are often either airlifted or carried by mules or porters. As a result, food prices reflect added transportation costs. Elsewhere, transportation costs have been found to be important factors influencing food price differences (see, e.g. Minten and Kyle (1999) for the former Zaire and Goletti (1994) for Bangladesh). Gurung (2010) argues that improved access to roads has lowered food costs in several hilly/mountainous districts of Nepal and provided several other benefits. These include greater production of cash crops, improved access to services, and increased employment and incomes. Gollin and Rogerson (2010) found complementarities between transportation and agricultural productivity in Uganda.

One of the main objectives of road and bridge construction in Nepal has been to connect rural and urban districts and improve market integration. Figure 12 shows data on national highways and feeder roads constructed between 2002 and 2010 in three representative districts of Nepal. As of 2010, Jumla, a mountainous district, has only earthen road and usually not in operation during monsoon season. Figure 13 shows data on bridge density (# of bridges per unit area (km^2) of a district) and population density in the selected districts of the country in 2005 and 2010. There is a linear and positive relationship between bridge density and population density. Sanogo (2008) suggests that better road infrastructure can improve the food security situation of the mid- and far-western districts of Nepal by reducing the cost of transportation and the time required to move food commodities to food-deficit areas. WFP/NDRI (2008) found that communities located farther away from markets were more likely to face higher food prices and to consume lower quality foods. I am aware of no published empirical research to date that documents the influence of roads and bridges on agricultural prices in Nepal.

Roads and bridges, of course, are only one element of transportation costs. Another important component is fuel. Nepal imports all of its required refined oil from India. The Nepal Oil Corporation Limited (NOC) is a state-owned trading company and is the sole organization responsible for import, transportation, storage, and distribution of petroleum products in Nepal. The country heavily subsidizes petroleum products. Although fuel prices in Nepal are not directly determined by the international market, increases in international fuel prices are usually passed through to domestic consumers by the NOC.[4]

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[4]Regardless of price movements in international markets, NOC sets domestic prices, which are approved by the GON.

As indicated by Figure 14, between 1986 and 2013 the nominal diesel price in Nepal increased nearly ten-fold although fuel price declined after 2013. Several temporary price spikes are observed as well.

Among fuel products, diesel is used in large volumes in Nepal. Diesel contributed about 66% of total fuel imports in 2013 (NOC 2013). It is the main source of fuel for the heavy vehicles that are involved in the transportation of foods. Petrol constitutes about 20% of fuel imports and is mainly used by light-duty vehicles. Liquefied petroleum gas (LPG) and kerosene are used for cooking in urban areas. This study focuses on diesel fuel, given its important role in food transportation.

Much of the empirical literature suggests that fuel prices influence agricultural commodity prices. An increase in world crude oil prices indirectly raises food prices by influencing food production (Esmaeili and Shokoohi 2011) and exchange rates (Nazlioglu 2011). By directly increasing transportation costs, an increase in fuel prices can have serious repercussions for an economy. In Nepal, since rice and other foods are typically transported from the Terai to the hilly and mountainous regions of the country, increases in fuel prices lead to higher food prices (WFP/NDRI 2008). According to traders, the fuel price is one of the most important factors influencing food prices in Nepal (WFP/NDRI 2008). To the best of my knowledge, no formal attention has been given to studying the correlation between fuel prices and food prices in Nepal, a shortcoming that I remedy below.

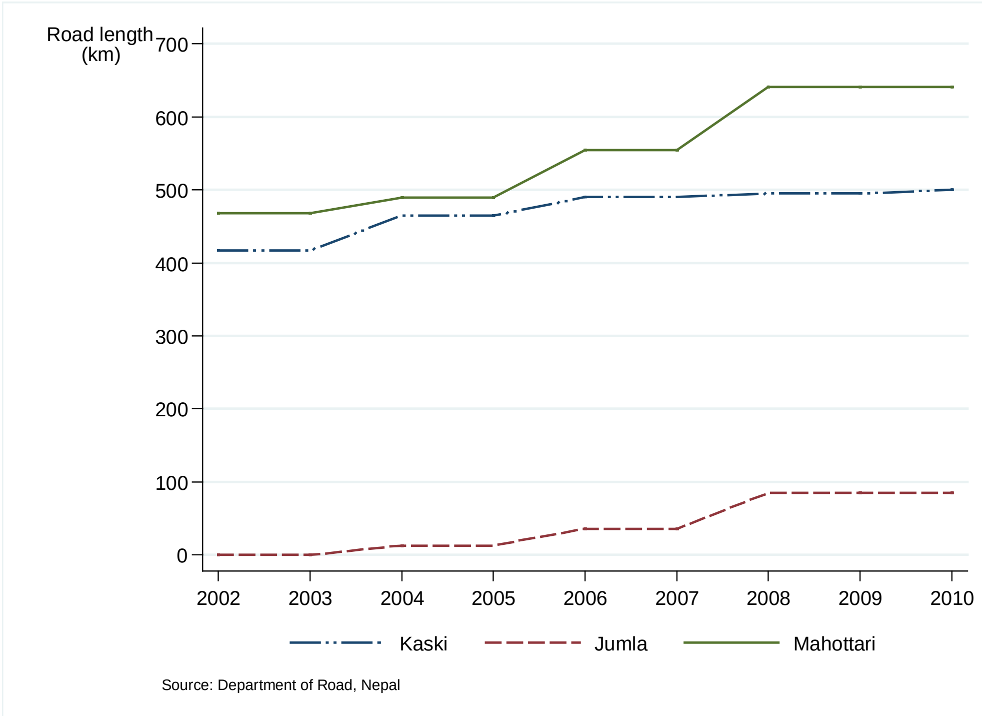

Figure 12. Strategic Road Length (km) in Jumla, Kaski, and Mahottari Districts (2002-2010)

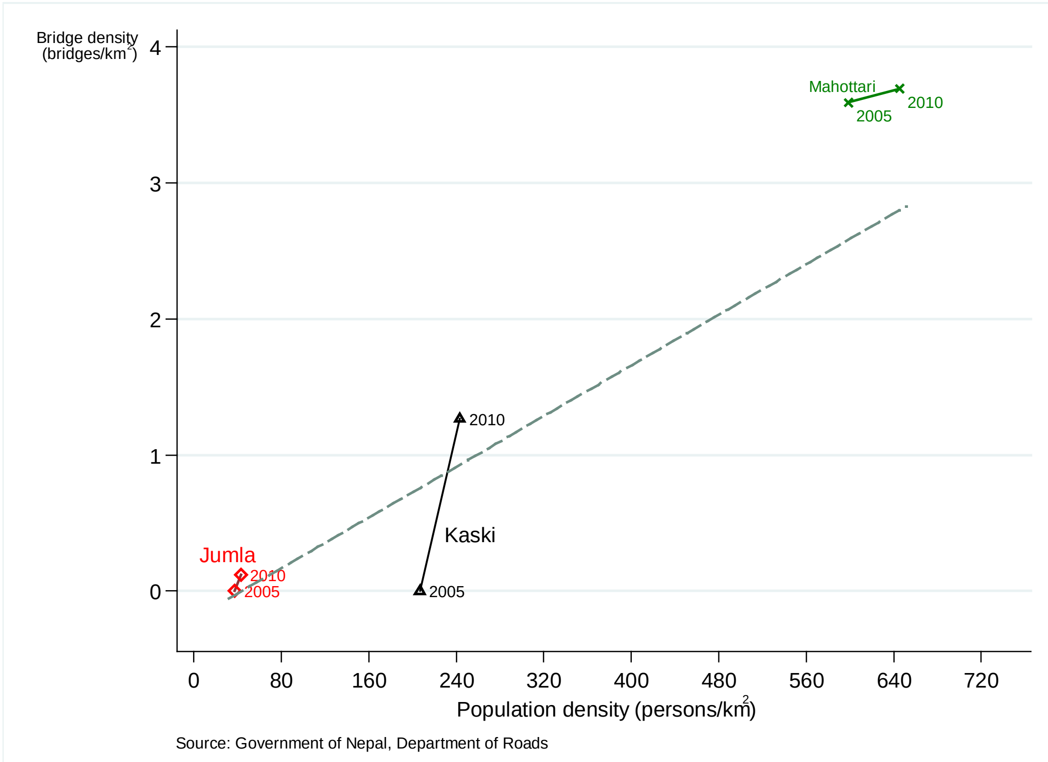

Figure 13. Relationship between Bridge Density and Population Density in Jumla (Mountain), Kaski (Hill) and Mahottari (Terai) Districts (2005 and 2010)

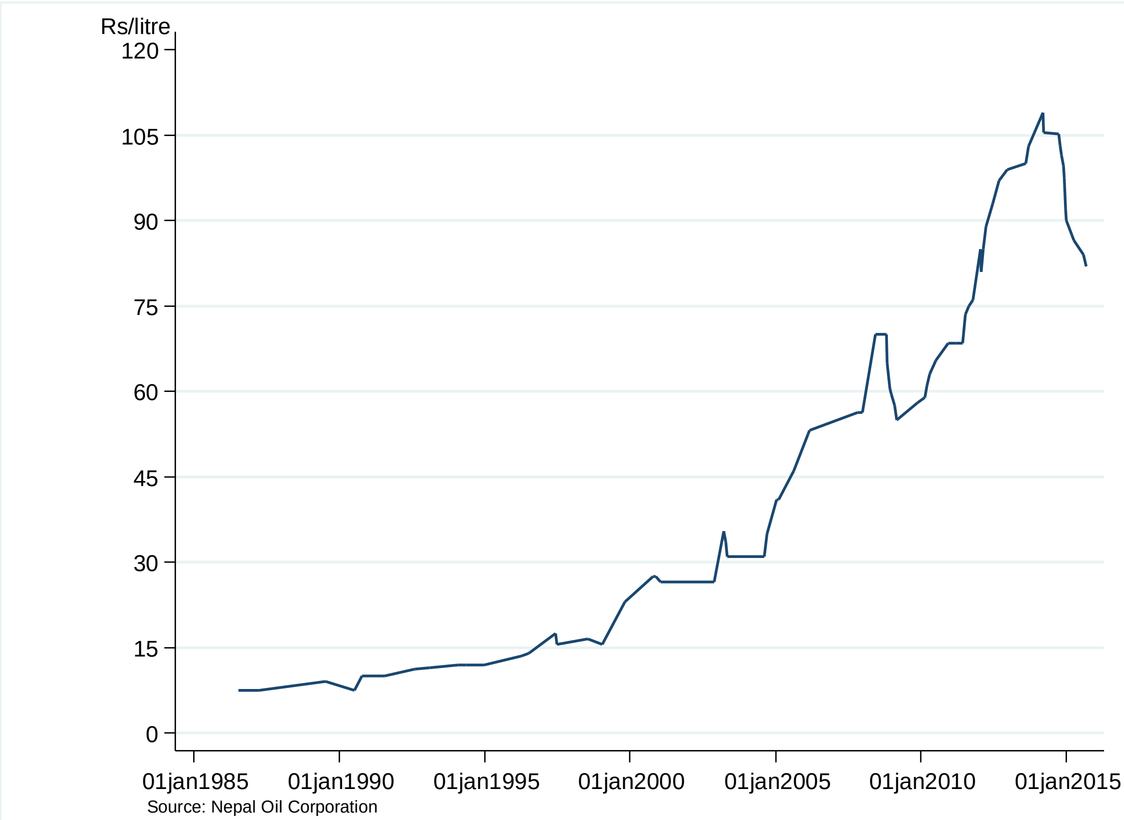

Figure 14. Nominal Retail Price of Diesel Fuel in Kathmandu, Nepal (1985-2015)

2.2.6. Agricultural production

Overall trends in yields and total production of rice and wheat in Nepal are positive (Figure 15). Total wheat production is considerably lower than rice production, but rice production and yields fluctuate more over time. One of the main reasons for these fluctuations is Nepal’s dependence on rainfed agriculture. About 52 per cent of total agricultural land does not have access to irrigation (NMOAD 2012). As a result, rice production depends on the timing and adequacy of monsoon rainfall. Between 1985 and 2011, minimum and maximum production in the country were 2.37 and 4.52 million tons for rice, and 0.53 and 1.74 million tons for wheat (NMOAD 2012), with coefficients of variation of 17% and 30%, respectively. Fluctuations in cereal prices are widely perceived to be related to fluctuations in crop production (NMOAD, FAO, and WFP 2013). During years of low production, local prices rise. During good years, prices fall.

Rice is planted in all ecological regions of the country. However rice productivity is higher in the Terai (3.48 tons/ha) than in the Hills (3.04 tons/ha) and Mountains (2.27 tons/ha) (NMOAD 2012). Although the Terai produces food in surplus, most of the hilly (central, far-western) and mountainous (western, mid-western and far-western) regions are food deficit areas (NMOAD 2012).

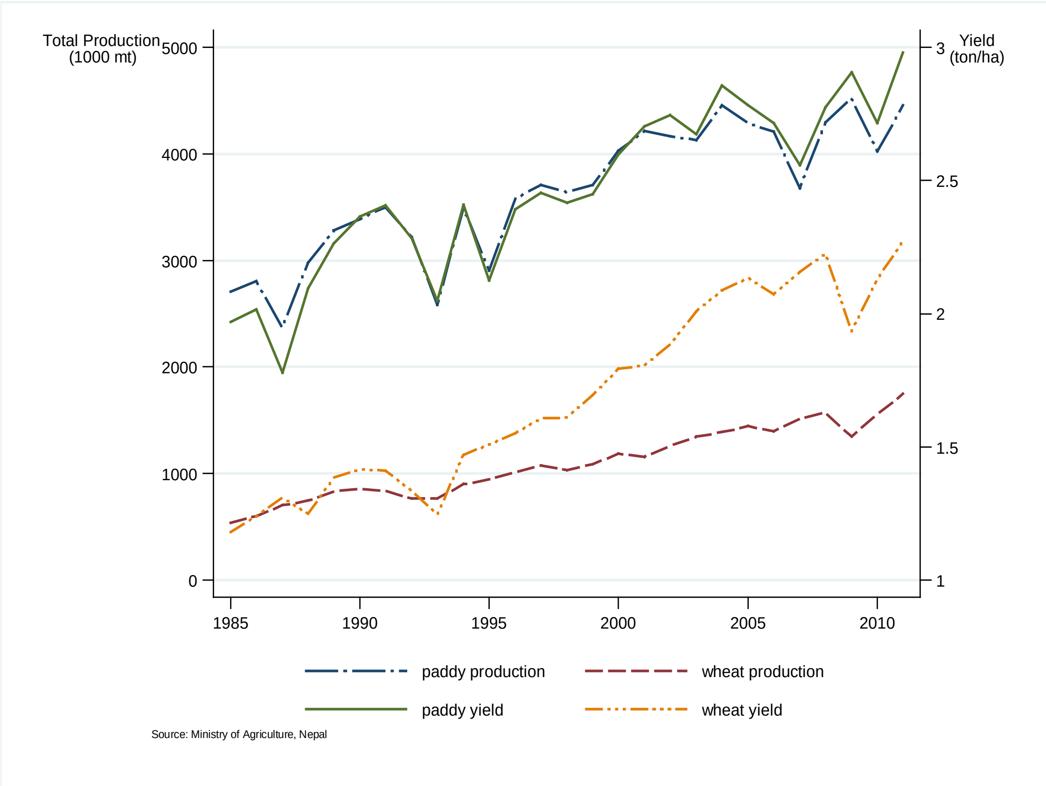

Figure 15. Total Rice (Paddy) and Wheat Production and Yield in Nepal (1985-2011)

2.3. Data

The average monthly nominal retail prices of coarse rice and wheat flour for 28 selected districts of Nepal and seven Indian border markets were obtained from the Nepal Agribusiness Promotion and Marketing Development Directorate. The price series covers a period of 108 months between January 2002 and December 2010. All prices have been deflated using the country-wide consumer price index (CPI). Any missing prices in a series were interpolated using the predicted values obtained from regressing prices on months, year, and district indicators. All analysis reported below uses real prices, in natural logs.

Road data were obtained from the Department of Roads (DOR), Ministry of Physical Planning, Works and Transport Management. The DOR publishes *Nepal Road Statistics* (NRS) in alternate years.[5] Annual progress reports prepared by the DOR list all roads completed in that year. Road data published by the DOR focus on National Highways and Feeder Roads. Similarly, bridge construction is reported by the bridge unit, Department of Road, and Department of Local Infrastructure Development and Agricultural Roads (DoLIDAR). I calculated the total number of bridges constructed in each district over the period of 2002-2010 using these data. Annual bridge density (number of bridges per 100 square kilometers) is calculated for each district. Nepal/India official exchange rates were obtained from the Nepal Rastra Bank.

Data on total area planted and harvested amounts were obtained from the Ministry of Agriculture Development (NMOAD), Nepal. Monthly rainfall data from January 2002 to December 2010 for 282 rainfall stations were obtained from the Department of Hydrology and Meteorology, Nepal. I align the rainfall data with the crop calendar. Because rice in most parts of the country is produced only once a year and depends heavily on the quantity and distribution of monsoon rainfall between May and September, I focus on this rainfall window for rice. For wheat, production usually starts

[5] Missing data for years in which NRS was not published were provided by the DOR's annual, unpublished, progress reports.

in October and ends in March, and so I calculate average rainfall measure for this five-month periods in the case of wheat. Local growing conditions are incorporated using the Normalized Difference Vegetation Index (NDVI). The NDVI was constructed using remotely sensed data from NASA's Moderate Resolution Imaging Spectroradiometer (MODIS), as described in Brown et al. (2014). The NDVI is an indicator of the photosynthetic activity of the observed area and provides an indication of agricultural potential. Possible values range between -1 and 1 with a typical range between 0.1 (indicative of sparse green vegetation) and 0.6 (indicative of dense green vegetation). Negative NDVI values indicates the presence of snow, water or ice. District average NDVI values (cluster based) were calculated by averaging NDVI values for the same five-month growing periods, used for rainfall (May-September in the case of rice; October-February in the case of wheat), and combined with the price data.

The definition and the descriptive statistics of variables used in the analysis are provided in Table 3. The average annual rice planted areas and total harvest is higher for rice than wheat. It is because rice is a major crop in Nepal. As rice is a rainy season crop and wheat is a winter season crop, it is not surprising to see the higher average rainfall received for rice growing season. An average NDVI is greater for rice than that of wheat because more land is allocated for the rice cultivation than that of wheat. Average rice prices are highest in the central market and lowest in border markets. Average wheat prices are highest in local markets and lowest in border markets. For road variable, I calculated a road index using weights that account for different road qualities and the travel time that they imply. Finally I expressed in terms of road density index (dividing by district area (km^2) and multiplying by 1000). I assume that a black-topped road is five times faster than a gravel road and fifty times faster than an earthen road.[6] The mean road density index is .035. The minimum value of road density index of 0 suggests that some districts in Nepal do not have strategic road length constructed. To account for demand-side sifters, I include annual district population, in 1000s, reported by NMOAD.

[6]Sensitivity analysis was conducted by assuming that the blacktopped road is ten/twenty times faster than a gravel road and forty/sixty times faster than an earthen road. The results are not sensitive to these different assumptions.

Table 3. Descriptive Statistics, January 2002 to December 2010

Variable	Obs	Mean	Std. Dev.	Min	Max
Rice harvest ('000 tons)	252	42.3	39.6	2.5	180.6
Wheat harvest ('000 tons)	252	17.0	16.2	1.5	64.5
Rice planted area ('000 ha)	252	16.4	14.5	1.4	65.0
Wheat planted area ('000 ha)	252	8.9	7.2	1.8	32.3
Average monsoon rainfall (May-September, in mm)	252	1186.2	1381.1	27.7	8362.0
Average winter rainfall (Oct-Feb, in mm)	252	92.7	107.6	0.0	792.5
Average monsoon NDVI (May-September, index)	252	630.5	54.8	443.9	747.7
Average monsoon NDVI (Oct-Feb, index)	252	602.3	50.2	419.	721.3
Local market coarse rice price (real Nepal Rs/kg)	3024	23.3	8.3	9.9	79.4
Regional market coarse rice price (real Nepal Rs/kg)	864	18.2	3.6	12.6	66.2
Central market coarse rice price (real Nepal Rs/kg)	108	23.7	4.4	17.0	36.5
Border market coarse rice price (real Nepal Rs/kg)	756	15.7	2.0	9.4	25.4
Local market wheat flour price (real Nepal Rs/kg)	3024	25.3	9.9	10.3	134.4
Regional market wheat flour price (real Nepal Rs/kg)	864	18.9	4.4	9.9	138.5
Central market wheat flour price (real Nepal Rs/kg)	108	21.0	2.1	17.4	27.8
Border market wheat flour price (real Nepal Rs/kg)	756	16.7	2.4	9.9	26.2
Index of road density in district (weighted km/km2)	252	49.3	44.7	0.0	157.8
Bridge density in district (#/km2)	252	0.7	1.0	0.0	3.7
Average diesel fuel price in district (real Nepal Rs/litre)	252	40.7	6.8	28.5	56.5
Monthly exchange rate (Nepal Rs/USD)	108	72.7	4.3	62.9	81.8

2.4. Empirical Strategy

Whenever the price of a commodity in one market exceeds the price of the same commodity in another market by more than the cost of transportation and marketing, traders have an opportunity to engage in arbitrage until prices converge, thereby restoring spatial equilibrium (Goodwin et al. 1990; Sexton et al. 1991; Badiane and Shively 1998). Adding the cost of storage, one can also derive conditions for temporal arbitrage. Figure 8 illustrates the market structure in Nepal and highlights the importance of hubs located in the Terai as suppliers to the rest of the country. Suppliers and traders in regional and transit hubs supply grain to various markets, adapting their marketing strategies to target destinations where there is the greatest arbitrage opportunity. Temporary equilibriums and shortages lead traders to shift their short-term focus among different areas and nodes. When markets are well connected and when price signals are completely transmitted among markets, temporary disequilibria are infrequent and quickly resolved. When markets are not well connected and transaction cost are very high, disequilibria may persist, suggesting potential pathways to improving overall welfare by raising prices for producers, lowering prices for consumers, or both.[7]

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[7]Disequilibrium may cause price instability, both for producers and consumers. Consumers lose and producers gain from price stability if the source of instability lies on the supply side, and vice-versa. As Willimas & Wright (1991) and Newbery and Stiglitz (1981) point out, who actually benefits from price instability depends on a range of factors (risk-taking behavior, slope of demand and supply curve, endowment, etc.) However, when markets are well-connected and prices return to equilibrium quickly, total social welfare is maximized in the long run.

To quantify the transmission of price signals as suggested by Figure 8, I use a modified version of Ravillion's (1986) model. I make two modifications. First, instead of focusing on a single market, I use a panel of local markets. For each local market, I posit one central market, one Nepal-India cross-border market, and one regional market. Second, in contrast to studies which treat a primary grain-supplying location as the central market, I assume that Nepal's central market is Kathmandu, the location of greatest market demand. The dynamic relationship for the local market price can be expressed as:

$$P_{ilt} = \alpha_{i0} + \alpha_{i1}T + \alpha_{i2}M + \alpha_{i3}Y + \alpha_{i4}L + \gamma_i P_{ilt-1} + \sum_{j=0}^{1}\sum_{k=1}^{3}\beta_{ik}P_{ikt-j} + \boldsymbol{\theta}'\mathbf{D} + \boldsymbol{\delta}'\mathbf{S} + \vartheta_i E_t + \mu_{ilt}, \quad i = 1 \text{ to } 2,\ l = 1 \ldots 28, t = 1.,T \tag{1}$$

where P_{ilt} represents the retail price for commodity *i* in market *l* at time *t*; T is a unit-step (monthly) time trend;. M, Y and L are month, year, and location (agro-ecological) fixed effects; P_{ikt-j} is the price observed for commodity *i* in the companion market *k* *(regional, central, and border)* at time *t*, with lag *j= (0 and 1*). Here $\alpha_{\mathrm{is}}, \gamma_i, \beta_{ik}$, $\boldsymbol{\theta}$, ϑ_i and $\boldsymbol{\delta}$ are parameters to be estimated. The error term, μ_{ilt}, is assumed to be independently and identically distributed across the observations. Parameters β_{ik} and γ_i are coefficients for spatial market price transmission and auto-regressive lags, respectively. Here ***D*** and ***S*** are column vectors representing demand and supply shifters and E_t is the exchange rate, which is assumed to influence both demand and supply. ***D*** includes annual district population and fuel price variables. ***S*** includes road (road density index), bridges (bridge density), interaction terms of road density index and bridge density with the agro-ecological zones, and production (harvest) variables. Directly incorporating production as an independent variable in equation ((1) could introduce an endogeneity problem because prices can influence production decisions. To circumvent this problem, I predict the quantity harvested (Q_{ilt}) using a time trend (T), NDVI (N_{ilt}), rainfall (R_{ilt}), total area planted (A_{ilt}) and a pair of ecological zone indicators (Z) for Terai (0/1) and Mountain (0/1). Here, NDVI and rainfall serve as instrumental variables. The maintained assumption is that they influence production but do not directly influence price. The harvested quantity equation is expressed as:

$$\mathrm{Q_{ilt}} = \beta_{i0} + \beta_{i1}\mathrm{T} + \beta_{i2}\mathrm{R_{ilt}} + \beta_{i3}\mathrm{N_{ilt}} + \beta_{i4}\mathrm{A_{ilt}} + \varphi \mathrm{Z} + \epsilon_{ilt} \qquad (2)$$

where β's and φ are the coefficients to be estimated. ϵ_{ilt} is the error term assumed to be independent and identically distributed for *i=1 to 2, l=1…28, t=1.,T.* Predicted output based on equation ((2) is included as a regressor in the estimated version of equation (1). Using the estimated coefficients from equation (1), a set of specific hypotheses regarding price determinants, market segmentation, and short- and long-run market integration can be tested. In a long-run equilibrium, market prices are assumed to be constant over time and undisturbed by local stochastic effects (Ravallion 1986). If $\beta_{ik} = 0\ \forall\ k,$ then the local market is segmented from other markets. If $\beta_{ik} = 1\ \forall\ k$ and $\gamma_i = 0,$ then local markets are integrated with other markets in the short-run. If markets are integrated in the long-run, then $\gamma_i + \sum \beta_{ik} = 1$, given the number of lags required for the equality to hold.

Given the overall negative effects of the price variances on the nutrition and food security status of the country, it is equally important to investigate the determinants of food price variances. Past studies conducted in Africa have included production measures, exchange rates and lagged market prices to help explain local market price variances (Shively 1996; Badaine and Shively 1998). Studies from different countries reveal mixed results on the effect of fuel prices on agricultural commodity prices. Studies (for example Abbott et al. 2008; Chang and Su 2010) indicate that oil prices are a main factor driving food prices. However some studies (for example Zhang et al. 2010; Gilbert 2010) find no strong linkages between oil and agricultural prices. Although fuel prices are directly set by the government and are less volatile in Nepal than elsewhere, during the last decade the fuel price has fluctuated (Figure 14), so it seems possible that fuel prices have influenced food price volatility in Nepal.

To the best of my knowledge, no previous studies, whether in Nepal or elsewhere, have been conducted to examine the impact of market infrastructure such as roads on food price volatility. When regional/border and local markets are not well-connected due to poor market infrastructure, one might expect price variances in local markets to be high. Under such conditions, local markets are not likely to receive price signals from supplying markets in a timely fashion. When it takes time for supply to reach a local market, a price increase is likely during the shortage period. Once shipped food arrives, price may moderate until the next shortage occurs. Generally, in such markets very few traders are engaged in temporal arbitrage because of high transaction and storage costs. For example, research from Ethiopia suggests that storage costs are very high and only a few farmers store grains for periods long enough to benefit from trade and temporal arbitrage (Tadesse and Guttormsen 2011). The model used here allows us to examine the linkage between road density index and food price variance. Because an increase in agricultural production is widely perceived to be one means to reduce food price variability (FAO et al. 2011), I also examine whether increased local agricultural production is associated with lower food price variance.

Any unanticipated price changes may lead to sub-optimal decisions for consumers, producers, traders and government agencies (FAO et al. 2011). When errors exhibit time-varying heteroskedasticity, failing to account for this can distort standard errors and mislead one regarding statistical inference. From a statistical point of view, efficiency gains are possible by using an autoregressive conditionally heteroskedastic (ARCH) estimation strategy instead of ordinary least squares (Engle 1982; Bollerslev et al., 1992). The process involves estimating the parameters of the mean and variance equations simultaneously. The Panel ARCH model can be written as:

$$P_{ilt} = \alpha_{i0} + \alpha_{i1}T + \alpha_{i2}M + \alpha_{i3}Y + \alpha_{i4}L + \gamma_i P_{ilt-1} + \sum_{j=0}^{1}\sum_{k=1}^{3}\beta_{ik}\,P_{ikt-j} + \boldsymbol{\theta}'\mathbf{D} + \boldsymbol{\delta}'\mathbf{S} + \vartheta_i E_t + \mu_{ilt}, i = 1 \text{ to } 2, l = 1 \ldots 28, t = 1., T \quad (3)$$

$$\sigma_{ilt}^2 = \gamma_{i0} + \gamma_{i1}\epsilon_{ilt-1}^2 + \gamma_{i2}T + \gamma_{i3}E_t + \gamma_{i4}L + \sum_{j=0}^{1}\sum_{k=1}^{3}\gamma_{ik}P_{ikt-j} + \boldsymbol{\psi}\mathbf{D} + \boldsymbol{\lambda}\mathbf{S} + \vartheta_{ilt} \quad (4)$$

This set up adds to the conditional mean equation ((3) the conditional variance equation (4). The variances of the regression disturbances (σ_{ilt}^2) are assumed to be conditional on the size of prior unanticipated innovations i.e., ϵ_{ilt-1}^2 (lagged values of the squared regression disturbances) and other factors expected to influence food price variances. In equation ((4), γ_{i1} are the ARCH parameters to be estimated. The ϑ_{ilt} are assumed to be independently and identically distributed with expected value zero. Since the conditional variances must be positive, the model requires γ_{i0}>0 and $\gamma_{i1} \geq 0$. If $\gamma_{i1} =$

0, then there are no dynamics in the conditional variance equation. If one adds to equation ((4) the lagged conditional variances, this results in the generalized autoregressive conditionally heteroskedastic (GARCH) regression introduced by Engle (1982) and Bollerslev (1986). GARCH (m,n) is a standard notation where m indicates the number of autoregressive lags (or ARCH terms) and n indicates the number of moving average lags (or GARCH terms). Although a GARCH model is conditionally heteroskedastic and mean reverting, unconditional variance is assumed to be constant. The panel GARCH (1,1) model for the current analysis can be written as:

$$\sigma_{ilt}^2 = \gamma_{i0} + \gamma_{i1}\epsilon_{ilt-1}^2 + \beta_{i1}\sigma_{ilt-1}^2 + \gamma_{i2}T + \gamma_{i3}E_t + \gamma_{i4}L + \sum_{j=0}^{1}\sum_{k=1}^{3}\gamma_{ik}P_{ikt-j} + \boldsymbol{\psi D} + \boldsymbol{\lambda S} + \vartheta_{ilt} \quad (5)$$

According to Bollerslev (1986), the condition $\gamma_{i1} + \beta_{i1} < 1$ is sufficient to guarantee covariance stationarity for each cross-section in the panel. If the expression equals 1, then I have an integrated GARCH model (IGARCH). The disturbances in model are assumed to be cross-sectionally independent.

Although the linearity property of the GARCH model facilitates parameter estimation and tests for homoscedasticity, GARCH models may suffer from various limitations (Nelson 1991). First, since the conditional variance must be non-negative, the model remains highly constrained. Second, standard GARCH models respond symmetrically to both positive and negative innovations. However price volatility might behave asymmetrically to positive and negative shocks. Shively (2001), for example, finds price thresholds relating to price volatility in Ghana’s maize market, arguing that isolated and thin markets, which tend to be less integrated both spatially and temporally, may be especially prone to non-linear and asymmetric adjustments in price. Agricultural price formation in some markets of Nepal may well be explained by an asymmetric GARCH model. There are many forms of asymmetric GARCH models, including the asymmetric GARCH (AGARCH) model of Engle (1990), and the threshold GARCH (TGARCH) model of Rabemananjara and Zakoian (1993), and Glosten et al. (1993). Adding the term $\gamma_{i2}\epsilon_{ilt-1}$ to equation (5) leads to the AGARCH (1,1) model:

$$\sigma_{ilt}^2 = \gamma_{i0} + \gamma_{i1}\epsilon_{ilt-1}^2 + \gamma_{i2}\epsilon_{ilt-1} + \beta_{i1}\sigma_{ilt-1}^2 + \gamma_{i3}T + \gamma_{i4}E_t + \gamma_{i5}L + \sum_{j=0}^{1}\sum_{k=1}^{3}\gamma_{ik}P_{ikt-j} + \boldsymbol{\psi}\mathbf{D} + \boldsymbol{\lambda}\mathbf{S} + \vartheta_{ilt} \quad (6)$$

Here, positive values for γ_{i2} imply that positive shocks will result in larger increases in price volatility than negative shocks of the same absolute magnitude. Adding the indicator function term $\gamma_{i2}(I_{\epsilon ilt>0})\epsilon_{ilt-1}^2$ to equation ((5) results in the threshold GARCH (TGARCH (1,1)) model of Glosten et al. (1993). This model allows the conditional variance to depend on the sign of the lagged innovations. The model is defined as:

$$\sigma_{ilt}^2 = \gamma_{i0} + \gamma_{i1}\epsilon_{ilt-1}^2 + (\gamma_{i2}(I_{\epsilon_{ilt-1}>0)}\ )\ \epsilon_{ilt-1}^2) + \beta_{i1}\sigma_{ilt-1}^2 + \gamma_{i3}T + \gamma_{i4}E_t + \gamma_{i5}L + \sum_{j=0}^{1}\sum_{k=1}^{3}\gamma_{ik}P_{ikt-j} + \boldsymbol{\psi}\mathbf{D} + \boldsymbol{\lambda}\mathbf{S} + \vartheta_{ilt} \quad (7)$$

The indicator function in equation (7) is 1 when the error is positive and 0 when it is negative. If γ_{i2} is positive, negative errors are leveraged and positive shocks have larger effects on volatility than negative shocks. Detailed information on the various forms of ARCH and GARCH models is provided by Bollerslev (2007). Below, I present results for five regression models: AR(1), ARCH(1), GARCH(1, 1), TGARCH(1, 1) and AGARCH(1, 1).

2.5. Results and Discussion

2.5.1. Agriculture production instrumenting equation

Table 4 displays the results for district-level regressions of annual rice and wheat production.[8] The time trend coefficients for both are positive, though insignificant, implying no significant technical progress, at least of a Hicks-neutral form, over the period. The coefficients for rice and wheat planted area are positive and statistically significant. These coefficients represent the average productivity (2.65 and 1.71 tons per hectare, respectively) over the period. Higher district-level rainfall in a year is associated with a larger harvest (of both rice and wheat). Similarly, NDVI, an indicator of local agricultural potential, is positively correlated with local production of rice and wheat although significant only for rice result. Rice and wheat yields are higher in the Terai than in the Hill and Mountain regions, reflecting the more favorable agro-climatic conditions of the Terai. The predicted values of annual, district-level rice and wheat production derived from these results are assumed to be exogenous to prices, and are used as regressors in the price regressions reported below.

2.5.2. Diagnostic testing

Before conducting the time series analysis on prices, I performed panel unit root tests

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[8] Although it would be desirable to include district-level use of fertilizers, irrigation, and purchased seed in these production functions, such data are not available. Since most parts of Nepal still practice traditional farming with very low utilization of modern inputs, the results likely do not suffer from omitted variable bias due to their exclusion.

to examine the time series properties of the monthly time series variables. I implemented a Harris-Tzavalis test with the assumption of a time trend for all price series. The objective of this test is to establish whether a series is stationary or not. The Harris-Tzavalis test is recommended when the number of panels tends to infinity while the number of time periods is fixed (Harris and Tzavalis 1999). Results reported in Table 5 indicate that all series are stationary at a test level of 1% or less. Consequently, differencing was not required for the price series.

The test for ARCH effects is a Lagrange multiplier (LM) test. The LM test is just the F-statistic for the regression of the squared residuals on their own lagged values where the F-statistic follows a chi-square distribution. Equation (1) was estimated for each crop using ordinary least squares and residuals were retained and used for the tests. For rice and wheat, the LM test statistics have values of 136.53 and 541.96, respectively. These are statistically significant when judged against the χ^2 1% critical value of 6.63. The null hypothesis of homoscedasticity can be rejected in favor of first-order autoregressive conditional heteroskedasticity. I also conducted Wooldridge tests of the null hypothesis of no first-order autocorrelation in panel data (Wooldridge 2002; Drukker 2003). The null hypothesis can be rejected in favor of the alternative hypothesis of first-order autocorrelation for both the rice and wheat flour price equations. This suggests a first order process for both commodities.[9]

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[9]For the coarse rice price equation, the Wooldridge test for autocorrelation in panel data (H_0: No first-order autocorrelation) yields the results F(1, 27) = 164.78 (Prob>F = 0.00). For the wheat flour price equation, the test yields F (1,27) = 36.43 (Prob>F = 0.00).

Table 4. Regression Results for District-level Rice and Wheat Production in 1000 tons (2002-2010)

Variables	Rice	Wheat
Time trend (annual unit step)	0.27812 (0.18358)	0.02550 (0.06842)
Terai (0/1)	3.20209 (5.59334)	10.29176*** (1.54323)
Mountain (0/1)	-2.58049** (1.17277)	-1.01572*** (0.31311)
Annual planted area: rice (1000 ha)	2.64958*** (0.14169)	-
Monsoon rainfall (May-September average, in mm)	0.00077*** (0.00028)	-
NDVI (Average, Index May-September)	0.03073** (0.01475)	-
Annual planted area: wheat (1000 ha)	-	1.71704*** (0.06953)
Monsoon rainfall (Average Oct-Feb, in mm)	-	0.00387*** (0.00117)
NDVI (Average, Index Oct-Feb)	-	0.00354 (0.00304)
Constant	-23.09113** (8.96905)	-2.53838 (1.96529)
Observations	252	252
R-squared	0.97	0.97

Note: [a] indicates the dummy variable, robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 5. Results from Panel Unit-root Test (Harris-Tzavalis test)

Variable	Rho	Z
Local market coarse rice price (real, log)	0.55	-5.83
Regional market coarse rice price (real, log)	0.49	-60.94
Central market coarse rice price (real, log)	0.66	-30.98
Border market coarse rice price (real, log)	0.64	-33.46
Local market wheat flour price (real, log)	0.49	-51.54
Regional market wheat flour price (real, log)	0.44	-57.13
Central market wheat flour price (real, log)	0.51	-48.95
Border market wheat flour price (real, log)	0.79	-16.06
Exchange rate (real, log)	0.94	-5.03
Fuel price, diesel (real, log)	0.95	-4.39

Notes: All values are statistically significant at less than 1% level, test for rho=0, null hypothesis is panels contain unit roots. trend is included for price series, number of panels: 28, number of periods:108

I estimated AR(1), ARCH(1), and three versions of GARCH and tested for the best fitting model. As indicated by AIC and BIC values, the AGARCH model of Engle (1990) best fits rice prices, and the TGARCH model of Glosten et al. (1993) best fits the wheat prices. For most variables, only a slight change in the magnitude of coefficients is observed across models, supporting the robustness of the results. I focus discussion on the results from the best fitting models. Results for all five regressions are reported in Table 6 (for rice) and Table 7 (for wheat).

2.5.3. Test of market segmentation and market integration

I also tested the hypothesis of local market segmentation and market integration between local and regional, central and border markets. Results reported in Table 6 and Table 7 imply rejection of the null hypothesis of local market segmentation. The coefficient on the regional market price is significant for coarse rice. The border market price is significant for wheat flour. Similarly, I can reject the short-run market integration hypothesis as the lagged local price coefficients are significant for both the coarse rice and wheat flour price models. I also tested the null hypothesis of long-run market integration: $\gamma_i + \beta_{ik}$=1. The null hypothesis of long-run market integration can be rejected for both rice and wheat.[10] These results indicate incomplete price transmission/pass-through of price changes from regional, (or central or border) markets to local markets. These results could be driven by high transaction costs and marketing margins that hinder the flow of price signals to economic agents and prohibit arbitrage. For example, Sanogo (2008) argues that poor infrastructure prevents price convergence across districts in Nepal.

2.5.4. Mean equation

Tables 6 and 7 report the results from the rice and wheat regressions. I focus on

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[10]For real coarse rice prices: F(1, 2962)=5.96, Prob> F=0.01, and for wheat flour prices : F(1, 2962)=21.27, Prob> F=0.00. The coefficients of first lag of local market prices and the current and first lag of regional, central and border market prices were used to test the long-run market integration hypothesis.

explaining results from the best fitting models —AGARCH(1,1) in the case of rice and TGARCH(1,1) for wheat. The time trend coefficient is positive and statistically significant only in the case of wheat. Coefficients for the first lag of local market prices are positive, less than one, and statistically significant. This means that a 1% increase in the real price of rice or wheat leads to price increases of 0.90% and 0.88% in the subsequent month. The local rice price is influenced by the regional and central markets while the local wheat price is influenced by the border market. In the case of coarse rice, the current price transmission elasticity between the regional market and the local market is about 0.06 and between the central market and the local market is about 0.03. For wheat, the current price transmission elasticity between the border market and the local market is 0.10. This suggests overall weak market integration in Nepal. However, these patterns do not preclude market integration between adjacent district markets or district markets and adjacent border markets.[11]

The estimated coefficient for the road density index is negative and statistically significant at less than 1% in all estimated models. However the estimated coefficient for the bridge density is negative and statistically significant only for rice price. Based on the

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[11]Sanogo and Amadou (2010) studied market integration between a regional market (Morang) and its neighboring border market (Jogbani) using monthly wholesale coarse rice prices. For these markets, border market price transmission to the regional market was very high. A one unit increase in the border market price increased the regional market rice price by 0.88 unit. However, they used a far more parsimonious regression that included just the border market price as a regressor, raising the possibility of omitted variable bias in their estimate and potential model misspecification.

estimated coefficients on agro-ecology, used as dummy variables after dropping hills, I find rice and wheat prices to be higher in mountain and lower in the Terai as compared to the hill. One of the reasons can be attributed towards the existing rich transportation infrastructure in the Terai region as compared to the hilly and mountainous region. Therefore I also incorporated interaction coefficients between agro-ecology and transportation infrastructure (road density and bridge density) in regression models. As expected, the estimated interaction coefficients between mountain and road density index are negative and statistically significant for both the rice and wheat flour price models, suggesting the prominent influence of the roads on food prices in the mountainous region. The estimated interaction coefficient between the Terai and bridge is positive and statistically significant. The result is unintuitive as I expect its sign to be negative. The estimated coefficient for the monthly fuel (diesel) price in rice price equation is positive and statistically significant at less than 10% in the best fitting model. The fuel price transmission elasticity[12] is about 0.06 for rice.

The estimated coefficient for the wheat production variable is negative and statistically significant at less than 5% in all models. A one per cent increase in wheat production is associated with 0.008% decrease in the wheat flour price. These results illustrate the importance of district-level wheat production to local wheat flour prices.

As expected, the estimated coefficients for annual district population are positive although only statistically significant for wheat flour price. Population is a demand shifter. The coefficients on the monthly exchange rate are negative but significant only for rice.

2.5.5. Variance equation

Results from the variance equations are presented in the lower panels of tables 6 and 7. In both cases, asymmetric GARCH effects are observed. This suggests that not only the magnitude of price shocks but also the direction of price shocks matter to price volatility. For rice, the positive and statistically significant value of the asymmetric term implies that a positive price shock is correlated with a larger increase in future price volatility than negative price shocks of the same absolute magnitude. The conditional variance is positive for the rice equation. In the case of wheat, the threshold effect is positive, which implies that positive shocks are amplified.

The variance equation results suggest that the lagged values of the squared regression disturbances are statistically significant at a 0.01 test level implying dynamics in the conditional variance equation. In both the rice and wheat price models, a higher lagged monthly border and central market prices are associated with greater local market price variance. However a higher regional market price is correlated subsequently with lower local price variance for rice. An increase in district-level rice production is correlated with lower local rice price variance while an increase in district-level wheat production is correlated with lower local wheat flour price. Road density index (a proxy for market infrastructure in general), is negatively correlated with price variance in the rice and wheat markets. Population density is positively correlated with price variance in the rice market. The fuel price is negatively correlated with price variance in the rice and wheat markets, a result that is unexpected.[13] A higher monthly exchange rate is associated with lower local market price variance.

[13]The fuel price only varies across ecological zones, so perhaps it is only an imprecise measure of local transport costs. A more precise way to measure transport cost would be to account for actual miles travelled and effort required, perhaps by accounting for changes in elevation.

Table 6. Regression Results for Real Rice Prices in Nepal, 2002-2010

	AR	ARCH	GARCH	AGARCH
Mean equation				
Time trend	-0.00008	0.00007	0.00006	-0.00002
(monthly unit-step)	(0.00016)	(0.00014)	(0.00015)	(0.00014)
Local price (t-1)	0.89480***	0.90023***	0.90903***	0.89875***
	(0.01192)	(0.00756)	(0.00801)	(0.00839)
Regional market price (current)	0.04293**	0.04775***	0.05241***	0.05940***
	(0.01709)	(0.01528)	(0.01488)	(0.01419)
Regional market price	-0.0545***	-0.05682***	-0.05458***	-0.0529***
(t-1)	(0.01807)	(0.01301)	(0.01413)	(0.01373)
Central market price	0.01696	0.02954*	0.02752*	0.02680*
(current)	(0.02076)	(0.01665)	(0.01594)	(0.01520)
Central market price	0.01540	0.00421	0.00631	0.01209
(t-1)	(0.01924)	(0.01581)	(0.01513)	(0.01472)
Border market price	-0.03120	-0.01315	-0.01280	-0.01681
(current)	(0.02681)	(0.01997)	(0.01966)	(0.01905)
Border market price	0.01931	0.01755	0.00806	0.00093
(t-1)	(0.02604)	(0.01737)	(0.01649)	(0.01648)
Road density	-0.00033***	-0.00021***	-0.00020***	-0.0002***
(weighted km/km^2)	(0.00008)	(0.00008)	(0.00007)	(0.00007)
Bridge density	-0.00312	-0.00400	-0.00458*	-0.00411**
(#/km^2)	(0.00289)	(0.00244)	(0.00241)	(0.00202)
Mountain×Road density (interaction)	-0.00060**	-0.00045*	-0.00038*	-0.0006***
	(0.00028)	(0.00025)	(0.00022)	(0.00021)
Mountain×Bridge density (interaction)	-0.05269	-0.01503	-0.03498	0.05004
	(0.17036)	(0.20403)	(0.16684)	(0.16839)
Terai×Road density (interaction)	-0.00011	-0.00004	-0.00009	-0.00013
	(0.00024)	(0.00026)	(0.00023)	(0.00020)
Terai×Bridge density (interaction)	0.00881	0.00834	0.01038**	0.01074**
	(0.00597)	(0.00572)	(0.00523)	(0.00468)
Monthly fuel price (Rs/liter)	0.07957**	0.04575	0.04351	0.05793*
	(0.03755)	(0.03427)	(0.03630)	(0.03338)
District population	0.00010**	0.00007	0.00007	0.00007
(#/km^2)	(0.00005)	(0.00005)	(0.00005)	(0.00004)
Rice production	-0.00339	-0.00354	-0.00356	-0.00389
(1000 MT)[a]	(0.00270)	(0.00328)	(0.00273)	(0.00267)
Monthly exchange rate	-0.13479***	-0.12664***	-0.12474***	-0.1284***
(Nepal Rs/USD)	(0.04555)	(0.04143)	(0.04281)	(0.03856)
Terai	-0.03282**	-0.03186**	-0.02717**	-0.02482**
(0/1)	(0.01288)	(0.01376)	(0.01216)	(0.01210)
Mountain	0.02787***	0.02227**	0.02009**	0.02670***
(0/1)	(0.01025)	(0.01063)	(0.00945)	(0.00901)
Constant	0.61458***	0.62435***	0.60167***	0.59155***
	(0.22557)	(0.18092)	(0.18151)	(0.17117)

Table 6 continued

	AR	ARCH	GARCH	AGARCH
Variance equation				
Time trend		0.00455***	0.00682***	0.00740***
(monthly unit-step)		(0.00076)	(0.00110)	(0.00114)
Regional market price		-0.77987***	-2.21806***	-2.43416***
(t-1)		(0.14763)	(0.29123)	(0.29883)
Central market price		0.60033***	1.26588***	1.58011***
(t-1)		(0.11020)	(0.15380)	(0.17657)
Border market price		0.49527***	1.10155***	0.70052***
(t-1)		(0.18156)	(0.27250)	(0.28274)
Road density		-0.01003***	-0.00949***	-0.01063***
(weighted km/km^2)		(0.00075)	(0.00088)	(0.00108)
Bridge density		-0.0115	0.01165	0.01459
(#/km^2)		(0.03056)	(0.03927)	(0.04467)
Monthly fuel price		-1.97709***	-1.86098***	-1.84647***
(Rs/liter)		(0.16292)	(0.21319)	(0.23355)
District population		0.00196***	0.00196***	0.00190***
(#/km^2)		(0.00033)	(0.00038)	(0.00041)
Rice production		-0.14883***	-0.12817***	-0.11667***
(1000 MT)[a]		(0.02609)	(0.02842)	(0.02735)
Monthly exchange rate		-2.98435***	-2.33552***	-2.47040***
(Nepal Rs/USD)		(0.31509)	(0.39992)	(0.48743)
Terai		0.17779*	0.05075	0.20506
(0/1)		(0.10564)	(0.12800)	(0.12894)
Mountain		0.51557***	0.45315***	0.43220***
(0/1)		(0.06624)	(0.07569)	(0.07204)
Constant		14.36779***	10.25043***	11.41434***
		(1.81379)	(2.16935)	(2.63677)
L.ARCH		0.08732***	0.11657***	0.12153***
		(0.01181)	(0.01317)	(0.01283)
L.GARCH			0.57090***	0.59246***
			(0.02991)	(0.02829)
L.AGARCH				0.01667***
				(0.00202)
Districts	28	28	28	28
Observations	2996	2996	2996	2996
AIC	-5544.7	-6025.8	-6104.4	-6142.8

Note: [a]Instrumented value; standard errors appear in parentheses; ***indicates p<0.01, **p<0.05, *p<0.1. Agricultural prices, fuel prices, exchange rate, and harvest variables have been converted to natural logarithm form. Agroecological zone (k=3), year, and monthly fixed effects are included in the mean equations.

Table 7. Regression Results for Real Wheat Prices in Nepal, 2002-2010

	AR	ARCH	GARCH	TGARCH
Mean equation				
Time trend	0.00030	0.00034**	0.00036**	0.00026*
(monthly unit-step)	(0.00021)	(0.00017)	(0.00015)	(0.00015)
Local price	0.78956***	0.81211***	0.86256***	0.88190***
(t-1)	(0.02887)	(0.01015)	(0.00792)	(0.00853)
Regional market price	0.01218	0.03948*	0.02416	0.02392
(current)	(0.02061)	(0.02113)	(0.01862)	(0.01876)
Regional market price	-0.01443	-0.02101	-0.02469	-0.01602
(t-1)	(0.01654)	(0.02323)	(0.01834)	(0.01883)
Central market price	0.04783	0.03701	0.00870	0.01842
(current)	(0.03534)	(0.02925)	(0.02556)	(0.02723)
Central market price	-0.10933***	-0.11982***	-0.11247***	-0.09984***
(t-1)	(0.03510)	(0.02518)	(0.01997)	(0.01958)
Border market price	0.01603	0.06440**	0.07663***	0.09580***
(current)	(0.03391)	(0.02513)	(0.02098)	(0.02104)
Border market price	-0.04839	-0.09121***	-0.10550***	-0.09930***
(t-1)	(0.03537)	(0.02451)	(0.01880)	(0.01919)
Road density	-0.00067***	-0.00034***	-0.00026***	-0.00026***
(weighted km/km^2)	(0.00013)	(0.00009)	(0.00007)	(0.00008)
Bridge density	-0.00111	-0.00418	-0.00183	-0.00001
(#/km^2)	(0.00335)	(0.00283)	(0.00218)	(0.00237)
Mountain×Road density	-0.00194***	-0.00159***	-0.00079***	-0.00083***
(interaction)	(0.00042)	(0.00030)	(0.00020)	(0.00024)
Mountain×Bridge	-0.04231	-0.06660	-0.19377	-0.08176
density	(0.16675)	(0.17643)	(0.14157)	(0.15305)
(interaction)				
Terai×Road density	0.00006	0.00034	0.00029	-0.00003
(interaction)	(0.00033)	(0.00031)	(0.00022)	(0.00024)
Terai×Bridge density	0.01021	0.00595	0.00527	0.00600
(interaction)	(0.00701)	(0.00661)	(0.00494)	(0.00555)
Monthly fuel price	0.02839	0.05308	0.02202	0.02776
(Rs/liter)	(0.04611)	(0.03986)	(0.03649)	(0.03651)
District population	0.00017**	0.00004	0.00005	0.00009*
(#/km^2)	(0.00007)	(0.00006)	(0.00005)	(0.00005)
Wheat production	-0.00904***	-0.00724***	-0.00710***	-0.00761***
(1000 MT)[a]	(0.00294)	(0.00246)	(0.00203)	(0.00255)
Monthly exchange rate	0.00193	-0.03195	-0.02396	-0.01675
(Nepal Rs/USD)	(0.06014)	(0.04684)	(0.04473)	(0.04497)
Terai	-0.07716***	-0.06341***	-0.05610***	-0.03108**
(0/1)	(0.01558)	(0.01496)	(0.01263)	(0.01348)
Mountain	0.09221***	0.08027***	0.05580***	0.05215***
(0/1)	(0.01878)	(0.01198)	(0.00920)	(0.01000)
Constant	0.83165***	0.80045***	0.83252***	0.57064***
	(0.28010)	(0.23691)	(0.20232)	(0.20937)

Table 7 continued

Variance equation	AR	ARCH	GARCH	TGARCH
Time trend		0.00129	-0.00708***	-0.00524***
(monthly unit-step)		(0.00090)	(0.00212)	(0.00183)
Regional market price		-0.00736	-0.74659	-1.05313*
(t-1)		(0.20387)	(0.59746)	(0.55190)
Central market price		1.43957***	2.88090***	3.48927***
(t-1)		(0.18308)	(0.65861)	(0.57218)
Border market price		0.32244**	2.71419***	2.27953***
(t-1)		(0.14027)	(0.40102)	(0.38763)
Road density		-0.01835***	-0.01063***	-0.00840***
(weighted km/km^2)		(0.00080)	(0.00202)	(0.00168)
Bridge density		-0.07387***	-0.06380	-0.02026
(#/km^2)		(0.02719)	(0.06526)	(0.04907)
Monthly fuel price		-1.76094***	-0.31702	-0.72249*
(Rs/liter)		(0.18917)	(0.45628)	(0.37968)
District population		0.00304***	0.00087	0.00091
(#/km^2)		(0.00037)	(0.00068)	(0.00060)
Monthly exchange rate		-1.13895***	3.51342***	3.03617***
(Nepal Rs/USD)		(0.35862)	(0.79815)	(0.73633)
Wheat production		0.03059*	-0.00506	-0.05806
(1000 MT)[a]		(0.01693)	(0.04632)	(0.03724)
Terai		-0.25986***	0.28289*	0.18971
(0/1)		(0.09341)	(0.15536)	(0.13774)
Mountain		0.22093***	0.34668***	0.49241***
(0/1)		(0.05332)	(0.11388)	(0.09583)
Constant		1.66744	-34.238***	-30.38417***
		(1.93264)	(4.14829)	(3.79918)
L.ARCH		0.20027***	0.30565***	0.14923***
		(0.02029)	(0.01821)	(0.01860)
L.GARCH			0.67056***	0.67763***
			(0.01373)	(0.01306)
L.TARCH				0.25168***
				(0.02879)
Districts	28	28	28	28
Observations	2996	2996	2996	2996
AIC	-4148.20	-4962.51	-5229.69	-5250.81

Note: [a]Instrumented value; standard errors appear in parentheses; ***indicates p<0.01, **p<0.05, *p<0.1. Agricultural prices, fuel prices, exchange rate, and harvest variables have been converted to natural logarithm form. Agroecological zone (k=3), year, and monthly fixed effects are included in the mean equations.

2.6. Conclusion and Policy Implications

The primary goal of this study was to assess the determinants of movements in the means and variances of rice and wheat prices in Nepal. Data from twenty-eight local districts were pooled for the study. Monthly retail coarse rice and wheat flour price data from 2002 to 2010 were used for the analysis. Panel ARCH effects were found to be significant in both price series. In addition, AIC tests confirmed that the asymmetric GARCH model was the best fit to rice prices and the threshold GARCH model was the best fit to wheat prices.

For rice, regional market and central market prices matter to both the local market price level and to local price variance. A price increase in the regional market is associated with an increase in the local price but a decrease in price variance. Lagged central market prices were found to be correlated with local price variance for rice. Although an increase in the border rice price was found to be associated with an increase in local price variance, no statistically significant evidence was found for the effect of border prices on the local rice price level. For wheat, an increases in the border price was correlated with both the mean and variance of local price.

Improved market infrastructure, i.e., increase of road density index were found to be associated with decrease in the mean and variances of the local rice and wheat prices. The effects of roads on food prices was higher and statistically significant in mountain while no significant effects was found for the Terai. The improvement of the bridge density was found to be significantly correlated with only the lower rice prices. District-level rice production is negatively correlated with rice price variance while district-level wheat production is negatively correlated with local wheat price level. Exchange rate movements are negatively correlated with price levels and variances for both rice. Threshold effects were found for both the rice and wheat prices suggesting the asymmetric effects of price shocks on price volatilities. I did not find the evidence of short-and long-run market integration. The weak price transmission was found between local and regional markets.

Based on the findings, several policy recommendations to decrease local food price levels and variances can be made for Nepal. Improving connection between local and regional markets through constructing bridges and improving road quality or spreading road network in remote areas of the country will possibly help to strengthen the market integration between local markets and regional markets. For rice, regional markets and the central market seem to be the appropriate point of entry for market interventions. Any market intervention that leads to reduce rice price by 1% in regional markets and the central market will most likely decrease rice price by about 0.06% and 0.03%, respectively, in local markets. Such type of market intervention on central and border markets will help to reduce local price variance. Border markets are more suitable for wheat prices. Any trade policies that helps to reduce border price by 1% will possibly reduce wheat price by about 0.10 %. Because fuel prices changes are passed through to food prices, government fuel policies may impact food prices. If government decides to reduce fuel price by 1%, the rice price will probably decrease by 0.06%. Investments in roads are likely to reduce food prices and price variances. Since district-level rice harvests are negatively correlated with food prices for wheat and price variances for rice, policies to increase agricultural productivity will moderate both prices and price volatility. Agricultural policy that leads to increase wheat production (1000 MT) by 1% will most likely decrease wheat prices by 0.01%. Implementation of such a policy for rice production similarly decreases price variances. All these findings and policy implications may also be applicable to other poor developing food-deficit countries.

CHAPTER 3. CHILD MALNUTRITION IN NEPAL: A HIERARCHICAL APPROACH

3.1. Introduction

In recent years, the child nutrition situation in Nepal has been improving. As Table 8 indicates, the wasting rate fell by 15 percent between 2006 and 2011, and the stunting rate fell by 17 percent. Despite these apparent improvements, however, child malnutrition remains pervasive in Nepal. Overall, about 41% of children less than five years of age are stunted (a measure of chronic malnutrition) and 12% are wasted (a measure of acute malnutrition) (Figure 16). The stunting rate is even higher, roughly 60%, in the mountainous districts of the country (NDHS 2011). Stunting prevalence in Nepal is similar to or worse than what one finds in the least developed African countries, including Sudan (40%) and Ethiopia (51%) (UNICEF 2009a).

The earthquakes of April and May 2015 led to the collapse of shelters, damage to roads and bridges, disruption of clean water and sanitation services, degradation of health facilities, and acute food shortages (NPC 2015).[14] In response, extensive migration

[14]A 7.8 magnitude earthquake struck on 25 April 2015 resulting in approximately 8,000 deaths and 14,000 injuries. A second quake of 7.3 magnitude hit on 12 May 2015, resulting in additional deaths and injuries.

towards unaffected areas has occurred, thus crowding people together and putting further pressure on food supplies and basic services. Due to all these factors, additional thousands of children, especially those residing in earthquake affected districts, are at high nutritional risk. Past studies have indicated deleterious effects of such calamities on children. For example, a study conducted six weeks following the deadly earthquake (of magnitude 7.0) that hit Haiti on 12 January 2010, found that children had a high mortality rate (Kolbe et al. 2010). About one-third of the victims were children in the 2004 tsunami in South-east Asia (UNICEF 2009b). Due to Indonesia's drought and financial crisis in 1997/98, average weight-for-height fell by more than one-third of a standard deviation (Block et al. 2004). Although there is a somewhat weak evidence base for what works best to safeguard nutrition during emergencies (Webb et al. 2014), Nepal's recent gains in child nutrition are likely to be eroded if relief and reconstruction do not occur promptly. Child malnutrition has been a silent emergency in Nepal, and will continue to be problematic in the post-quake period.

Table 8. Child Malnutrition Indicators in Nepal, 2006 and 2011

Indicator	2006	2011	change
Average HAZ	-1.96	-1.71	+13%
Average WHZ	-0.84	-0.67	+21%
% stunted (HAZ<-2.0)	50.4	42.1	-17%
% wasted (WHZ<-2.0)	12.5	10.7	-15%
N	5,237	2,335	

Source: computed by the authors using 2006 and 2011 Nepal DHS data

Child malnutrition deserves serious attention as it negatively affects individual well-being and undermines long-term economic development (Mankew et al.1992; Jo and Dercon 2012). According to the World Bank, the economic cost of under-nutrition is significant: some countries have lost 2 to 3% of their potential gross domestic product (GDP) each year as a result of poor nutrition. Horton and Steckel (2013) estimate that poor nutrition lowers Asia's and Africa's GNP by 11% every year. African Union Commission (2014) estimates that the GDPs of Egypt, Ethiopia, Swaziland, and Uganda have been lowered by 1.9%, 16.5%, 3.1%, and 5.6%, respectively. Any effort to prevent the stunting of children under three reduces the probability of their living in a household below the poverty line (Hoddinott et al. 2013). One study from Africa revealed that children who are not undernourished perform better in school, earn 20% more in the labor market as adults, and are 10% more likely to own a businesses compared to their undernourished peer (IDS 2013). It has been estimated that preventing micronutrient deficiencies could save 5 billion dollars per year in China and 2.5 billion dollars per year in India (Shekar and Lee 2006). Bhutta et al. (2008) indicate that nutrition-specific interventions are likely to decrease stunting by one-third globally and reduce child mortality by one-quarter. For such interventions, they find the estimated benefit-cost ratio is 16 to 1.

Realizing the importance of child nutrition, the government of Nepal and various national/international agencies are actively implementing programs to improve child nutrition outcomes. One such program is *Suaahara*, a five-year USAID-funded multi-sectoral nutrition program (August 2011-August 2016) that aims to improve nutrition, health, and agricultural productivity. With assistance of development partners and civil society representatives, the government recently launched the country's new "Multi-Sector Nutrition Plan 2013-2017." To reduce the currently unacceptable rates of child malnutrition and shorten the timescale required to attain the Millennium Development Goals (MDGs), it is imperative that the research and policy community better understand the factors influencing malnutrition in Nepal.

This essay focuses on identifying the factors strongly associated with child nutrition in Nepal. At a landscape scale, there appears to be some degree of explicit clustering of child nutrition outcomes. For example, nutrition maps of Nepal that show district-level incidences of stunting (Figure 17) and wasting (Figure 18) suggest stunting is highest in mountainous and hilly districts and wasting is highest in the Terai districts. Political instability, geographical disparity, remoteness, weak infrastructure, and poor agricultural sector performance may contribute to these patterns. In recognition of the hierarchical and spatial nature of under-nutrition in Nepal, this study investigates a broad set of determinants of child malnutrition using a series of hierarchical regression models that incorporate spatial effects at the district-level. This essay has two main objectives: (1) to identify factors that play a role in explaining patterns of child malnutrition in Nepal (2) and to specifically assess what factors might account for the observed improvements in average nutrition outcomes between 2006 and 2011. By approaching these twin goals of measurement and explanation using nationally representative data and mixed models that account for spatial effects, I also demonstrate a methodological advancement for the wider community of nutrition researchers.

Several regional and district-specific studies of child stunting and wasting have previously been conducted for Nepal. Sah (2005) used binary logistic regressions to study the determinants of child malnutrition in Dhanusha district of Nepal in 2003. Similarly,

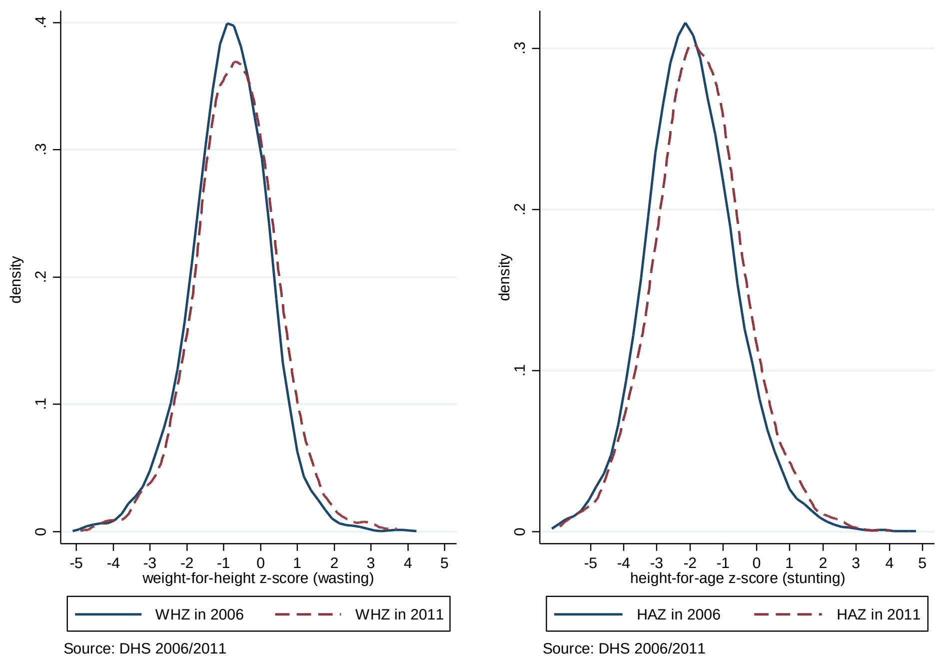

Figure 16. Kernel Densities of HAZ and WHZ in 2006 and 2011

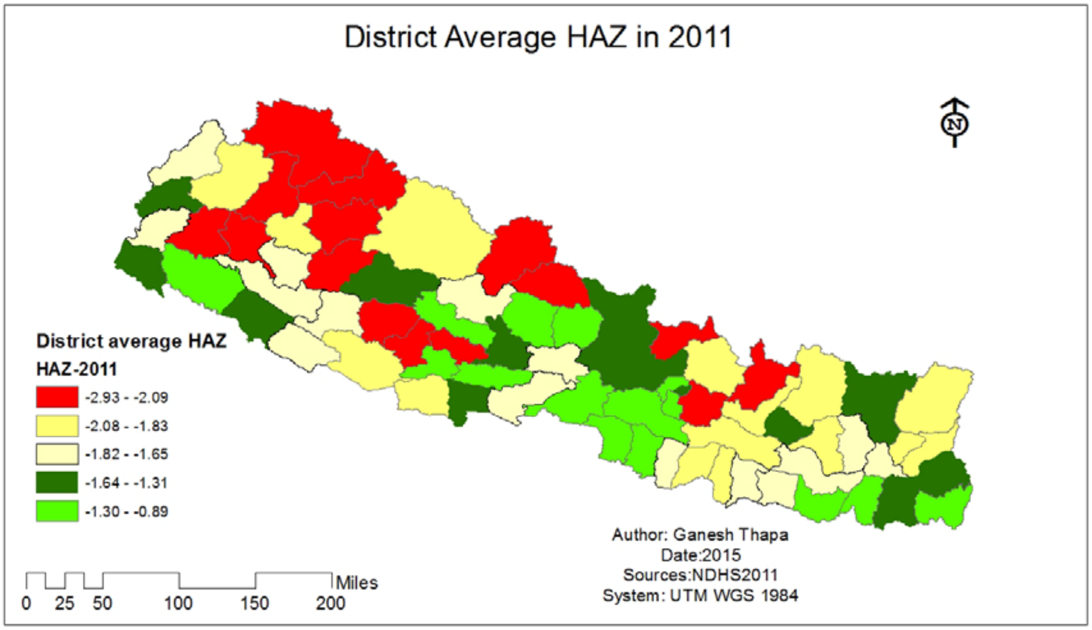

Figure 17. District Average Height-for-Age Z-Score Distribution in 2011

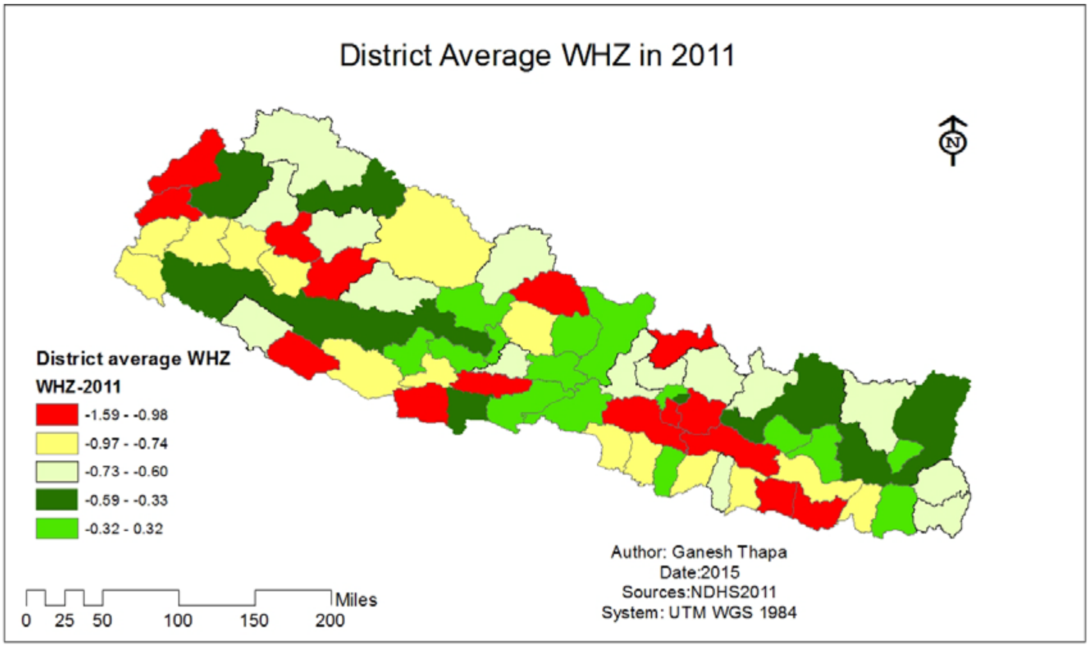

Figure 18. District Average Weight-for-Height Z-Score Distribution in 2011

Singh et al. (2009) used logistic regression to assess factors influencing underweight and stunting among children in Sunsari district in 2005. Shively and Sununtnasuk (2015) find connections between agricultural practices and patterns of child growth and Shively et al. (2015) demonstrate how environmental variability in Nepal is related to patterns of child nutrition and growth. Shrestha (2007) used a multilevel modeling approach to study the role of maternal human capital on childhood stunting in Nepal. Smith (2014) studied the determinants of long-term nutrition indicators using multilevel model. However, none of these studies were able to explicitly account or control for spatial patterns of child nutrition outcomes. Such spatial effects can be important. From a conceptual point of view, the nutritional status of children in one area could be influenced by the characteristics of neighboring areas through multiple pathways, including spread of diseases or access to health and education infrastructure. Empirically, using a country-level dataset of life expectancy in the U.S. in 1999, Arcaya et al. (2012) found evidence of spatial and geographical membership effects in patterning of area variations in health. Building on such past work, in this essay I make two contributions. First, I use a comprehensive set of data and a broad range of variables measured at the level of the child, cluster, household and district to study the factors influencing child nutrition in Nepal. Second, I account for the nested, hierarchical structure of the data while simultaneously controlling for spatial dependency of selected variables at the district level. This approach provides a clearer and more robust understanding of the factors correlated with child malnutrition in Nepal than past analyses.

3.2. Background

Nepal is the poorest country in South Asia and ranks as the 13th poorest country in the world. Approximately 77% of the population lives on $2.50 a day (WB 2014). Although the country experienced a series of political changes in recent years that were widely viewed as beneficial, including a shift from monarchy to democracy, the changes were accompanied by a protracted civil war, and a widely expected economic boom failed to materialize. Nepal faces multiple development challenges. The country has been unable to attract much foreign direct investment (Pant 2010), and GDP growth during the last decade (2002-2013) has been just 3.9% per year on average, the lowest among the South

Asian countries. Inflation, including food price inflation, increased from 5.7% to 9.0% between 2007 and 2013 (WB 2014) and substantial out-migration, especially of young men, has reduced much of the available labor in the countryside, resulting in widespread "feminization" of agriculture in the country (Tamang et al. 2014).

Due to geographical disparity, the hilly and mountainous regions of the country, which account for more than three-fourths of the land area, are relatively less accessible and developed compared with the Terai (CBS 2011). The country has weak infrastructure and two districts (Humla and Dolpa) remain unconnected by roads to the rest of the country (DOR 2013). Out of the total available government posts for doctors in the nation, only 27% were occupied in 2014. Government positions for pediatricians and gynecologists are available in only 19 and 25 of the 75 districts of the country (NMOHP 2014). About 80% of the Nepalese population live in rural areas, and agricultural systems are dominated by low use of inputs, small land holdings, and subsistence orientation (CBS 2011). The main staples are produced at 50 per cent of the maximum attainable yield (NMOAD 2004) and highly variable weather jeopardizes production in many years. Public and private food storage capacity, less than 100,000 metric tons, is very low (NFC 2011). Public storage accounts for less than 2% of the country's annual consumption requirement (NMOAD 2011), which provides almost no buffer against shortfalls in production. The World Food Program (WFP) estimates that about 3.4 million people in Nepal suffer from acute food insecurity in most years (NeKSAP 2011).

Nepal is representative of global nutrition challenges. The worldwide disease burden attributable to undernutrition is 17.5 % (WHO 2002). According to UNICEF (2011), about 2.6 million children die each year globally due to undernutrition. Children who are poorly nourished between conception and age two suffer from adverse lifelong consequences that are not generally reversed by adequate nutrition later in life. Such children will be vulnerable to increased risk of death from infectious illness such as diarrhea and pneumonia (WHO 2002). Even if such malnourished children survive, they lose their chance to thrive cognitively and physically, perform very poorly in school and have lower productivity in adult life (Shariff et al. 2000; Galler and Barrett 2001; Glewwe et al. 2001). Stunted children are twice as likely to die as non-stunted children (IDS 2013).

This human suffering and waste is preventable, and since much malnutrition originates with food insecurity, many observers have focused on the agricultural sector as a target for improving child nutrition outcomes. Both nutrition-specific programs (addressing the problem of inadequate diets) and nutrition-sensitive programs (addressing food security more generally) may include agriculture as a component. As Haddad (2000) and Hoddinott (2011) argue, the agricultural sector can promote better nutrition through a number of pathways. The World Bank (2007) identifies five pathways that link agriculture with food consumption and human nutrition along the food supply chain: (i) increased consumption from increased food production; (ii) increased income from the sale of agricultural commodities; (iii) empowerment of women agriculturists; (iv) reduction in real food prices associated with an increased food supply; and (v) agricultural growth leading to poverty reduction and improved nutrition outcomes. Smith and Haddad (2000) argue that a rise in per capita food availability led to nearly one-quarter of the decline in child undernutrition rates over the past 25 years in developing countries. Results from country-level analysis generally find agricultural infrastructure to be an important determinant of the rate of chronic malnutrition in children (e.g. Apodaca 2008).

Child malnutrition can be influenced by multiple, complex and interrelated factors. Improving a mother's knowledge with respect to correct feeding and weaning practices, reducing household size, breast feeding, educating mothers, and increasing household incomes were all found to reduce acute child malnutrition in Pakistan (Garcia et al. 1989). Tharkan and Suchindran (1999) found biological (age, birth-weight, breast-feeding duration), social (gender of family head, residence, house type, toilet facility, education of mother and father), cultural (child caretaker), economic (intake levels of milk and dairy products, staple foods and cereals, and beverages) and morbidity factors (incidence of cough and diarrhea) as key determinants of malnutrition in Botswana. Biological factors such as child's age and mother height, and socio-economic factors such as household wealth and mother's education were found to influence a child's nutrition status in Ethiopia (Silva 2005). Maternal education was found to be an important factor determining child malnutrition in Morocco (Glewwe 1999). Ethnic minority groups in northern regions in Vietnam were found to have higher rates of malnutrition than groups elsewhere in the country, suggesting that a range of social factors influence outcomes (Haughton and Haughton 1997). Maternal malnutrition and urban concentration of households were identified as two risk factors for child malnutrition in India (Debnath and Bhattacharjee 2014). Food insecurity, seasonal events and climatic shocks were found to be correlated with child malnutrition in the Malawian district of Salima (Sassi 2013). Thomas and Strauss (1992) found local infrastructure (water and sewerage facilities) to be correlated with child height in Brazil. Higher food prices, especially higher sugar and dairy prices, lowered child height in Brazil. Using longitudinal data from rural Zimbabwe, Alderman et al. (2006a) found that improved preschooler nutritional status was associated with increased height as a young adult and better performance at school. Gulati et al. (2012) indicates that improving agricultural productivity reduced undernutrition in India. UNICEF (2009) indicates that poverty, inequity, low maternal education and women's social status are major factors influencing undernutrition and need to be emphasized to reduce it in a sustained manner.

3.3. Conceptual Framework

As highlighted above, child nutrition and health are influenced by a large number of factors. Mosley and Chen (1984) provide an analytical framework for the study of the determinants of child survival in developing countries. Pitt and Rosenzweig (1986) present a framework for studying the determinants and consequences of changes in health for farm households in Indonesia. UNICEF (1998) presents a conceptual framework of the determinants of child undernutrition. Behrman and Deolalikhar (1998) presents the nutrition model mainly based on the Becker (1981) household economic model. Smith and Haddad (2000) build on the framework presented by UNICEF (1990); UNICEF (1998); and Engle et al. (1999) to study the determinants of child nutritional status in developing countries. My notation and framework rely mainly on Smith and Haddad

(2000). In their framework, a child's nutritional status is influenced by immediate determinants (child characteristics). Immediate determinants are further influenced by underlying determinants (household and cluster characteristics). Finally, underlying determinants are influenced by basic determinants (district and national characteristics). This multi-level approach is explicitly adopted in the econometric model and empirical analysis.

My conceptual framework is developed in the context of a multimember household economic model. The household is composed of a mother (*i*=*M*), other adults (*i*=1,…, *D*), and one or more children (*i*=1,…, *J*). The household maximizes the total household welfare by maximizing the utility of each member of the household (U^i). The welfare function is represented as:

$$W^H = W\left(U_M, U^1, \dots U_{ad}^D, U^1, \dots U_{ch}^J; \beta\right) \quad \beta = \left(\beta^M, \beta^1, \dots \beta_{ad}^D\right) \tag{8}$$

where the βs indicate the status of each adult household member that affects the household decision-making process. The utility function for each individual can be expressed as:

$$U^i = U(N, F, X_0, T_L) \; i = 1, \dots, n = 1 + D + J \tag{9}$$

where an individual derives utility from his or her nutritional status, *N*, from the consumption of food, *F*, from nonfood consumption, X_0, and from leisure time, T_L. Thus nutritional status, *N*, is considered to be a household-produced good. The nutrition production function for child *i* is expressed as:

$$N^i = N\left(C^i, F^i, X_N^i; K_i, \xi^i, H_i, \Omega_{ag}, \Omega_p, \Omega_f\right), i = 1, \dots, J \tag{10}$$

where C^i is the care received by the i^{th} child; X_N^i indicates nonfood commodities (like medicines and health services) purchased for child caregiving purposes; K_i indicates the child's observable characteristics and health condition (like season born, age, sex, vaccination status or illness condition); ξ^i is the physical endowment of the child; H_i represents the mother's characteristics and the household's characteristics; Ω_{ag} indicates district-level agricultural characteristics; Ω_p represents district-level market indicators; and Ω_f represents district-level health, infrastructure indicators.

The child's care, C^i, is treated as a household-provisioned service and depends on the mother's education (E^M), her employment status (S^M), time availability of the mother and other adults in the households (T_c^i) to provide care to children, mother's own nutritional status (N^M), and ethnicity factors that may influence child-care practices (Ω_c). The child' care is itself a function:

$$C^i = C(T_c^i, N^M; E^M, S^M, \Omega_c), i = 1 \ldots J \quad (11)$$

The mother's own nutritional status (N^M), is also a function of observed factors:

$$N^M = N(F^M, C^M, X_N^M; \xi^M, H_i, \Omega_{ag}, \Omega_p, \Omega_{f,} \beta^M) \quad (12)$$

Here β is an exogenous variable indicating mother's status especially her decision making power relative to other adult members. The household also faces budget and time constraints. These are expressed as:

$$PF + P'X_0 = wL + Q \quad (13)$$

where P is the price of food and P' is the price of nonfood commodities including health inputs and services. The household derives income from selling its labor at the wage rate w, and also receives income Q. The household faces time constraint in terms of selling its labor, which is expressed as:

$$L = T - T_c - T_h - T_L \tag{14}$$

where T represents the total time endowment available to the households that can be allocated to child care (T_c), household maintenance (including cooking) (T_h), and leisure (T_L). It is assumed that complete markets exist and consumption decisions are not expected to affect production decisions. When constraints (6) and (7) are combined, I obtain the full-income constraint (I) expressed as:

$$PF + P'X_0 = w(T - T_c - T_h - T_L) + Q = I \tag{15}$$

The household maximizes total welfare (8) with respect to (9), (10), (11), (12) and (15), which leads to the following reduced-form equation for child nutrition outcomes:

$$N^{i*} = \left(\beta, \xi^1, \ldots .\xi^J, \xi^M, K_i, E^M, S^M, \Omega_c, H_i, \Omega_{ag}, \Omega_p, \Omega_{f,} P, P', w, Q, T\right) \;\; i = 1, \ldots J \tag{16}$$

The relationship expressed in (16) is the basis for the empirical analysis outlined below.

3.4. Empirical Strategy

I use 2006 and 2011 data provided by the Nepal Demographic and Health Surveys (DHS). These data are discussed in detail below, but it is important to point out that the DHS data are collected in a naturally hierarchical manner, which informs my empirical approach. In the DHS the child appears as the primary (lowest) unit of analysis. Household data are common to children, cluster data are common to households and children, and district data are common to the cluster, households and children. This suggests four levels of nesting: district, clusters within districts, households within clusters, and children within households. There are 75 districts, 317 clusters, 5,797 unique households, and 7,572 unique children in sample. Cluster, the primary sampling unit (PSU) for the DHS survey, represents the community level. Children born in the same household, cluster and district share common household, cluster and district characteristics. As a result, it seems likely that nutrition outcomes will be correlated within households, clusters or districts. In this case, estimating a regression using ordinary least squares which fails to recognize the effects coming from different hierarchical levels, can lead to incorrect inferences. Therefore I use hierarchical (multilevel) models to study nutrition outcomes. This approach provides an opportunity to model observed outcomes that depend on variables organized in a nested hierarchy (Goldstein 1986). The basic multilevel or mixed linear model is formulated according to Goldstein (1986). I estimate the first-level relationship between child nutritional status and child characteristics, with households, clusters, and districts as second, third and fourth levels.

To begin, I estimate a model without predictor variables (i.e. an empty, or null model). I use this to compute the intra-class correlation coefficient to assure the correct specifications of the four-level model. This null model is:

$$Z_{ijkl} = \beta_{0jkl} + e_{ijkl} \tag{17}$$

where Z_{ijkl} represents the HAZ or WHZ child Z-score. The outcome variable for the i^{th} child in the j^{th} household in the k^{th} cluster within the l^{th} district is equal to the average outcome for all children in the j^{th} household in the k^{th} cluster within the l^{th} district (β_{0jkl}) plus a child-level error term (e_{ijkl}). Since children are nested within the households, there may also be an effect that is common to all children within the same households. This is captured by specifying a separate equation for the intercept term (β_{0jkl}):

$$\beta_{0jkl} = \beta_{00kl} + \gamma_{0jkl} \tag{18}$$

where β_{00kl} is the average outcome for all children in the k^{th} cluster within the l^{th} district, and γ_{0jkl} is a household-level error term. As children in a household are nested within cluster, there may also be an effect that is common to all cluster within the same district. This is captured by specifying a separate equation for the intercept term (β_{00kl}):

$$\beta_{00kl} = \beta_{000l} + \gamma_{00kl} \tag{19}$$

where β_{000l} is the average outcome for all children in the district and γ_{00kl} is a cluster-level error term. Since all children in a cluster are nested within the same district, there may also be an effect that is common to all children within the same district. This is captured by specifying a separate equation for the intercept term (β_{000l}):

$$\beta_{000l} = \beta_{0000} + \gamma_{000l} \tag{20}$$

where β_{0000} is the average outcome for all children in the sample and γ_{000l} is a district-level error term. Combining equations (17), (18), (19) and (20) yields:

$$Z_{ijkl} = \beta_{0000} + \gamma_{000l} + \gamma_{00kl} + \gamma_{0jkl} + e_{ijkl} \tag{21}$$

Denoting the variance of e_{ijkl} as σ^2, γ_{0jkl} as σ_u^2, γ_{00kl} as σ_v^2, and γ_{000l} as σ_s^2, the percentage of observed variation in child Z-scores that can be explained by household, cluster, and district levels can be calculated as follows:

$$\rho_h = \frac{\sigma_u^2}{\sigma^2 + \sigma_u^2 + \sigma_v^2 + \sigma_s^2} \tag{22}$$

$$\rho_c = \frac{\sigma_v^2}{\sigma^2 + \sigma_u^2 + \sigma_v^2 + \sigma_s^2} \tag{23}$$

$$\rho_d = \frac{\sigma_s^2}{\sigma^2 + \sigma_u^2 + \sigma_v^2 + \sigma_s^2} \tag{24}$$

In equations (22), (23) and (24), ρ_h, ρ_c, and ρ_d are referred to as the intra-class correlation coefficients (ICCs) for the household, cluster and district levels, respectively. The proportion of variance that can be explained at the child-level is $(1- \rho_h - \rho_c - \rho_d)$. Given the multi-level nature of the DHS data, I assume (and test whether) the variance components $(\sigma_u^2, \sigma_v^2, \sigma_s^2)$ are significantly different from zero. I specify several models by adding variables at different levels to account for variation at the child, household, cluster and district levels. These are discussed below.

3.4.1. Level-1 model (child-level)

One of the objectives of this analysis is to discover which levels and associated variables are promising in terms of explaining the right-ward shift in the distribution of Z-scores between 2006 and 2011 in Nepal. To do this, I begin by adding a binary indicator to the child level regression including a dummy-variable ($Y2011$) that indicates the survey year and, accordingly, the year in which a child was measured. Equation (17) becomes:

$$Z_{ijkl} = \beta_{0jkl} + \beta_{1jkl}(Y2011) + e_{ijkl} \tag{25}$$

One might ask which model best explains the improvement in Z-scores between 2006 and 2011. In subsequent models, I simply add variables at the child, cluster, household and district levels to assess which levels and variables help to “explain away” the observed improvement in child nutrition outcomes. Adding other child-level covariates, equation (17) becomes:

$$Z_{ijkl} = \beta_{0jkl} + \beta_{1jkl}(Y2011) + \sum_{p=2}^{P} \beta_{p,jkl}\ C_{p,jkl} + e_{ijkl} \tag{26}$$

where $\beta_{p,jkl}$ is the child level coefficient of the p^{th} explanatory variables $C_{p,jkl}$ for child i, e_{ijkl} is a random variable with $E\left(e_{ijkl}\right) = 0$, and var($e_{ijkl}) = \sigma^2$.

3.4.2. Level-2 model (household-level)

For a household level model, I consider two specifications: (1) with mother characteristics only, and (2) with mother and household characteristics. This is mainly done to separately examine the importance of mother characteristics from household characteristics in explaining Z-score patterns. As mentioned above, β_{0jkl} is a random intercept parameter that varies between households in clusters within districts due to household-level characteristics. Adding household-level variables (mother’s characteristics), equation (18**)** becomes:

$$\beta_{0jkl} = \beta_{00kl} + \sum_{n=1}^{N_p} \beta_{0,nkl}\ M_{m,jkl} + \gamma_{0jkl} \tag{27}$$

Adding household variables to equation (27) leads to:

$$\beta_{0jkl} = \beta_{00kl} + \sum_{w=1}^{W_p} \beta_{0,wkl}\ H_{w,jkl} + \gamma_{0jkl} \tag{28}$$

where $\beta_{00kl}$is a random intercept parameter that varies between clusters, $\beta_{0,wkl}$ is the household-level coefficient for the w^{th} explanatory variable $H_{w,jkl}$ for household j, γ_{0jkl} is an error term variable with $E(\gamma_{0jkl}) = 0$, and var$(\gamma_{0jkl}) = \sigma_u^2$.

3.4.3. Level-3 model (cluster-level)

I use predicted NDVI values, predicted rainfall, and altitude as cluster-level variables. A detailed explanation of these variables is provided in the data section. In addition, I observe some variables of interest at the household level but transform them to indicators that represent sample percentages of households in a cluster to control for community effects. These variables include the percentage of households that are poor, the percentage of households that own land, the percentage of households with a bank account, the percentage of households that fall in to the unprivileged group, and the percentage of households that own a refrigerator. These variables are expected to capture the background economic context for each location. Adding these variables, equation (19) becomes:

$$\beta_{00kl} = \beta_{000l} + \sum_{s=1}^{S_{pw}} \beta_{0,0sl}\ A_{s,jkl} + \gamma_{00kl} \tag{29}$$

where $\beta_{0,0sl}$ is the cluster level coefficient for the sth explanatory variable $A_{s,jkl}$ for cluster *k*.

3.4.4. Level-4 model (district-level)

For the district-level, I consider three separate specifications using variables mainly derived from the NLSSS: (1) with agriculture-related variables, (2) with market infrastructure indicators, and (3) with health infrastructure indicators. At the district level, there are 75 distinct observations in each survey year and some variables do not vary over survey years, so considering degrees of freedom, all district-level variables cannot be included in the same model. Adding agriculture variables, equation (20) becomes:

$$\beta_{000l} = \beta_{0000} + \sum_{t=1}^{T_{pws}} \beta_{000t} \, A_{t,l} + \gamma_{000l} \tag{30}$$

where β_{000t} is the district level coefficient for the t^{th} explanatory variable $A_{t,l}$ for district *l*.

Similarly, adding market infrastructure variables, equation (20) becomes:

$$\beta_{000l} = \beta_{0000} + \sum_{r=1}^{R_{pws}} \beta_{000r} \, F_{r,l} + \gamma_{000l} \tag{31}$$

where β_{000r} is the district-level coefficient for the r^{th} explanatory variable $F_{r,l}$ for district *l*. Finally, adding health infrastructure variables, equation (20) becomes:

$$\beta_{000l} = \beta_{0000} + \sum_{q=1}^{Q_{pws}} \beta_{000q} \, I_{q,l} + \gamma_{000l} \tag{32}$$

where β_{000q} is the district-level coefficient for the q^{th} explanatory variable $I_{q,l}$ for district *l*. γ_{000l} is a random variable with $E(\gamma_{000l}) = 0$, and var$(\gamma_{000l}) = \sigma_s^2$.

Combining equations, the four-level random-intercept linear regression model can be written:

$$Z_{ijkl} = \beta_{0000} + \beta_{1jkl}(Y2011) + \sum_{p=2}^{P} \beta_{p,jkl}\ C_{p,jkl} + \sum_{w=1}^{W_p} \beta_{0,wkl}\ H_{w,jkl} + \sum_{s=1}^{S_{pw}} \beta_{0,0sl}\ A_{s,jkl} + \sum_{f=1}^{F_{pws}} \beta_{000f}\ D_{f,l} + (\gamma_{0jkl} + \gamma_{00kl} + \gamma_{000l} + e_{ijkl}) \quad (33)$$

In equation (33), $D_{f,l}$ represents the district-level variables (agriculture, market infrastructure, or health infrastructure). In equation (33), none of the explanatory variables are treated as random effects. Furthermore, variances are assumed to be independent across levels. Although I do not have information on wages and prices of health inputs and services, I do not expect these to vary significantly within districts. They may differ across districts. Thus the unobserved heterogeneity parameter (random intercept) at the district level is expected to capture influences of these missing factors in the models. As written, the models specified above do not yet account for possible spatial effects at district level.

In Nepal, there is an explicit clustering of child malnutrition with high incidence of stunting in districts from mountainous and hilly regions, and a high incidence of wasting in the Terai. Using specific variables identified at a district level in a mixed model captures district information. However such an approach can’t capture spatial dependency between districts. Outcomes for a child residing in one district can be influenced by conditions in adjacent districts through multiple pathways. For example, a district with a low public food storage capacity may witness low food price volatility if neighboring districts have substantial public storage capacity or levels of agricultural production, but high price volatility if it is surrounded by districts with low storage capacity and low production. Similarly, children in a district might benefit from being adjacent to districts with improved health facilities, well-paved roads, or bridges that provide better access to markets and health facilities. Districts which are close to each other in geographical space may share a common physical environment, which can influence disease vectors, agricultural performance, or other things that might matter to nutrition outcomes in ways that are otherwise difficult to observe or measure. To deal with such problems, I use a spatial cross-regressive lag model. This adds spatial lags for some of the district-level independent variables to the multi-level model.[15] To account for the spatial arrangement of the districts, a neighbor set is specified for each district through a pre-specified spatial weights matrix $W_{n\times n}$ that is non-negative, and contains diagonal elements equal to zero. A contiguity first order queen matrix is specified for the spatial weights matrix. I created spatial lags for public food storage capacity, road density, bridge density, primary health centers, zonal hospitals, and private hospitals. The variables were constructed by multiplying each variable with the spatial weights matrix $W_{n\times n}$. These spatial lag variables are incorporated as district-level variables $D_{f,l}$ in a modified version of equation (26).

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[15]Although one might wish to consider using a spatial error model, due to potential spatial dependency in the data (arising, for example, from correlated measurement errors during the survey or omission of spatially-dependent variables), I was not able to estimate the spatial error model in the multilevel context owing to complexities brought about by including spatial errors in the multilevel model. This remains as future work.

3.5. Data and Variables

This analysis combines data from various sources. The sources and variables extracted from each source are described below.

3.5.1. The Nepal demographic and health survey (NDHS)

Data on child nutrition indicators, and child and household characteristics come from the 2006 and 2011 NDHS surveys. The DHS data were collected by trained enumerators under the supervision of the Ministry of Health and Population (NMOHP) Nepal. The DHS is a comprehensive and nationally representative geo-referenced household survey where samples are selected using a stratified two-stage cluster design. DHS data provide key health measurements and indicators across all ecological zones and development regions. A total of 5,237 children were included in the 2006 survey, and 2,335 were included in the 2011 survey, providing observations on a total of 7,572 children under age 5. These children constitute the units of analysis for this study. For each child, height, age, and weight were recorded. Based on these measures, indicators of long-term nutrition outcomes (HAZ) and short-term nutrition outcomes (WHZ) were calculated (WHO 2002). These serve as the dependent variables in this study. I work with continuous Z-score measures and unweighted samples.

Variables related to child, mother, and household are obtained from the NDHS. Since characteristics of fathers were not available for all children sampled, I exclude father information from the analysis. The child-related binary variables for the WHZ equation are gender, season of birth, whether the child is a twin, and indicators for recent health condition (diarrhea or fever in the last two weeks, and fever in the last two weeks).

Continuous independent variables are age of the child and square of the age of the child. All variables used in the WHZ regressions are included in the HAZ regressions, except I replace the short-term health condition variables with the cumulative total number of vaccines received during the child's life. The reasoning behind the choice of variables is provided below.

Gender is a potentially important variable. Past studies have indicated that sons are preferred over daughters in South Asian countries (Arnold et al. 2002; Pande 2003). Since Nepal is a patriarchal society, male children may receive preferential treatment compared with female children. Children may be more susceptible to diseases at an early age. As age increases, the child may better adapt to the environment. Therefore, I include age and age squared. I control for the season of birth, since this may matter to nutrition outcomes, by including a set of binary indicators for summer, monsoon, winter, and autumn. The general literature has well documented the intra-annual fluctuations of anthropometric measures of children (Panter-Brick 1997; Maleta et al. 2003). A recent study from Ethiopia found that both rural and urban households consumed fewer calories in the lean season and observed high seasonal fluctuations in household diets (Hirvonen et al. 2015). Nepal's main crop is rice, and its planting occurs in the monsoon season. Members of households are very busy during this period, food stocks are often at their lowest, and market prices are at their highest. Thus a child born in the monsoon season may not receive adequate attention, care or feeding, resulting in poorer nutrition compared with a child born in other seasons. Although twin's born children is likely to have lower birth weight (Hatkar and Bhide 1999), whether a child is born as a twin may matter to nutrition outcomes. Single born children likely receive greater care and feeding than a child born as a twin. Children suffering from fever or diarrhea in last two weeks will be physically weak and may have lost weight. As a result, I expect WHZ to be lower for such children. Diarrheal illness was found to cause malnutrition in Brazil (Guerrant et al. 1992). Vaccines strengthen the immune system, and the number of vaccines received may also serve as a proxy for general interactions with the health system. I expect that children receiving a higher number of vaccines will suffer less from diseases, and have better long-term nutrition outcomes (HAZ).

Mother's characteristics that are binary in nature include employment status (unemployed, employed in agriculture, and employed in other sectors), ethnicity (Brahmin, Mongolian, Chettri, Madhesi and Unprivileged), whether the mother smokes cigarettes, is currently breast feeding, has a husband living at home, whether the place of delivery is home, and whether the head of the household is female. Continuous variables for mothers include age, age squared, and total number of children born in the family. Mother employment status may play an important role in child growth and development. For example, a mother working in agriculture may spend most of her time in the field. Other things equal, she may be less likely to devote time to her children. Mothers employed in the non-farm sector are relatively highly educated, earn higher income, and may be more conscious of child health. Mother's education, especially her nutritional knowledge was found to influence children's diets (Variyam et al. 1999). Each ethnic group has its own culture and unique food habit in Nepal. For example, mothers from Brahmin families avoid meat and meat products. They also fast frequently. Mothers from unprivileged groups are less educated and relatively poorer. Acharya and Alpass (2004) found lower weight babies delivered from lower caste ethnic groups in Nepal which was attributed to lower nutritional intake. Unprivileged households were found to suffer from caste discrimination in India. van den Bold et al.(2015) indicated that caste affects food access in India. Especially Dalits faced exclusion and caste discrimination during the implementation of the government's mid-day meal scheme and public distribution system (Thorat and Lee 2003). Children born from older mothers (beyond age thirty) are less likely to be healthy. To capture this, I include mother's age and its square. The coefficient of mother's age is expected to be positive and square term to be negative. If there is large number of children in a family, mothers may not be able to properly take care of all children. Children born to mothers who smoke can suffer from prenatal and post-natal exposure. These children have higher chances of suffering from respiratory and heart diseases. It is strictly advised for mothers to breastfeed their babies during the first year following birth. However, at later ages, children are often not breast fed. It is believed that breastfed children have better nutrition outcomes. In most settings, delivering a baby at a hospital is considered highly preferred to delivering a baby at home. Babies born at a hospital typically receive better care and treatment, and may have better subsequent growth outcomes than children born at home. A husband at home is expected to provide a better care environment, but a husband at home will not be sending remittances, and so the household might not be able to buy adequate food or afford health amenities. Thus the sign of this variable is ambiguous. Female-headed households may have better child nutrition outcomes, especially if a female head can prioritize household purchases in ways that benefit child growth and development.

All household-related variables are binary in nature. I expect that urban households will have better nutrition outcomes than rural households. Children from urban areas have better access to hospitals, markets and other facilities compared with children in rural areas. Open defecation is a serious sanitary problem in Nepal contributing to diseases like diarrhea and cholera. Households with a sanitary toilet facility should have better child nutrition outcomes. Smoke-producing fuels can cause or exacerbate respiratory diseases, with potentially negative growth consequences. Children drinking treated water should have better nutrition outcomes. Electricity/power is very important to daily life, both for cooking and refrigeration. Children from households owning land and livestock may consume fresh products, including those with animal protein, at higher rates, which should help to improve child nutrition outcomes. However households may replace time required for child care with agricultural activities. As a result, children in agricultural households may not be nourished in a timely fashion, resulting in an undernutrition problem. Households with a bank account are less likely to face liquidity problems and may be better able to smooth consumption and nutrition over time. Thus I expect that households holding bank accounts should have better child nutrition outcomes than those without. Bed nets offer direct protection against disease vectors and also indicate a higher level of health consciousness. Households from the bottom two-wealth quintiles are considered “poor” in this analysis. Poor households do not have necessary income to buy food and provide adequate care and treatment. Thus I hypothesize that the children from poor households will have worse nutrition outcomes.

Clusters in the DHS contain the units wards and sub-wards. GPS information such as latitude, longitude, and elevation is available at the cluster level. I incorporate altitude as a continuous variable. An increase in altitude in Nepal is associated with remoteness and lower agricultural production. I aggregate several household variables at the cluster level to create indicators of community wealth. These include the percentage of households with a refrigerator, the percentage of unprivileged households, the percentage of land-owning households, the percentage of poor households, and the percentage of households with a bank account.

3.5.2. The Nepal living standards survey (NLSS)

NLSS data come from two nationally representative household surveys: the 2004 and 2010 Nepal Living Standard Surveys (NLSS). The NLSS was conducted by the Central Bureau of Statistics, Nepal and followed the methodology of the World Bank’s Living Standard Measurement Survey using a two-stage stratified random sampling technique. The survey asked questions related to agriculture, food consumption and expenditure, farm and off-farm income, migration, labor, access to facilities and market infrastructure, and other measures at individual and household levels. A number of agriculture-related variables have been extracted from the 2004 and 2010 NLSS. Using the NLSS data, district-level average values were calculated for all agricultural variables and these values have been merged onto corresponding DHS observations to provide information regarding the overall agricultural and economic environment in which households operate.

District-level variables include district food deficit status, a binary indicator, along with several continuous variables: percentage of households using irrigation, percentage of households producing milk, percentage of households producing eggs, mean crop yields (kg/ha), mean share of vegetables in crop diversity, mean share of agricultural income in total income, mean annual income, mean distance to hospital (in minutes by foot), mean distance to cooperative/sajha (in minutes by foot) and total public food storage capacity (mt). I expect all these variables to account some of the unexplained HAZ/WHZ variances at the child level.

3.5.3. The normalized difference vegetation index (NDVI)

The NDVI was constructed using remotely sensed data from NASA's Moderate Resolution Imaging Spectroradiometer (MODIS), as described in Brown et al. (2014). The NDVI is a graphical indicator of the photosynthetic activity of the observed area and provides a proxy for agricultural potential. The possible value ranges between -1 and 1, with a typical range between -0.1 (indicative of sparse green vegetation) and 0.6 (indicative of dense green vegetation).[16] Negative NDVI values indicate the presence of snow, water or ice. Since NDHS and NDVI datasets are geo-referenced, the monthly

[16] Before use, NDVI values are multiplied by 1000 to remove small rounding errors.

NDVI values (covering the period February 2000 to May 2012) could be merged onto the NDHS datasets. All households within a cluster (with a total of 317 unique clusters in the NDHS) are assigned the same NDVI values. These NDVI values proxy the local growing conditions and allow us to test whether better growing conditions are associated with improved child nutrition outcomes. To test this hypothesis, I created average NDVI variables by averaging NDVI values from July to September of each year. In Nepal, these three months correspond to the main rice growing season. Higher NDVI values in these months indicate greater greenness and higher photosynthetic activity, and hence higher crop yield. I hypothesize that the children born following a season with high NDVI values will have higher HAZ. I matched children born between October and December with the average NDVI values from rice growing seasons of the same year. However children born between January and September are matched with the average NDVI values from rice growing season of the previous year. For models of short-term nutrition outcomes WHZ, I matched children measured in 2006 with the average NDVI values from rice growing season of 2005. Similarly, children measured in 2011 were matched to the 2010 average NDVI values.

It is important to note that observed NDVI values may be correlated with the error terms of the child nutrition outcome equations for one of two reasons. First, money that could go to food or child care might be used instead to purchase fertilizer, seeds, pumping water or agricultural labor, resulting in higher agricultural activity and, therefore, higher NDVI values. In such a case, greater greenness would be negatively correlated with child growth by construction. Second, higher NDVI values may indicate that mothers, fathers and other family members are spending time in crop production, rather than allocating time to health and nutrition provisioning. Again, this would mean that greater greenness would be negatively correlated with child growth by construction. To purge the regressions of this potential problem of correlation between NDVI and the error term, I predict NDVI values using rainfall, while controlling for year, months, clusters, and district fixed effects. I incorporate this predicted NDVI variable in the regression to strengthen the causal interpretation of the impact of "growing conditions" on child growth.

3.5.4. Rainfall

Monthly rainfall data from January 1998 to December 2012 were obtained from the Department of Hydrology and Meteorology, Nepal. These cover 280 meteorological stations covering all districts of Nepal. I estimated monthly rainfall using latitude, longitude, altitude, month and year dummies from 1998 to 2012. Using these estimated coefficients, I predicted average rainfall received between May and September for each year in a cluster. Later these predicted rainfall were matched with the average NDVI values between July and September to predict NDVIs. In case of modelling the long-term nutrition outcomes, the average rainfall received from May to September in the year of a child's birth is used as a control variable for children born between May and December. However for children born between January and April, I use the average rainfall received from May to September in the prior year. For the short-term nutrition measures (WHZ), average rainfall received from May to September in the year prior to child measurement is used. One reason for including rainfall as a control variable in the analysis is that rainfall and moisture may influence nutrition outcomes by contributing to the burden of disease through impacts on sanitation and disease.

3.5.5. Agriculture production and storage

Information on food surplus and deficit districts, and annual district production of cereals and fruits were obtained from Ministry of Agriculture, Nepal. Data on the total storage capacity of public warehouses located in different districts of Nepal were obtained from the Nepal Food Corporation (NFC). Deficit districts are those where annual cereal production was considered by the government as not able to meet the annual food requirement of the district population.

3.5.6. Transportation

Road data were obtained from the Department of Road (DOR), Ministry of Physical Planning, Works and Transport Management. The DOR has been publishing Nepal Road Statistics (NRS) in alternate years.[17] Road data from 2002 to 2011 were compiled for all districts of Nepal. Annual progress reports prepared by the DOR list all roads and bridges completed in that year. Road data published by the DOR focus on national highways and feeder roads. Bridge data were obtained from DOR Bridge Management System, which is

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[17] Missing data for alternate years were imputed using annual progress reports published by DOR.

a critical part of governance under the Strategic Road Network (SRN) program. Child nutrition outcomes are worst in remote and isolated parts of the country. Thus I assess whether higher road and bridge densities are associated with better child nutrition outcomes. For modeling long-term nutrition outcomes (HAZ), the road density index and the cumulative bridge density (for roads constructed up to and including the year of the child's birth) are used. For short-term nutrition (WHZ), the total road density index and bridge density in the surveyed year are used. Since transportation infrastructure can have geographically dispersed effects on socio-economic outcomes (Van de Walle 2009), I also include the spatial lags of road density and bridge density to account for potential spatial spillovers on child nutrition outcomes. I calculated a road index using weights that account for different road qualities and the travel time that they imply. I assume that a black-topped road is five times faster than a gravel road and fifty times faster than an earthen road. [18]

3.5.7. Health infrastructure

Health infrastructure data were obtained from the Ministry of Health and Population, Nepal (NMOHP). The total number of health facilities (health post, sub-health post, primary health center, nursing home, zonal hospital, district hospital, ayurvedic hospital) including filled and vacant post of doctors such as gynecologist and pediatrician positions

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[18] Sensitivity analysis was conducted by assuming that the blacktopped road is ten/twenty times faster than a gravel road and forty/sixty times faster than an earthen road. The results are not sensitive to these different assumptions.

were obtained for each district from the NMOHP. However their GPS locations are not available. Although these data are reportedly updated each year, the NMOHP has failed to maintain the time series data. Only data for 2014 were available. These are used here. The maintained assumption is that these values have changed very little over the past decade. I created the binary variable pediatrician (1 if pediatrician posting available in government hospital, 0 otherwise). I hypothesize that districts having a pediatrician position in government hospital will have better child nutrition outcomes. The continuous variables are total number of private hospitals and its spatial lag, total number of zonal hospitals and its spatial lag, number of vacant posts of doctors in a district divided by district population. I expect that districts with a higher number of private hospitals and presence of zonal hospitals will have better child nutrition outcomes. Although health care worker positions are available in remote areas of mountainous and hilly districts, most of these positions are vacant. I hypothesize that districts with a higher number of vacant posts of doctors in a district (per capita) will have lower child nutrition outcomes. A zonal hospital is the largest government hospital category, with a higher number of health-care workers and facilities. This is followed by primary health centers, health posts, and sub-health posts. Nepal also has private hospitals. These provide better services but are more expensive than government hospitals. Instead of visiting the closest, but poorly-equipped health facilities, care-seekers often prefer to go to a higher-level health facility, even though it might be located faraway (Montana et al. 2001; Baker and Liu 2006). In Nepal, Zonal hospitals, private hospitals, and primary health centers are considered as higher level health facilities and provide services to more than one district.

Therefore I create spatial lags for these variables to account for potential spatial spillovers.

3.6. Results

3.6.1. Descriptive results

Table 9 provides descriptive statistics for the variables included in the HAZ and WHZ models. The average WHZ is -0.79 with standard deviation of 1.08. The average HAZ is -1.88. Fifty-one percent of children in the sample are male. The average age of a child is 2.5 years. Twenty eight percent of children sampled were born in the monsoon season, which is the highest percentage of children born in any season. January, February and March are considered to be winter. The summer season consists of April, May and June. July, August and September comprise of monsoon. Finally, October, November and December are considered autumn. Only about one percent of the children are born twins. Thirteen percent of children had diarrhea in the previous two weeks and nineteen percent had fever in previous two weeks. On average, a child received about seven vaccines. Roughly five percent of the children in the sample did not receive any vaccine.

Seventy-one percent of mothers in the sample are employed in agriculture. Only about eight percent of mothers are engaged in non-farm activities. The largest percentage of children are from the unprivileged group (27%), followed by Mongolian (23%), Chetri (19%), Brahmin (16%) and Madhesi (15%). The average age of a mother in the sample is 27 years. The minimum age is 15 years and the maximum age is 49 years. Average mother's education is 3 years. About 57% of the mothers are uneducated. The maximum years of mother's education is 14. On average, three children were born in a household. The maximum number of children in a household is 15. About 81% of children are found to be breast-feeding. It is very common to breast feed children during the first and second year of life. About 48% of the children that are breast fed are under age of 2 years. Sixty-seven percent of households have a husband living at home. In remote parts of the country where there is no access to transportation, it takes several hours by foot to reach a delivery center. As a result, seventy-six percent of children were delivered at home. Roughly one-quarter of children in the sample come from female-headed households.

Seventy-eight percent of children are from a rural location. Fifty-five percent of the households are defecating in an open environment. Governmental and non-governmental agencies are implementing various programs to stop open defecation. Eighty-nine percent of the households use smoke-producing fuels. Only eleven percent of households drink treated water. Forty-nine percent of households have access to electricity. Eighty-three percent of households rear livestock. Forty-nine percent of the households own a bank account and seventy-one percent of households own land usable for agriculture. Fifty percent of the households falls within the lower fourth and fifth wealth quintile and are considered as poor.

Table 9. Definition and Descriptive Statistics of Variables Used in the Regression for Child Z-scores

Variable	Description	Mean	Std. Dev.	Min	Max
Dependent Variables					
HAZ	Height-for-age Z-score	-1.88	1.35	-5.96	4.59
WHZ	Weight-for-height Z-score	-0.79	1.08	-4.94	4.07
Year					
2011†	Observation for 2011	0.31	0.46	0	1
2006†	Observation for 2006	0.69	0.46	0	1
Child					
Male†	Male child	0.51	0.50	0	1
Female†	Female child (base)	.23	.42	0	1
Age	Child age(months)	30.04	17.0	0	59
Square age	Child age (months square)	1194.02	1054.28	0	3481
Summer†	Born season (summer)	0.22	0.42	0	1
Monsoon†	Born season (monsoon)	0.28	0.45	0	1
Winter†	Born season (winter)	0.25	0.43	0	1
Autumn†	Born season (autumn)	0.25	0.43	0	1
Twin†	Born twin	0.01	0.10	0	1
Vaccine	Total vaccines received	6.85	2.29	0	8
Diarrhea†	Had diarrhea in last two weeks	0.13	0.34	0	1
Fever†	Had fever in last two weeks	0.19	0.39	0	1
Mother					
Unemployed†	Mother do not work	0.21	0.41	0	1
Employed in agriculture†	Mothers works in agriculture	0.71	0.45	0	1
Employed in other sectors†	Mother has good quality job (base)	.081	.27	0	1

Table 9 continued

Variable	Description	Mean	Std. Dev.	Min	Max
Brahmin†	Mother ethnicity is Brahmin	0.16	0.37	0	1
Mongoliad†	Mother ethnicity is Mongoloid	0.23	0.42	0	1
Madhesi†	Mother ethnicity is Madhesi (base for WHZ)	0.15	0.36	0	1
Unprivileged†	Mother ethnicity is from lower cast	0.27	0.44	0	1
Chettri†	Mother ethnicity is from Chettri (base for HAZ)	0.19	0.39	0	1
Age	Age of mother in years	26.94	6.06	15	49
Age square	Square of mother age	762.6	362.41	225	2401
Education	Single years	2.82	3.82	0	14
Children	Total children ever born in the family	3.02	1.94	1	15
Breast feeding†	Currently mother is breast feeding	0.81	0.40	0	1
Stay husband†	Husband living with wife at home	0.67	0.47	0	1
Delivery home†	Mother delivers baby at home	0.76	0.43	0	1
Female head†	Female heads household	0.23	0.42	0	1
Household					
Urban†	Urban area	0.22	0.41	0	1
Rural†	Rural area (base)	0.78	0.41	0	1
Open defecation†	Defecating in open environment	0.55	0.50	0	1
Smoke fuel†	Smoke producing fuels	0.89	0.31	0	1
Water safe†	Anything done to water to make safe to drink	0.11	0.32	0	1
Electricity†	Has electricity facility	0.49	0.50	0	1
Bed net†	Has bed net	0.57	0.50	0	1
Livestock†	Household rear livestock	0.83	0.38	0	1

Table 9 continued

Variable	Description	Mean	Std. Dev.	Min	Max
Bank account†	Household owns a bank account	0.49	0.50	0	1
Own land†	Own land usable for agriculture	0.71	0.45	0	1
Poor	Poorest and poorer wealth category	0.50	0.50	0	1
Cluster					
NDVI birth	Predicted average NDVI (July, August, September)	667.5	60.1	153.5	805.2
Rainfall birth	Predicted average rainfall(May-September), (mm)	323.0	3.59	313.3	332.9
NDVI survey	Predicted average NDVI (July, August, September	673.50	69.63	110.73	823.41
Rainfall survey	Predicted average rainfall (May-September)	319.93	3.11	313.36	329.17
Poor cluster	Percentage of poor households	50.27	31.94	0	100
Bank account cluster	Percentage of households with bank account	48.61	22.05	0	100
Refrigerator	Percentage of households with refrigerator	8.35	0.00	54.55	3.78
Unprivileged cluster	Percentage of unprivileged households	26.60	23.91	0	100
Land own cluster	Percentage of land owned households	70.76	21.08	0	100
District-agriculture					
Food deficit†	District is food deficit	0.47	0.50	0	1
Irrigation	% of HH with irrigation facilities	0.64	0.19	0	1
Eggs	% of HH producing eggs	0.79	0.33	0	1

Table 9 continued

Variable	Description	Mean	Std. Dev.	Min	Max
Milk	Milk producing households (%)	0.84	0.26	0.05	1
Crop yield	(mean) crop yields in kg/ha	3290.62	779.90	1425.99	5980.10
Vegetable diversity	Mean share of vegetables in crop diversity	0.34	0.08	0.13	0.64
Agricultural income share	Share of agricultural income in total income	0.52	0.16	0.03	0.89
Storage	Total public food storage capacity (mt)	1830.02	2756.61	0	11000
District-market infrastructure					
Bridge survey	Bridge density in surveyed year (2006 and 2011)	0.01	0.02	0	0.116
Bridge spillovers	Spillovers of bridges on child nutrition	17.56	14.92	0	65.5
Road born	Road density index in born year (km/km2)	0.12	0.26	0	1.972
Road spillovers	Spillovers of roads on child nutrition	0.13	0.14	0	1.061
Distance coop	(mean) distance to coop in min by foot	587.30	643.33	7.59	2989.96
Distance hospital	(mean) distance to hospital in min by foot	334.13	605.49	7.83	4020.63
District-health infrastructure					
Child doctor†	Pediatrician/ gynecologist position available in government hospital	0.44	0.50	0	1

Table 9 continued

Variable	Description	Mean	Std. Dev.	Min	Max
Primary health center	# primary health center/ district population (‘000)	0.00	0.00	0	0.00007
Zonal hospital	# zonal health hospital in a district	0.31	0.52	0	2
Vacant post	# vacant post of doctors in a district /district population (‘000)	0.00	0.00	0.000008	0.0002
Private hospital	# private hospital	1.76	5.53	0	40
Terai†	District from Terai	0.32	0.47	0	1
Hill†	District from Hill	0.27	0.44	0	1
Mountain†	District from Mountain (Base variable)	.10	.30	0	1

Note:† Denotes a binary variable. Z-scores > 6.0 or < -6.0 removed from the dataset.

The predicted average NDVI for July, August, and September is 667.55, and the predicted average rainfall between May and September is 323.04 mm. Only about eight percent of households, on average, have a refrigerator in a cluster. There are some clusters where all households belong to the unprivileged group. The average altitude measured in a cluster is 827.35 meters above sea level. The percentage of households with a bank account and the percentage of poor households in a cluster are 49 and 50 percent, respectively.

On average, forty-seven percent of the districts were food deficit in 2006 and 2011. Similarly, sixty-four percent of households had access to irrigation facilities in a district. Seventy-nine percent of households produced eggs while 84% of the households produced milk on average in a district. The mean share of vegetables in crop diversity is 0.34. The mean income share of agriculture in total income is 52 percent which underscores the importance of agriculture in household welfare. The average public food storage capacity of a district is 1,830 metric tons.

The average bridge density (number of bridges per km^2) in a district is 0.01 while the average road density index in one year prior to the survey year is 0.12. The average mean distance required to reach a hospital by foot is 334.13 minutes. The mean distance to a cooperatives/sajha by foot is about 587.31 minutes. Only twenty-five percent of districts have a pediatrician position in the government hospital. It is very unlikely to find a pediatrician in a district on a regular basis if a pediatrician is not available in a government hospital. Nineteen percent of the districts have a zonal hospital. Only twenty-seven percent of doctor posts are filled. These descriptive statistics underscore the poor transportation and health infrastructure in Nepal.

3.6.2. Empirical results

Results from the spatial multi-level model are reported in Table 10A (height-for-age) and Table 10B (weight-for-height). I first estimate the HAZ and WHZ models with only the intercept term. Then I calculate the intra-class correlation coefficient for district, cluster, and household levels. In this way, I partition the variances arising from different levels. About 5%, 4%, and 19% of the variance in the dependent variable (children HAZs) stems from between-group differences (district, cluster, household), respectively. The remaining 72% of the variance stems from within-group (child) differences.

Similarly, 4%, 3%, 21% of the variance of the dependent variable (children WHZs) arise from district, cluster, and household differences, respectively, while 72% of the variance in dependent variable emerge from child differences. All variances at the higher levels are statistically significant at less than a five percent level of significance supporting use of higher level variables to account for some of this unexplained variations in the Z-scores.

Models 1A (HAZ) and 1B (WHZ) provide base cases for my analysis. These “base” models contain only the binary indicator for 2011, and therefore the point estimates on the 2011 indicator provide a measure of the unconditional difference in means between 2006 and 2011. These differences, which are significantly different from zero at a 1% test level, are 0.27 for HAZ and 0.16 for WHZ. These results confirm the differences reported in Table 8 and substantiate observations of an improvement in the nutrition situation in Nepal over the period. In the following paragraphs, I interpret only those variables that are statistically significant at a 10 percent test level or greater.

Model 2 adds to Model 1 a set of child level variables. All variables included in Model 3A and Model 3B are the same except that the total number of vaccines received is not incorporated in Model 3B, and the health condition variable (diarrhea and fever) is not incorporated in Model 3A. Results from Model 3A indicate that an increase in child age is significantly correlated with a decrease in HAZ. The negative sign on age and the positive sign on the square of age indicates that age has a positive effect on HAZ until a turning point is reached, e.g. $0.10/(2\times0.0013)=38.4$ months. Beyond 38 months, additional months of age have a negative contribution to HAZ. This indicates the non-linear impact of age on nutrition status consistent with the findings from past studies (Shrimpton et al. 2001; Alderman et al. 2006b). A child born as a twin has a HAZ that is 0.73 lower (statistically significant at less than 1 percent). Each additional vaccine is associated with an increase in HAZ of 0.03. Results from Model 3B indicate that season of birth, twin status, and health condition matters to WHZ. Children born in the autumn seasons have WHZs that are lower by 0.12 compared with children born in the winter season. Children born as twins have a WHZ that is lower by 0.48, on average compared with non-twins. Diarrhea and fever are found to be significantly correlated with lower WHZ, by 0.15 and 0.14 points, respectively.

Table 10A. Mixed Model Regression Results for HAZ in Nepal

Variables	Model 1A (Base)	Model 2A (Child)	Model 3A (Mother)	Model 4A (Households)	Model 5A (Cluster)	Model 6A (NLSS)	Model 7A (Market)	Model 8A (Health)
Year 2011	0.2730***	0.26257***	0.11257***	0.10994***	0.09964***	0.07637	0.08284	0.09133
(1=2011; 0 otherwise)	(0.0290)	(0.03196)	(0.03145)	(0.03427)	(0.03421)	(0.09727)	(0.07584)	(0.07255)
Gender		-0.00526	-0.00757	-0.01018	-0.01037	-0.00997	-0.01024	-0.00977
(1=Male,0=Female)								
		(0.03705)	(0.03593)	(0.03591)	(0.03347)	(0.03342)	(0.03344)	(0.03338)
Age of child in months		-0.1004***	-0.0952***	-0.09447***	-0.0936***	-0.0933***	-0.0938***	-0.09363***
		(0.00499)	(0.00487)	(0.00486)	(0.00497)	(0.00497)	(0.00499)	(0.00498)
Square of child age		0.00125***	0.00116***	0.00115***	0.00114***	0.00114***	0.00114***	0.00114***
		(0.00008)	(0.00008)	(0.00008)	(0.00008)	(0.00008)	(0.00008)	(0.00008)
Child born season		-0.06793	-0.06031	-0.05834	-0.06022	-0.06316	-0.05918	-0.05943
(1=Monsoon, 0 otherwise)								
		(0.04421)	(0.04419)	(0.04344)	(0.04975)	(0.04974)	(0.04983)	(0.04962)
Child born season		-0.06146	-0.05112	-0.04964	-0.05067	-0.05280	-0.04898	-0.05014
(1=Summer, 0 otherwise)								
		(0.04794)	(0.04673)	(0.04611)	(0.04648)	(0.04635)	(0.04686)	(0.04645)
Child born season		-0.04780	-0.03961	-0.03637	-0.03982	-0.04207	-0.03909	-0.03945
(1=Autumn, 0 otherwise)								
		(0.04890)	(0.04884)	(0.04874)	(0.04860)	(0.04854)	(0.04854)	(0.04862)
Child born twin		-0.7347***	-0.6281***	-0.62770***	-0.6228***	-0.6239***	-0.6249***	-0.62278***
(1=born twin,0 single)								
		(0.17306)	(0.16687)	(0.16721)	(0.17621)	(0.17697)	(0.17602)	(0.17637)
Number of vaccines received		0.03076***	0.01208	0.00837	0.00686	0.00680	0.00690	0.00704
		(0.00976)	(0.00988)	(0.00989)	(0.01026)	(0.01027)	(0.01023)	(0.01029)

Table 10A continued

Variables	Model 1A (Base)	Model 2A (Child)	Model 3A (Mother)	Model 4A (Households)	Model 5A (Cluster)	Model 6A (NLSS)	Model 7A (Market)	Model 8A (Health)
Mother’s not working			-0.10980**	-0.10839**	-0.11533**	-0.11880**	-0.11665**	-0.11208**
(1=yes; 0=no)			(0.04750)	(0.04778)	(0.04697)	(0.04687)	(0.04705)	(0.04662)
Mother’s working in farm			-0.1957***	-0.13078***	-0.1261***	-0.1283***	-0.1268***	-0.12622***
(1=yes; 0=no)			(0.04268)	(0.04582)	(0.04840)	(0.04859)	(0.04856)	(0.04886)
Ethnicity: Brahmin			-0.2063***	-0.21617***	-0.1723***	-0.1661***	-0.1659***	-0.17144***
(1=Brahmin; 0 otherwise)			(0.04785)	(0.05038)	(0.04959)	(0.04950)	(0.04927)	(0.04928)
Ethnicity: Mongoloid			-0.15033**	-0.14638**	-0.10246**	-0.11466**	-0.10426**	-0.10453**
(1=Mongoloid; 0 otherwise)			(0.05908)	(0.05962)	(0.04454)	(0.04518)	(0.04436)	(0.04521)
Ethnicity: Chhetri			-0.1281***	-0.13439***	-0.08639*	-0.08840*	-0.08539*	-0.09000*
(1=Chhetri; 0 otherwise)			(0.04455)	(0.04551)	(0.04646)	(0.04717)	(0.04706)	(0.04737)
Ethnicity: Unprivileged			-0.1999***	-0.18334***	-0.1634***	-0.1614***	-0.1552***	-0.15870***
(1=Unprivileged; 0 otherwise)			(0.04277)	(0.04269)	(0.04144)	(0.04094)	(0.03986)	(0.04037)
Age of mother in years			0.05218**	0.04132*	0.04071**	0.04063**	0.04094**	0.04046**
			(0.02164)	(0.02154)	(0.01907)	(0.01902)	(0.01902)	(0.01893)
Square of mother’s age			-0.00068*	-0.00053	-0.00052	-0.00053*	-0.00053*	-0.00052
			(0.00037)	(0.00036)	(0.00032)	(0.00032)	(0.00032)	(0.00032)
Mothers' education (years)			0.05131***	0.03843***	0.03724***	0.03748***	0.03711***	0.03712***
			(0.00456)	(0.00474)	(0.00484)	(0.00478)	(0.00488)	(0.00483)
Total children born			-0.0378***	-0.03150***	-0.0321***	-0.0307***	-0.0316***	-0.03167***
			(0.01013)	(0.00999)	(0.01133)	(0.01131)	(0.01138)	(0.01135)
Mother smokes cigarettes			-0.3079***	-0.27976***	-0.2741***	-0.2746***	-0.2759***	-0.27463***
(1=yes; 0=no)			(0.03607)	(0.03483)	(0.03920)	(0.03901)	(0.03912)	(0.03908)
Currently breast feeding			-0.2615***	-0.24253***	-0.2448***	-0.2438***	-0.2459***	-0.24480***
(1=yes; 0=no)			(0.04195)	(0.04290)	(0.03810)	(0.03785)	(0.03774)	(0.03763)
Husband living with wife at			0.03173	0.03533	0.03996	0.03682	0.04115	0.03867
home (1=yes; 0=no)			(0.02482)	(0.02506)	(0.03151)	(0.03186)	(0.03176)	(0.03207)

Table 10 A continued

Variables	Model 1A (Base)	Model 2A (Child)	Model 3A (Mother)	Model 4A (Households)	Model 5A (Cluster)	Model 6A (NLSS)	Model 7A (Market)	Model 8A (Health)
Place of delivery			-0.2058***	-0.16949***	-0.1627***	-0.1608***	-0.1617***	-0.16167***
(1=at home,0=not at home)			(0.04876)	(0.05114)	(0.05491)	(0.05489)	(0.05469)	(0.05490)
Female headed household			-0.00443	0.00416	0.00733	0.00770	0.00803	0.00703
(1=yes; 0=no)			(0.02723)	(0.02742)	(0.02930)	(0.02954)	(0.02942)	(0.02973)
Urban/rural				0.04394	0.01739	0.02417	0.01895	0.01134
(0=rural, 1=urban)				(0.03873)	(0.04141)	(0.04009)	(0.04087)	(0.04091)
Open defecation				-0.06805***	-0.07041**	-0.06859**	-0.07054**	-0.06965
(1=yes; 0=no)				(0.02630)	(0.02808)	(0.02760)	(0.02804)	(0.02794)
Smoke producing fuels				-0.15529***	-0.1413***	-0.1315***	-0.1402***	-0.13389***
(1=yes; 0=no)				(0.04837)	(0.04526)	(0.04616)	(0.04615)	(0.04679)
Anything done to water to make safe to				0.04925	0.06198	0.05207	0.06474	0.06093
drink (1=yes; 0=no)				(0.03713)	(0.04013)	(0.04114)	(0.04051)	(0.04021)
Has electricity facility				0.04935	0.04845	0.04779	0.04925	0.04664
(1=yes; 0=no)				(0.03792)	(0.03707)	(0.03793)	(0.03750)	(0.03741)
Has bed net for sleeping				0.08775***	0.02162	0.02071	0.02060	0.02138
(1=yes; 0=no)				(0.03311)	(0.03590)	(0.03589)	(0.03638)	(0.03582)
Household rear livestock				0.06277*	0.07003*	0.06836*	0.07045*	0.07208*
(1=yes; 0=no)				(0.03637)	(0.03998)	(0.03979)	(0.03992)	(0.03979)
Household owns a bank account				0.02752	0.00619	0.00691	0.00595	0.00708
(1=yes; 0=no)				(0.02481)	(0.02770)	(0.02785)	(0.02818)	(0.02788)
Own land usable for agriculture				-0.01205	0.00329	0.01079	0.00820	0.00612
(1=yes; 0=no)				(0.03485)	(0.02852)	(0.02801)	(0.02847)	(0.02840)
Poor (1=yes; 0=no)				-0.09320***	-0.08020**	-0.08027**	-0.07903**	-0.08253**
				(0.03191)	(0.04015)	(0.04077)	(0.04013)	(0.04051)
Average NDVI (July, August,					0.00026	0.00017	0.00031	0.00027
September), birth year					(0.00028)	(0.00030)	(0.00030)	(0.00030)
Average rainfall(May-September),					-0.00252	-0.00384	-0.00239	-0.00265
birth year					(0.00684)	(0.00681)	(0.00689)	(0.00692)

Table 10 A continued

Variables	Model 1A (Base)	Model 2A (Child)	Model 3A (Mother)	Model 4A (Households)	Model 5A (Cluster)	Model 6A (NLSS)	Model 7A (Market)	Model 8A (Health)
Percentage of poor households					-0.00011 (0.00059)	0.00045 (0.00065)	-0.00008 (0.00065)	-0.00014 (0.00063)
Percentage of households with bank account					0.00261*** (0.00067)	0.00271*** (0.00067)	0.00258*** (0.00073)	0.00265*** (0.00071)
Percentage of households with refrigerator					0.00290* (0.00157)	0.00263 (0.00164)	0.00296* (0.00156)	0.00272 (0.00161)
Altitude (masl, via GPS)					-0.0002*** (0.00003)	-0.0002*** (0.00004)	-0.0002*** (0.00004)	-0.00018*** (0.00004)
Districts food deficit status (1= if food deficit, 0 otherwise)						-0.1115*** (0.04304)		
% of HH using irrigation						0.06268 (0.09710)		
% of HH producing eggs						0.01416 (0.09210)		
Mean share of vegetables in crop diversity						0.04598 (0.25837)		
Mean share of ag income in total income						-0.06352 (0.13204)		
Total public food storage capacity in a district (mt)						-0.00000 (0.00001)		
Spillovers of the public food storage capacity						0.00006*** (0.00001)		
Eco Zone: Hills (1=Hills; 0 otherwise)						0.02473 (0.07029)	0.02745 (0.06180)	0.01654 (0.06063)
Eco Zone: Terai (1=Terai; 0 otherwise)						-0.04526 (0.08122)	-0.06349 (0.08414)	-0.03538 (0.08288)

Table 10 A continued

Variables	Model 1A (Base)	Model 2A (Child)	Model 3A (Mother)	Model 4A (Households)	Model 5A (Cluster)	Model 6A (NLSS)	Model 7A (Market)	Model 8A (Health)
Bridge density in born year							0.00167***	
							(0.00058)	
Spillovers of bridges							-0.00016	
							(0.00113)	
Road density index in born year							0.00951	
							(0.06021)	
Spillovers of roads							-0.09343	
							(0.11145)	
Mean distance to sajha/coop in min by foot							-0.00002	
							(0.00003)	
Pediatrician (1=available in district hospital, 0 not available)								0.07769**
								(0.03919)
Numbers of zonal hospital in a district								0.01349
								(0.03032)
Spillovers of zonal hospital on child nutrition								0.01579
								(0.06861)
Number of primary health center divided by district population								3460.00900
								(5111.98300)
Spillovers of primary health center on child nutrition								-6.83011***
								(1.31777)
Constant	-1.970***	-0.5961***	-0.71416**	-0.52079	0.14756	0.52718	0.05198	0.20074
	(0.0155)	(0.07923)	(0.33322)	(0.33526)	(2.16429)	(2.19170)	(2.17344)	(2.19292)

Table 10 A continued

Variables	Model 1A (Base)	Model 2A (Child)	Model 3A (Mother)	Model 4A (Households)	Model 5A (Cluster)	Model 6A (NLSS)	Model 7A (Market)	Model 8A (Health)
Random Effects								
District: Stand.Dev (ln)	-1.2009	-1.2458	-1.6247	-1.7135	-1.7089	-1.7807	-1.7378	-1.76673
	(0.0538)	(0.0535)	(0.0884)	(0.1011)	(0.0860)	(0.1263)	(0.1003)	(0.11129)
Cluster: Stand.Dev (ln)	-1.2930	-1.2921	-1.7359	-1.7980	-1.8880	-1.8766	-1.8797	-1.87691
	(0.0755)	(0.0658)	(0.1364)	(0.1482)	(0.2358)	(0.2216)	(0.2254)	(0.22497)
Household: Stand.Dev (ln)	-0.5356	-0.3325	-0.4072	-0.4093	-0.4123	-0.4123	-0.4115	-0.41215
	(0.0142)	(0.0121)	(0.0121)	(0.0122)	(0.0120)	(0.0120)	(0.0121)	(0.01205)
Stand.Dev (Residual) (ln)	0.1341	-0.0667	-0.0660	-0.0671	-0.0672	-0.0671	-0.0671	-0.06698
	(0.0298)	(0.0301)	(0.0304)	(0.0304)	(0.0357)	(0.0357)	(0.0357)	(0.03568)
Intra-class correlation (null-model)								
Level one (Children)	72%							
Level two (Household)	19%							
Level three (Cluster)	4%							
Level four (District)	5%							
Number of children	7511	7511	7511	7511	7511	7511	7511	7511
Number of households	5749	5749	5749	5749	5749	5749	5749	5749
Number of clusters	317	317	317	317	317	317	317	317
Number of districts	75	75	75	75	75	75	75	75
AIC	25296.55	23841.49	23398.6	23370.32	23349.75	23359.48	23359.57	23356.05

Notes: Standard errors, bootstrapped for 50 replications, appear in parentheses, *** indicates $p<0.01$, ** $p<0.05$, * $p<0.1$. Replications greater than 50 did not change the inferences. At the cluster level, the NDVI (proxy of agricultural potential in the child surrounding) is predicted using rainfall. Standard errors of such variable are incorrect. Thus I bootstrapped the standard errors.

Table 10B. Mixed Model Regression Results for WHZ in Nepal

Variables	Model 1B (Base)	Model 2B (Child)	Model 3B (Mother)	Model 4B (Households)	Model 5B (Cluster)	Model 6B (NLSS)	Model 7B (Market)	Model 8B (Health)
Year 2011	0.15911***	0.16922***	0.13769***	0.1268***	0.04850	0.08057	0.07821	-0.03017
(1=2011; 0 otherwise)	(0.02428)	(0.02520)	(0.02406)	(0.0241)	(0.03527)	(0.08743)	(0.07261)	(0.05514)
Gender		-0.01283	-0.01985	-0.0239	-0.02371	-0.02250	-0.02269	-0.02411
(1=Male,0=Female)		(0.02864)	(0.02862)	(0.0287)	(0.02861)	(0.02858)	(0.02861)	(0.02862)
Age of child in years		0.00166	0.00310	0.0029	0.00288	0.00256	0.00279	0.00282
		(0.00336)	(0.00331)	(0.0033)	(0.00329)	(0.00329)	(0.00330)	(0.00330)
Square of child age		0.00007	0.00005	0.0001	0.00006	0.00006	0.00006	0.00006
		(0.00005)	(0.00005)	(0.0001)	(0.00005)	(0.00005)	(0.00005)	(0.00005)
Child born season		-0.06177	-0.04971	-0.0509	-0.04985	-0.04861	-0.04808	-0.04811
(1=Summer, 0 otherwise)		(0.04574)	(0.04477)	(0.0446)	(0.04454)	(0.04451)	(0.04468)	(0.04430)
Child born season		-0.06958	-0.06244	-0.0637	-0.06058	-0.05897	-0.05738	-0.05827
(1=Monsoon, 0 otherwise)		(0.04438)	(0.04399)	(0.0438)	(0.04373)	(0.04318)	(0.04354)	(0.04360)
Child born season		-0.11862***	-0.11388***	-0.1127***	-0.1099***	-0.10656**	-0.10858***	-0.10957***
(1=Autumn, 0 otherwise)		(0.04217)	(0.04142)	(0.0414)	(0.04145)	(0.04152)	(0.04122)	(0.04135)
Child born twin		-0.47679**	-0.47866**	-0.4779**	-0.46503**	-0.46851**	-0.47196**	-0.46607**
(1=born twin,0 single)		(0.20169)	(0.20442)	(0.2053)	(0.20400)	(0.20495)	(0.20435)	(0.20488)
Diarrhea		-0.14743***	-0.15202***	-0.1474***	-0.1472***	-0.1478***	-0.14826***	-0.14992***
(1= had in last two weeks;0 otherwise)		(0.04685)	(0.04713)	(0.0472)	(0.04706)	(0.04731)	(0.04739)	(0.04733)
Fever		-0.13946***	-0.15377***	-0.1557***	-0.1547***	-0.1587***	-0.15939***	-0.15901***
(1= had in last two weeks;0 otherwise)		(0.04098)	(0.04143)	(0.0418)	(0.04170)	(0.04167)	(0.04123)	(0.04135)
Mother's not working (1=yes; 0=no)			-0.08271**	-0.0883**	-0.06664*	-0.06519*	-0.06030*	-0.05813
			(0.03755)	(0.0368)	(0.03621)	(0.03626)	(0.03597)	(0.03604)
Mother's working in farm			-0.15602***	-0.1207***	-0.1233***	-0.1263***	-0.11379***	-0.11555***
(1=yes; 0=no)			(0.03455)	(0.0391)	(0.03870)	(0.03719)	(0.03702)	(0.03820)

Table 10 B continued

Variables	Model 1B (Base)	Model 2B (Child)	Model 3B (Mother)	Model 4B (Households)	Model 5B (Cluster)	Model 6B (NLSS)	Model 7B (Market)	Model 8B (Health)
Ethnicity: Brahmin			-0.12370***	-0.1294***	-0.1234***	-0.0954***	-0.10589***	-0.10508***
(1=Brahmin; 0 otherwise)			(0.03728)	(0.0368)	(0.03617)	(0.03631)	(0.03478)	(0.03588)
Ethnicity: Mongoloid			0.16049***	0.1698***	0.17208***	0.17883***	0.18263***	0.17506***
(1=Mongoloid; 0 otherwise)			(0.02698)	(0.0273)	(0.02817)	(0.02758)	(0.02836)	(0.02831)
Ethnicity: Madheshi			-0.35619***	-0.3462***	-0.2788***	-0.2722***	-0.26933***	-0.26795***
(1=Madheshi; 0 otherwise)			(0.03839)	(0.0384)	(0.03901)	(0.04025)	(0.03889)	(0.03985)
Ethnicity: Unprivileged			-0.06778**	-0.0522*	-0.01030	0.00705	0.01342	0.01312
(1=Unprivileged; 0=otherwise)			(0.02688)	(0.0279)	(0.03448)	(0.03577)	(0.03624)	(0.03612)
Age of mother in years			-0.02164	-0.0274*	-0.02504*	-0.02489*	-0.02682*	-0.02718*
			(0.01478)	(0.0148)	(0.01477)	(0.01460)	(0.01472)	(0.01470)
Square of mother's age			0.00036	0.0004*	0.00037	0.00037	0.00040	0.00041
			(0.00025)	(0.0003)	(0.00025)	(0.00025)	(0.00025)	(0.00025)
Mothers' education in single years			0.01633***	0.0068	0.00723*	0.00791*	0.00824*	0.00775*
			(0.00385)	(0.0042)	(0.00431)	(0.00435)	(0.00424)	(0.00430)
Total children ever born in the family			-0.01067	-0.0066	-0.00397	-0.00286	-0.00388	-0.00366
			(0.01078)	(0.0105)	(0.01039)	(0.01016)	(0.01041)	(0.01042)
Currently breast feeding			-0.02355	-0.0119	-0.00797	-0.00661	-0.00784	-0.01074
(1=yes; 0=no)			(0.03131)	(0.0313)	(0.03075)	(0.03021)	(0.03121)	(0.03096)
Husband living with wife at home			-0.09687***	-0.0920***	-0.1011***	-0.1066***	-0.10429***	-0.10290***
(1=yes; 0=no)			(0.02212)	(0.0216)	(0.02115)	(0.02141)	(0.02139)	(0.02139)

Table 10 B continued

Variables	Model 1B (Base)	Model 2B (Child)	Model 3B (Mother)	Model 4B (Households)	Model 5B (Cluster)	Model 6B (NLSS)	Model 7B (Market)	Model 8B (Health)
Place of delivery (1=at home,0=not at home)			-0.08822**	-0.0594	-0.06189	-0.05563	-0.05675	-0.05550
			(0.04266)	(0.0432)	(0.04314)	(0.04347)	(0.04313)	(0.04311)
Female headed household (1=yes; 0=no)			-0.03202	-0.0221	-0.02796	-0.03012	-0.02594	-0.02772
			(0.02483)	(0.0251)	(0.02498)	(0.02461)	(0.02506)	(0.02483)
Urban/rural (1=urban; 0=rural)			0.0797***	0.08406***	0.07642***	0.08515***	0.09301***	0.0797***
			(0.0237)	(0.02363)	(0.02462)	(0.02428)	(0.02391)	(0.0237)
Open defecation				-0.0793**	-0.05113	-0.04713	-0.05504	-0.05381
(1=yes; 0=no)				(0.0353)	(0.03562)	(0.03422)	(0.03456)	(0.03498)
Smoke producing fuels				-0.0493	-0.04307	-0.01039	-0.00265	-0.01110
(1=yes; 0=no)				(0.0407)	(0.04121)	(0.04166)	(0.04155)	(0.04110)
Anything done to water to make safe to				0.0998**	0.07437*	0.06948*	0.07090*	0.07392*
drink (1=yes; 0=no)				(0.0409)	(0.04063)	(0.03927)	(0.04077)	(0.04014)
Has electricity facility				0.0782**	0.06542**	0.05586*	0.07218**	0.06416**
(1=yes; 0=no)				(0.0305)	(0.03026)	(0.02906)	(0.02845)	(0.02966)
Household rear livestock				0.0329	0.03041	0.03065	0.03980	0.03562
(1=yes; 0=no)				(0.0376)	(0.03941)	(0.03926)	(0.03894)	(0.03912)
Household owns a bank account				-0.0001	-0.00476	-0.00461	-0.00129	0.00068
(1=yes; 0=no)				(0.0204)	(0.02029)	(0.02014)	(0.02098)	(0.02076)
Own land usable for agriculture				0.0412	0.04008	0.04948*	0.04301	0.04724*
(1=yes; 0=no)				(0.0253)	(0.02742)	(0.02743)	(0.02773)	(0.02777)
Poor				-0.0069	-0.04308	-0.04204	-0.03676	-0.03446
(1=yes; 0=no)				(0.0273)	(0.02817)	(0.02863)	(0.02910)	(0.02828)
Percentage of households with refrigerator					0.00400***	0.00320**	0.00322**	0.00336**
					(0.00137)	(0.00144)	(0.00141)	(0.00144)

Table 10 B continued

Variables	Model 1B (Base)	Model 2B (Child)	Model 3B (Mother)	Model 4B (Households)	Model 5B (Cluster)	Model 6B (NLSS)	Model 7B (Market)	Model 8B (Health)
Average NDVI (July, August, September)					0.00028	0.00012	0.00037**	0.00023
in a cluster, one year prior of surveyed year					(0.00018)	(0.00017)	(0.00018)	(0.00018)
Average rainfall (May-September) received					0.02476***	0.01754***	0.01883***	0.02346***
by a cluster, one year prior of survey					(0.00499)	(0.00591)	(0.00564)	(0.00545)
Percentage of unprivileged households					-0.00073	-0.00049	-0.00068	-0.00073
					(0.00059)	(0.00059)	(0.00058)	(0.00059)
Percentage of land owned households					-0.00012	0.00032	0.00049	0.00045
					(0.00070)	(0.00070)	(0.00074)	(0.00074)
Altitude (masl, via GPS)					0.00020***	0.00019***	0.00015***	0.00018***
					(0.00002)	(0.00003)	(0.00003)	(0.00003)
Mean crop yields in kg/ha						0.00008***		
						(0.00001)		
Districts food deficit status						-0.1096***		
(1= if food deficit, 0 otherwise)						(0.02932)		
% of HH producing milk						-0.01118		
						(0.11579)		
% of HH producing eggs						0.15566**		
						(0.07936)		
Total public food storage capacity in a						0.00002***		
district (mt)						(0.00000)		
Spillovers of the public food storage						0.00000		
capacity						(0.00001)		
Mean annual ag income(rps)						0.00000		
						(0.00000)		
Eco Zone: Terai						-0.15693**	-0.12134*	-0.17243***
(1=Terai; 0 otherwise)						(0.07172)	(0.07070)	(0.06690)

Table 10 B continued

Variables	Model 1B (Base)	Model 2B (Child)	Model 3B (Mother)	Model 4B (Households)	Model 5B (Cluster)	Model 6B (NLSS)	Model 7B (Market)	Model 8B (Health)
Eco Zone: Hills						0.00730	-0.01333	-0.01860
(1=Hills; 0 otherwise)						(0.05971)	(0.05599)	(0.05733)
Bridge density in surveyed year (2006 and 2011)							0.63071 (0.69231)	
Spillovers of bridges							-0.00082 (0.00097)	
Road density index in surveyed year (2006 and 2011)							0.25066*** (0.04521)	
Spillovers of roads							-0.00860 (0.07372)	
Mean distance to hospital in min by foot							-0.00008* (0.00004)	
Districts where pediatrician/ gynecologist position are available								0.04036 (0.03227)
Total numbers of zonal health hospital in a district								0.04083* (0.02191)
Spillovers of zonal hospital on child nutrition								0.21045*** (0.04194)
Number of vacant post of doctors in a district divided by district population								-1,426.3177*** (457.02042)
Total numbers of private nursing home in a district								0.01460*** (0.00202)
Spillovers of private hospitals on child nutrition								13.05717** (5.61818)
Constant	-0.793*** (0.01400)	-0.80813*** (0.06068)	-0.21151 (0.23154)	-0.1894 (0.2372)	-8.48786 1.622749	-6.2693*** (2.1998)	-6.67274*** (1.86457)	-8.06622*** (1.81966)

Table 10 B continued

Variables	Model 1B (Base)	Model 2B (Child)	Model 3B (Mother)	Model 4B (Households)	Model 5B (Cluster)	Model 6B (NLSS)	Model 7B (Market)	Model 8B (Health)
Random Effects								
District: Stand.Dev (ln)	-1.50258	-1.49142	-1.82552	-1.91901	-2.18759	-2.50089	-2.42538	-2.39166
	(0.05535)	(0.05517)	(0.09029)	(0.10461)	(0.160254)	(1.32225)	(1.46510)	(2.361269)
Cluster: Stand.Dev (ln)	-1.69719	-1.71670	-2.03213	-2.07482	-2.11156	-2.17508	-2.09255	-2.12094
	(0.08167)	(0.08887)	(0.26618)	(1.32539)	(1.327809)	(1.84168)	(1.28376)	(1.191682)
Household: Stand.Dev (ln)	-0.70073	-0.64562	-0.65868	-0.66049	-0.66497	-0.66548	-0.66476	-0.66592
	(0.01316)	(0.01215)	(0.01243)	(0.01240)	(0.012464)	(0.01256)	(0.01252)	(0.012491)
Stand.Dev (Residual) (ln)	-0.08988	-0.11856	-0.12538	-0.12602	-0.12574	-0.12659	-0.12667	-0.12642
	(0.02610)	(0.02631)	(0.02615)	(0.02627)	(0.026285)	(0.02642)	(0.02654)	(0.02637)
Intra-class correlation (null-model)								
Level one (Children)	72%							
Table 3B continued								
Level two (Household)	21%							
Level three (Cluster)	4%							
Level four (District)	3%							
Number of children	7511	7511	7511	7511	7511	7511	7511	7511
Number of households	5749	5749	5749	5749	5749	5749	5749	5749
Number of clusters	317	317	317	317	317	317	317	317
Number of districts	75	75	75	75	75	75	75	75
AIC	22055.14	21908.07	21719	21701.41	21671.95	21645.22	21658.13	21655.76

Notes: Standard errors, bootstrapped for 50 replications, appear in parentheses, *** indicates p<0.01, ** p<0.05, * p<0.1. Replications greater than 50 did not change the inferences. At the cluster level, the NDVI (proxy of agricultural potential in the child surrounding) is predicted using rainfall. Standard errors of such variable are incorrect. Thus I bootstrapped the standard errors.

For Model 3 I add to Model 2 a set of mother-level variables. Results from Model 3A indicate that all variables except two (husband at home and female headed) are statistically significant at less than a five percent test level. Children of mothers who are unemployed and working on farm have a HAZ that is lower by 0.11 and 0.20 points, than those of mothers working in the non-farm sector. Children from Brahmin, Mongolid, Chhetri and Unprivileged households have HAZ scores lower by 0.21, 0.15, 0.13, and 0.20 points, respectively compared to Madheshi children. Madhesi people reside in the Terai, which is highly fertile, agriculturally productive, and benefitting from a higher density of facilities. Mother's age has a positive effect on HAZ i.e., each year of increase in a mother's age is associated with an increase in HAZ by 0.05 until a turning point is reached, e.g. 0.0522/(2×.0007)=37.29 or 37 years. However after this age, each additional year of a mother's age reduces HAZ (by .0007). A child nutrition study from Senegal indicated that children born to young mothers have relatively worse anthropometric status (Linnemayr et al. 2008). Each additional child in a family is associated with a 0.4 point reduction in HAZ. Children born at home have HAZ lower by 0.21 than children born at hospitals. The HAZ of children whose mothers smoke are lower by 0.31. This is because smoking during pregnancy adversely affects fetal growth (Ko 1999). Block and Webb (2009) found that an increase in expenditure on smoking products was associated with lower child nutrition outcomes in rural Indonesia. An additional year of mother's education is associated with an increase in HAZ of 0.05. The negative and statistically significant coefficient on the breast-feeding variable is unexpected. Two possible explanations are that poor children might have been breastfed for a longer period of time or sick children may be breastfed at higher rates. Results from Model 3B indicate that children from mothers working on a farm have lower WHZ by 0.16 than children from mothers having a non-agricultural job. Children from Brahmin, Mongoloid and Madheshi ethnic groups have average WHZ that are lower by 0.12, 0.16, and 0.36 compared with Chhetri children. Each additional increase in mother's education (in years) is correlated with an increase in WHZ of 0.02. Generally speaking, mothers working outside agriculture have higher incomes and are better-educated, perhaps positioning them to provide better care and nutrition for their children. Webb and Block (2004) found that a mother's education is more important for HAZ than for WHZ. Children born at home have 0.09 lower WHZ compared with children born in a hospital. Tiwari et al. (2008) found home delivery, low income, and prolonged breastfeeding are some of the risk factors for stunting in Nepal. The coefficient on husband at home is negative and statistically significant. The absence of father at home is correlated with an increase of child WHZ of 0.10. Generally, husbands and adult males emigrate to earn higher income. As a result, such households may have more food purchases, and better child nutrition outcomes. According to NLSS (2011) data, households report that a major share of remittance income is used for food purchases.

Model 3 adds to Model 4 household-related variables. Results from Model 4A indicate that, controlling for other factors, households defecating in the open have a HAZ that is lower by 0.07, on average, compared with households with proper sanitation facilities. Households that use smoke-producing fuels such as firewood and animal dung have children with HAZs that are 0.16 points lower, on average, than those households that uses fuels that do not produce smoke (such as electricity, kerosene, gas). Jagger and Shively (2014) found positive and significant relationship between the amount of fuelwood used by households and incidence of acute respiratory infection for children in Uganda. Households that have bed nets for sleeping have higher HAZ by 0.09. Households that rear livestock have children with HAZs that are 0.06 points higher, on average, than those households that do not rear livestock. Children from the bottom two quintiles have HAZ scores that are 0.09 points lower, on average, than those from the upper three wealth quintiles. Results from Model 4B indicate that urban children, those who drink treated water, and those who live in households with electricity have WHZ that are higher by 0.08, 0.10, and 0.08, respectively. Children residing in households that defecate in the open have WHZ that are lower by 0.08 than those who have improved sanitation facilities. From country-level regressions, Spears (2013) found a positive influence of sanitation facilities on human capital.

Model 4 adds to Model 5 a set of variables that characterize the cluster in which children reside. Results from Model 5A indicate that a one percent increase in the percentage of households with a bank account in a cluster is correlated with 0.003 unit increase of HAZ. One meter increase in altitude is correlated with 0.0002 unit decrease of HAZ. Results from Model 5B indicate that one percent increase in the percentage of household with a refrigerator in a cluster is associated with 0.004 unit increase of WHZ. An increase of rainfall by a millimeter (mm) in a cluster is correlated with increase WHZ of 0.025. Although the coefficients on NDVI are positive in both models, they are not statistically significant at standard test levels. The altitude coefficient is positive and statistically significant. One reason is likely that an increase in altitude is associated with a higher stunting, and since shorter stature gets expressed as higher WHZ, the correlation between altitude and WHZ is positive.

Model 5 adds to Model 6 a set of variables that are derived from the NLSS surveys. These variables characterize average agricultural conditions prevailing in a district. Results from Model 6A indicate that being in a food deficit district is associated with a lower HAZ of 0.12. Although I do not find a significant direct correlation between public food storage capacity and HAZ, its spillover effect on HAZ is significant. The coefficients on other agricultural variables have the expected signs but are not significant. Results from Model 6B indicate that the WHZ for children from food deficit districts by 0.11 points lower than for children from food surplus districts. A higher local average crop yield (kg/ha) is associated with higher WHZ of 0.0001. An increase of one-percentage households producing eggs in a district is correlated with the increased children WHZ of 0.16. An increase in the total public food storage capacity is correlated with a higher WHZ. General literature reveals a very sparse evidence on significant linkages between agriculture and nutrition outcomes. Although Jones and Brauw (2015) does not establish the direct linkages between agriculture and child nutrition, the study has found the positive connection between agriculture and child health, and then provides further implications to the child nutrition. The study found that the consumption of orange sweet potatoes reduced diarrhea in young children in Mozambique. Olney et al. (2015) also studies the linkage between agriculture and child nutrition where they evaluated the impact of the enhanced homestead food production (E-HFP) program on maternal and child nutrition outcomes in Burkina Faso. The study found positive impact of the program leading to the increase of dietary diversity and decrease of wasting, diarrhea, and anemia in the program operating villages compared to the control villages. Similarly, program beneficiaries' women had higher intake of nutrient-rich foods and reduction of thinness.

Model 5 adds to Model 7 a set of variables that are related to market infrastructure, including roads and bridges. Model 7A indicates that a one-unit increase of bridge density is significantly correlated with a 0.0017 unit increase in HAZ. The remaining infrastructure variables are not significant in model 7A. Model 7B indicates that a one unit increase in the road density index is correlated with 0.25 unit increase in WHZ. An increase in the mean distance to a hospital is associated with a lower WHZ.

Model 5 adds to Model 8 a set of variables that are related to the health infrastructure. In Model 8A, none of the variables, except the pediatrician and spatial lag of the primary health center variable, in Model 8A are significant. On an average, the presence of pediatrician in a district is correlated with 0.08 unit increase in HAZ. None of the other health infrastructure variables are statistically significant suggesting weak influence of these health infrastructure indicators on long-term child nutrition outcomes. However, some of the variables are highly significant in Model 8B suggesting significant correlation between health infrastructure and short-term child nutrition outcomes. I find positive and statistically significant direct (0.04) and spillovers (0.21) of zonal hospitals on WHZ. The coefficient on the vacant post variable is negative and highly significant. This suggests that where doctor posts are vacant, WHZ scores are lower in a district. The coefficients of the private hospital (both the direct and spillovers) are positive and statistically significant emphasizing its importance as an indicators of conditions that support short-term child nutrition.

One of the objectives of this study is to assess what factors might account for the observed improvements in average nutrition outcomes between 2006 and 2011. In Table 10A, Model 1A explains the improvements in average HAZ outcomes between 2006 and 2011, without controlling for any explanatory variables. Then I add child-, mother-, household-, cluster-, and district-level variables in subsequent models. Among all models, Model 3A, which incorporates mother-related variables, explains the biggest improvement in average HAZ outcomes from 0.27 to 0.11. This suggests that mother-level variables are very important for child nutrition outcomes. Between 2006 and 2011, average years of mother's education increased, mothers got better jobs, male immigration was higher, more babies were delivered in hospitals (compared with home), a lower percentage of mothers smoked cigarettes, and households had fewer children (NDHS 2006; NDHS 2011). Variables such as mother's education, husband living at home, place of delivery, mother's smoking, and total children ever born in the family should play a role in the observed improvement. However, once I add district-level variables, the observed contributions lose much of their significance. This indicates that district-level variables are also important in explaining the observed improvement in HAZ between 2006 and 2011. Model 1B in Table 10B indicates the difference between average WHZ between 2006 and 2011 without controlling for any explanatory variables. The coefficient on the year variable is statistically significant for Models 2B, 3B, 4B, and 5B that incorporates child-, mother-, household- and cluster-related variables, respectively. However once cluster and district level variables are added to the model, the coefficient on year is not statistically significant. This suggests that the cluster- and district-level variables are very important in explaining the observed improvements in WHZ between 2006 and 2011. Haddad et al. (2014) indicate that Maharastra, one of the wealthiest state of India, witnessed large decline in stunting rates from 37% to 24% between 2006 and 2012. Some of the factors responsible for this improvement were increase of mothers age, mothers literacy rate, antenatal clinic visits, percentage of mothers giving birth at improved health facilities, increase vaccination rates, improved child feeding practices and exclusive breastfeeding, lower defecation rates, increasing decision making process of women about their health status, and overall improvement of integrated child development care services. Bangladesh also made significant achievement in reducing stunting rates over last decade. The percentage of stunting for children below five reduced from 59 percent to 40 percent between 1997 and 2011. Headey et al. (2014) analyzed the possible drivers responsible for this decline. Increase of health care usage, higher parental education, more coverage of sanitation facilities, and improvement of household assets were found to be important factors for the improvement of the long-term child nutrition outcomes. Increase in parental education and household assets contributed about one quarter of the explained changes of children stunting in Bangladesh.

Finally, I assessed which model best fits the data. For HAZ, Model 5A, which contains child-, mother-, household-, and cluster-related variables is the best fitting model, as indicated by the lowest value of Akaike Information Criterion (AIC). For WHZ, model 6B, which contains child-, mother-, household-, cluster-and district-level agriculture variables is the best fitting model with the lowest value of AIC.

I plotted the random intercepts by districts for both the HAZ and WHZ (figures 19 and 20). These graphs help to compare different districts in terms of average HAZ and WHZ. The ten districts with the lowest HAZ are Achham, Rolpa, Mahotari, Jumla, Bajura, Siraha, Mustang, Humla, Jajarkot and Mugu. Only a few districts are from the Terai (Siraha and Mahotrai) and hilly districts (Accham and Rolpa). A majority of districts are from the Mountainous region (Jumla, Bajura, Mustang, Humla, Jajarkot, and Mugu). Similarly, the ten districts with the highest HAZ are Sunsari, Jhapa, Kathmandu, Kaski, Makwanpur, Illam, Saptari, Morang, Rupandehi, and Lamjung. None of these districts are from the Mountainous region. Five districts are from the hilly region (Kathmandu, Kaski, Makwanpur, and Lamjung). The remaining five districts are from the Terai (Sunsari, Jhapa, Spatari, Morang and Rupandehi). The ten districts with the lowest WHZ are Banke, Rautahat, Rasuwa, Mahotari, Kapilbastu, Siraha, Kalikot, Jajarkot, Baitadi, and Parsa. Only Jajarkot and Rasuwa are from hilly and mountainous regions, respectively. The rest of the districts are from the Terai. The ten districts with the highest WHZ are Kathmandu, Solukhumbu, Rolpa, Bhaktapur, Sindhupalchowk, Dhading, Gorkha, Pancthar, Myagdi, and Taplejung. None of the districts are from the Terai region. Seven districts (Kathmandu, Rolpa, Bhaktapur, Dhading, Gorkha, Panchthar, Myagdi) are from the hilly region and three districts (Solukhambu, Sindhupalchowk, and Taplejung) are from the Mountainous region.

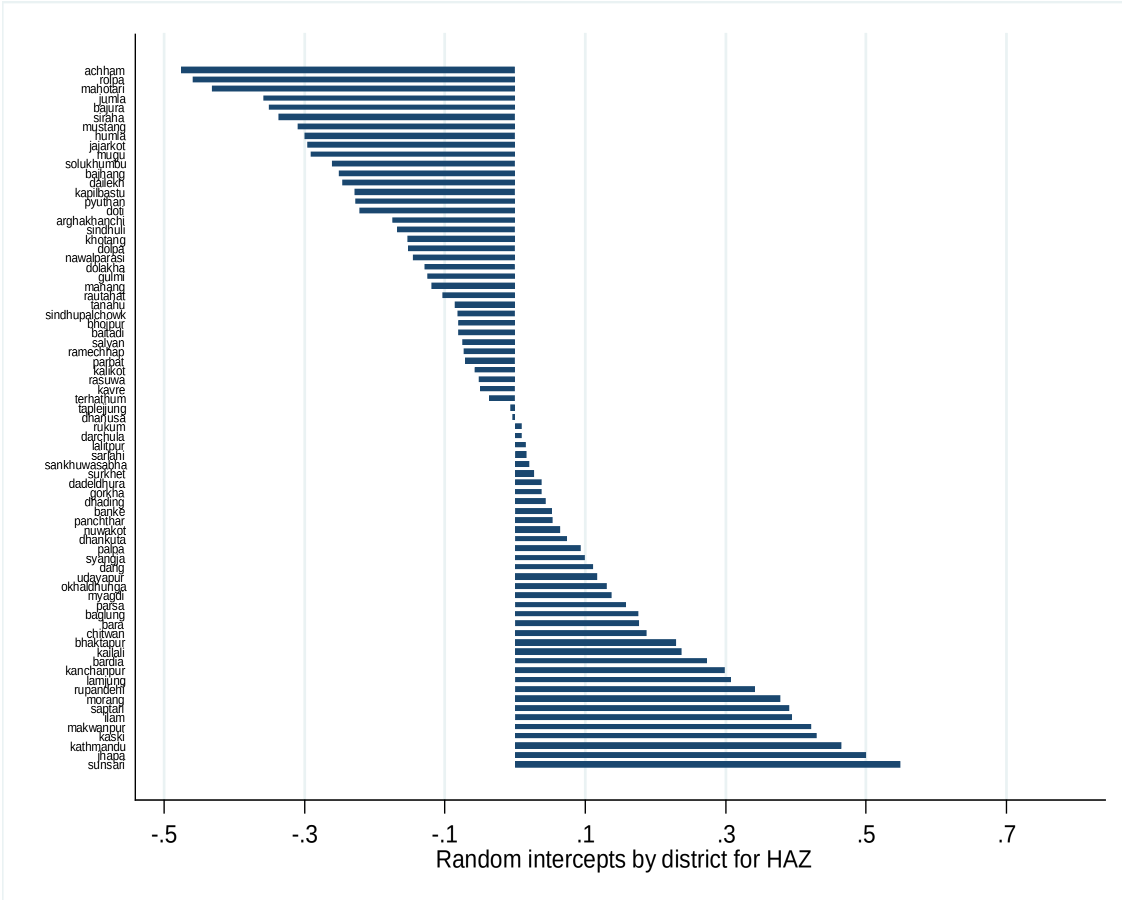

Figure 19. Random Intercept by District, HAZ

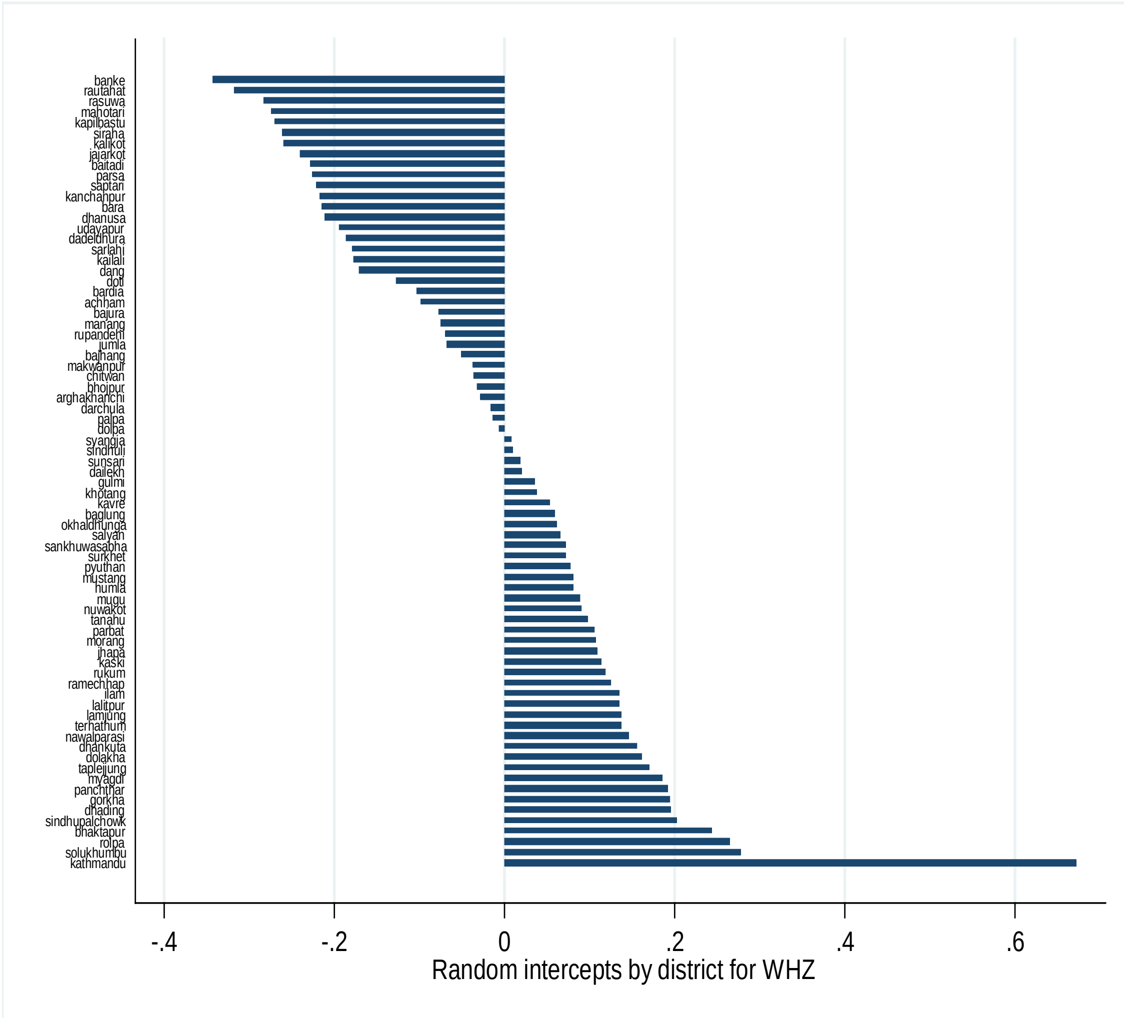

Figure 20. Random Intercepts by District, WHZ

3.7. Robustness Check

About 22% of the children in our sample come from urban areas. As indicated by results reported above, WHZ is significantly higher for children living in urban areas compared to those living in rural areas. Although significant differences are not found for HAZ, clearly agricultural conditions and characteristics may not be directly relevant to children from urban areas. In the regressions reported above, I have included these variables mainly at the district level. To test the robustness of the results, I repeat the regressions for Models 6A and 6B after changing the sample sizes and specifications. First, I only consider the rural sample and formulate two models — with and without agriculture — related variables. Second, I consider the urban sample only and exclude agriculture — related variables at the district level. Table 11 provides the regression results for both HAZ and WHZ. Although there is a slight change in magnitude and sign of some of the coefficients for the rural sample, with and without exclusion of the agriculture variables, results seems to be highly robust for both the HAZ and WHZ models. However, when I consider only the urban sample, after excluding the agricultural related variables, results are not highly robust as compared to the rural sample. This suggest that the core results from Models 6A and 6B should be cautiously interpreted in the case of the urban sample.

Table 11. Robustness Check

Variables	HAZ Model 6A NLSS (urban+rural) [a]	Model 6A (NLSS) (rural) [a]	Model 6A (NLSS) (rural) [b]	Model 6A (NLSS) (urban) [b]	WHZ Model 6B NLSS (urban+rural) [a]	Model 6B (NLSS) (rural) [a]	Model 6B (NLSS) (rural) [b]	Model 6B (NLSS) (urban) [b]
Year 2011	0.07637	0.1356	0.11024	0.05014	0.08057	0.08362	0.00434	-0.05210
(1=2011; 0 otherwise)	(0.09727)	(0.1006)	(0.07558)	(0.16552)	(0.08743)	(0.09502)	(0.08086)	(0.10526)
Gender	-0.00997	-0.0096	-0.00949	-0.01131	-0.02250	-0.03653	-0.03752	0.01888
(1=Male,0=Female)	(0.03342)	(0.0411)	(0.04115)	(0.09648)	(0.02858)	(0.03237)	(0.04062)	(0.09223)
Age of child in months	-0.09327***	-0.0957***	-0.09573***	-0.09330***	0.00256	0.00211	0.00232	0.00541
	(0.00497)	(0.0051)	(0.00505)	(0.01184)	(0.00329)	(0.00463)	(0.00342)	(0.00927)
Square of child age	0.00114***	0.0012***	0.00119***	0.00106***	0.00006	0.00008	0.00008	-0.00002
	(0.00008)	(0.0001)	(0.00008)	(0.00017)	(0.00005)	(0.00007)	(0.00005)	(0.00015)
Child born season	-0.06316	-0.0612	-0.05095	-0.07361	-0.05897	-0.07594	-0.07658	0.02448
(1=Monsoon, 0 otherwise)	(0.04974)	(0.0569)	(0.06147)	(0.14061)	(0.04318)	(0.05406)	(0.05563)	(0.10332)
Child born season	-0.05280	-0.0504	-0.06061	-0.08635	-0.04861	-0.07938	-0.08147	0.08308
(1=Summer, 0 otherwise)	(0.04635)	(0.0618)	(0.05677)	(0.13973)	(0.04451)	(0.05421)	(0.05387)	(0.10757)
Child born season	-0.04207	-0.0407	-0.04063	-0.05698	-0.10656**	-0.12490**	-0.12707**	0.00090
(1=Autumn, 0 otherwise)	(0.04854)	(0.0544)	(0.05448)	(0.13510)	(0.04152)	(0.05139)	(0.05371)	(0.11779)
Child born twin	-0.62399***	-0.6415***	-0.63997***		-0.46851**	-0.54356**	-0.54356**	
(1=born twin,0 single)	(0.17697)	(0.1925)	(0.19283)		(0.20495)	(0.23397)	(0.21664)	
had diarrhea in last two weeks					-0.14777***	-0.54356**	-0.15243***	-0.10560
(0/1)					(0.04731)	(0.23397)	(0.05282)	(0.09738)
had fever in last two weeks (0/1)					-0.15868***	-0.54356**	-0.17742***	-0.12337
					(0.04167)	(0.23397)	(0.04315)	(0.10191)
Number of vaccines received	0.00680	0.0013	0.00157	0.03592				
	(0.01027)	(0.0102)	(0.01011)	(0.03004)				

Table 11 continued

	Model 6A NLSS (urban+rural) [a]	Model 6A (NLSS) (rural) [a]	Model 6A (NLSS) (rural) [b]	Model 6A (NLSS) (urban) [b]	Model 6B NLSS (urban+rural) [a]	Model 6B (NLSS) (rural) [a]	Model 6B (NLSS) (rural) [b]	Model 6B (NLSS) (urban) [b]
Mother's not working	-0.11880**	-0.1144**	-0.11426**	-0.10523*	-0.06519*	-0.08961	-0.09074	-0.03101
(1=yes; 0=no)	(0.04687)	(0.0566)	(0.05656)	(0.06353)	(0.03626)	(0.06383)	(0.06154)	(0.07324)
Mother's working in farm	-0.12831***	-0.1268**	-0.12209**	-0.14608**	-0.12625***	-0.15320***	-0.14725***	-0.04376
(1=yes; 0=no)	(0.04859)	(0.0547)	(0.05406)	(0.07219)	(0.03719)	(0.05824)	(0.04637)	(0.08642)
Ethnicity: Brahmin	-0.16613***	-0.2780***	-0.28488***	0.12766	-0.09543***	-0.14218***	-0.15275***	0.00963
(1=Brahmin; 0 otherwise)	(0.04950)	(0.0660)	(0.06549)	(0.10047)	(0.03631)	(0.05149)	(0.05056)	(0.09059)
Ethnicity: Mongoloid	-0.11466**	-0.2908***	-0.29362***	0.41207***	0.17883***	0.13475***	0.13049***	0.31603***
(1=Mongoloid; 0 otherwise)	(0.04518)	(0.0567)	(0.05571)	(0.09981)	(0.02758)	(0.03984)	(0.04714)	(0.08083)
Ethnicity: Chhetri	-0.08840*	-0.1846***	-0.18672***	0.14075				
(1=Chhetri; 0 otherwise)	(0.04717)	(0.0598)	(0.05941)	(0.10018)				
Ethnicity: Unprivileged	-0.16136***	-0.2694***	-0.26698***	0.15454*	0.00705	-0.06695	-0.05891	0.24723***
(1=Unprivileged; 0 otherwise)	(0.04094)	(0.0560)	(0.05583)	(0.08602)	(0.03577)	(0.05409)	(0.04513)	(0.08774)
Ethnicity:					-0.27218***	-0.30846***	-0.29953***	-0.06629
Madhesi,(1=Madhesi; 0 otherwise)					(0.04025)	(0.04554)	(0.05221)	(0.08088)
Age of mother in years	0.04063**	0.0449**	0.04353**	0.02137	-0.02489*	-0.04138***	-0.04326***	0.03927
	(0.01902)	(0.0225)	(0.02244)	(0.04032)	(0.01460)	(0.01525)	(0.01513)	(0.03715)
Square of mother's age	-0.00053*	-0.0005	-0.00051	-0.00037	0.00037	0.00057**	0.00060**	-0.00047
	(0.00032)	(0.0004)	(0.00037)	(0.00070)	(0.00025)	(0.00026)	(0.00026)	(0.00063)
Mothers' education in single	0.03748***	0.0340***	0.03410***	0.04683***	0.00791*	0.01268***	0.01289**	-0.00492
years	(0.00478)	(0.0055)	(0.00551)	(0.00791)	(0.00435)	(0.00453)	(0.00561)	(0.00927)

Table 11 continued

	Model 6A NLSS (urban+rural) [a]	Model 6A (NLSS) (rural) [a]	Model 6A (NLSS) (rural) [b]	Model 6A (NLSS) (urban) [b]	Model 6B NLSS (urban+rural) [a]	Model 6B (NLSS) (rural) [a]	Model 6B (NLSS) (rural) [b]	Model 6B (NLSS) (urban) [b]
Total children ever born in the family	-0.03071*** (0.01131)	-0.0410*** (0.0123)	-0.04138*** (0.01207)	-0.00473 (0.02467)	-0.00286 (0.01016)	0.00603 (0.01133)	0.00545 (0.00975)	-0.04067* (0.02300)
Mother smokes cigarettes (1=yes; 0=no)	-0.27459*** (0.03901)	-0.3008*** (0.0426)	-0.30256** (0.04283)	-0.09971 (0.09120)				
Currently breast feeding (1=yes; 0=no)	-0.24377*** (0.03785)	-0.2254*** (0.0403)	-0.22608*** (0.04007)	-0.30826*** (0.07022)	-0.00661 (0.03021)	-0.00984 (0.03413)	-0.01040 (0.03862)	-0.02940 (0.07821)
Husband living with wife at home (1=yes; 0=no)	0.03682 (0.03186)	0.0525 (0.0337)	0.05229 (0.03349)	-0.02455 (0.07274)	-0.10662*** (0.02141)	-0.09855*** (0.03392)	-0.09421*** (0.03135)	-0.13066** (0.06359)
Place of delivery (1=at home,0=not at home)	-0.16082*** (0.05489)	-0.1826*** (0.0524)	-0.18179*** (0.05247)	-0.10707 (0.11701)	-0.05563 (0.04347)	-0.07990 (0.04972)	-0.08288 (0.06089)	-0.01392 (0.10370)
Female headed household (1=yes; 0=no)	0.00770 (0.02954)	0.0431 (0.0371)	0.04239 (0.03697)	-0.13828** (0.05712)	-0.03012 (0.02461)	-0.02632 (0.03261)	-0.02521 (0.03100)	-0.05580 (0.07183)
Urban/rural (0=rural, 1=urban)	0.02417 (0.04009)				0.07642*** (0.02462)			
Open defecation (1=yes; 0=no)	-0.06859** (0.02760)	-0.0609* (0.0361)	-0.06364* (0.03603)	-0.10247 (0.08268)	-0.04713 (0.03422)	-0.03044 (0.04307)	-0.03409 (0.03460)	-0.06871 (0.06187)
Smoke producing fuels (1=yes; 0=no)	-0.13153*** (0.04616)	-0.0427 (0.0721)	-0.04061 (0.07220)	-0.17290*** (0.06782)	-0.01039 (0.04166)	-0.01972 (0.06242)	-0.02057 (0.05319)	-0.04786 (0.06410)
Anything done to water to make safe to drink (1=yes; 0=no)	0.05207 (0.04114)	-0.0190 (0.0532)	-0.01998 (0.05411)	0.11718 (0.07660)	0.06948* (0.03927)	0.08406 (0.06032)	0.08774 (0.05357)	0.07558 (0.05336)
Has electricity facility (1=yes; 0=no)	0.04779 (0.03793)	0.0142 (0.0394)	0.01964 (0.03725)	0.32651*** (0.11470)	0.05586* (0.02906)	0.07618** (0.03130)	0.08394** (0.03965)	-0.05312 (0.08900)

Table 11 continued

	Model 6A NLSS (urban+rural) [a]	Model 6A (NLSS) (rural) [a]	Model 6A (NLSS) (rural) [b]	Model 6A (NLSS) (urban) [b]	Model 6B NLSS (urban+rural) [a]	Model 6B (NLSS) (rural) [a]	Model 6B (NLSS) (rural) [b]	Model 6B (NLSS) (urban) [b]
Has bed net for sleeping	0.02071	0.0304	0.03018	-0.01312				
(1=yes; 0=no)	(0.03589)	(0.0345)	(0.03438)	(0.08440)				
Household rear livestock	0.06836*	0.0589	0.06277	0.10856	0.03065	0.10775**	0.11604**	-0.13014**
(1=yes; 0=no)	(0.03979)	(0.0463)	(0.04697)	(0.06843)	(0.03926)	(0.04574)	(0.04824)	(0.05661)
Household owns a bank	0.00691	0.0050	0.00505)	0.03383	-0.00461	-0.01591	-0.01521	0.03328
account (1=yes; 0=no)	(0.02785)	(0.0348)	(0.03464)	(0.06145)	(0.02014)	(0.02552)	(0.02578)	(0.04911)
Own land usable for	0.01079	0.0354	0.03519	-0.11782***	0.04948*	0.00289	0.00174	0.16143***
agriculture	(0.02801)	(0.0285)	(0.02842)	(0.05012)	(0.02743)	(0.02877)	(0.03244)	(0.05493)
(1=yes; 0=no)								
Poor	-0.08027**	-0.0812**	-0.07869**	0.06607	-0.04204	-0.05030	-0.05016	-0.08211
(1=yes; 0=no)	(0.04077)	(0.0397)	(0.03876)	(0.10220)	(0.02863)	(0.03595)	(0.03455)	(0.11512)
Average NDVI (July,	0.00017	0.0004	0.00040**	0.00062	0.00012	0.00011	0.00027	0.00019
August, September), birth	(0.00030)	(0.0002)	(0.00023)	(0.00055)	(0.00017)	(0.00018)	(0.00017)	(0.00036)
year								
Average rainfall(May-	-0.00384	-0.0025	-0.00237	-0.00168	0.01754***	0.01901***	0.02256***	0.01559
September), birth year	(0.00681)	(0.0078)	(0.00764)	(0.01551)	(0.00591)	(0.00693)	(0.00543)	(0.01258)
Percentage of poor	0.00045	-0.0002	-0.00041	0.00210*				
households	(0.00065)	(0.0008)	(0.00069)	(0.00124)				
Percentage of households	0.00271***	0.0023***	0.00208***	0.00425***				
with bank account	(0.00067)	(0.0008)	(0.00079)	(0.00145)				
Percentage of households	0.00263	0.0024	0.00279	0.00069	0.00320**	0.00476**	0.00599***	0.00291
with refrigerator	(0.00164)	(0.0024)	(0.00247)	(0.00211)	(0.00144)	(0.00220)	(0.00168)	(0.00204)
Percentage of unprivileged					-0.00049	-0.00001	-0.00007	-0.00088
households					(0.00059)	(0.00066)	(0.00067)	(0.00136)

Table 11 continued

	Model 6A NLSS (urban+rural)[a]	Model 6A (NLSS) (rural)[a]	Model 6A (NLSS) (rural)[b]	Model 6A (NLSS) (urban)[b]	Model 6B NLSS (urban+rural)[a]	Model 6B (NLSS) (rural)[a]	Model 6B (NLSS) (rural)[b]	Model 6B (NLSS) (urban)[b]
Percentage of land owned households					0.00032 (0.00070)	0.00146* (0.00089)	0.00151* (0.00090)	-0.00137 (0.00159)
Altitude (masl, via GPS)	-0.00016*** (0.00004)	-0.0001*** (0.0000)	-0.00011*** (0.00004)	-0.00027*** (0.00007)	0.00020*** (0.00002)	0.00017*** (0.00003)	0.00015*** (0.00003)	0.00013* (0.00007)
Districts food deficit status (1= if food deficit, 0 otherwise)	-0.11147*** (0.04304)	-0.0872** (0.0363)			-0.10957*** (0.02932)	-0.08603*** (0.03207)		
Mean crop yields in kg/ha					0.00008*** (0.00001)	0.00006*** (0.00002)		
% of HH using irrigation	0.06268 (0.09710)	0.0493 (0.0872)						
% of HH producing eggs	0.01416 (0.09210)	0.0792 (0.0902)			0.15566** (0.07936)	0.16146** (0.06600)		
% of HH producing milk					-0.01118 (0.11579)	-0.02815 (0.13700)		
Mean share of vegetables in crop diversity	0.04598 (0.25837)	-0.2528 (0.2751)						
Mean share of ag income in total income	-0.06352 (0.13204)	-0.2053 (0.1636)						
Total public food storage capacity in a district (mt)	-0.00000 (0.00001)	0.0000 (0.0000)	0.00001 (0.00001)	0.00001 (0.00001)	0.00002*** (0.00000)	0.00001* (0.00001)	0.00001** (0.00001)	0.00004*** (0.00001)
Spillovers of the public food storage capacity	0.00006*** (0.00001)	0.0001*** (0.0000)	0.00007*** (0.00001)		0.00000 (0.00001)	0.00000 (0.00001)	-0.00000 (0.00001)	
Mean annual ag income(rps)					0.00000 (0.00000)	0.00000 (0.00000)		

Table 11 continued

	Model 6A NLSS (urban+rural) [a]	Model 6A (NLSS) (rural) [a]	Model 6A (NLSS) (rural) [b]	Model 6A (NLSS) (urban) [b]	Model 6B NLSS (urban+rural) [a]	Model 6B (NLSS) (rural) [a]	Model 6B (NLSS) (rural) [b]	Model 6B (NLSS) (urban) [b]
Eco Zone: Hills	0.02473	0.0521	0.05083	-0.11699	0.00730	0.01797	0.00929	0.00737
(1=Hills; 0 otherwise)	(0.07029)	(0.0761)	(0.06917)	(0.12928)	(0.05971)	(0.05218)	(0.06139)	(0.12096)
Eco Zone: Terai	-0.04526	-0.0363	-0.03260	-0.08218	-0.15693**	-0.17221**	-0.16608*	-0.08542
(1=Terai; 0 otherwise)	(0.08122)	(0.1000)	(0.09476)	(0.16444)	(0.07172)	(0.08209)	(0.09598)	(0.14855)
Constant	0.52718	0.0443	-0.13959***	-0.57653	-6.2693***	-6.64399***	-7.56389***	-6.44481
	(2.19170)	(2.4696)	(2.42374)	(5.01967)	(2.1998)	(2.20928)	(1.77689)	(4.15740)
Random Effects								
District: Stand.Dev (ln)	-1.7807	-1.90840	-2.00267	-2.31987	-2.50089	-2.6148	-2.42132	-2.75319
	(0.1263)	(0.18339)	(0.18891)	(7.20553)	(1.32225)	2.6364	0.366858	7.09482
Cluster: Stand.Dev (ln)	-1.8766	-1.51558	-1.50431	-16.34487	-2.17508	-1.9692	-1.91453	-2.63497
	(0.2216)	(0.14777)	(0.14146)	(6.98512)	(1.84168)	0.2173	0.167376	6.19869
Household: Stand.Dev (ln)	-0.4123	-0.43408	-0.43324	-0.40704	-0.66548	-0.6965	-0.69649	-0.56998
	(0.0120)	(0.01341)	(0.01334)	(0.02417)	(0.01256)	0.0169	0.016231	0.02610
Stand.Dev (Residual) (ln)	-0.0671	-0.07110	-0.07135	-0.05091	-0.12659	-0.1266	-0.12689	-0.13536
	(0.0357)	(0.02374)	(0.02369)	(0.08104)	(0.02642)	0.0323	0.036081	0.06779
Number of children	7511	5877	5877	1634	7511	5877	5877	1634
Number of households	5749	4437	4437	1325	5749	4437	4437	1325
Number of clusters	317	277	277	147	317	277	277	147
Number of districts	75	75	75	41	75	75	75	41
AIC	23355.31	18221.65	18215.15	5144	21645.22	16882.65	16889.35	4795.436

Notes: [a] indicates the model with the agriculture variables at district level, [b] indicates the model without agriculture variables at district level, Standard errors, bootstrapped for 50 replications, appear in parentheses, *** indicates p<0.01, ** p<0.05, * p<0.1. Replications greater than 50 did not change the inferences. At the cluster level, the NDVI (proxy of agricultural potential in the child surrounding) is predicted using rainfall. Standard errors of such variable are incorrect. Thus I bootstrapped the standard errors.

3.8. Conclusions, Policy Implications and Limitations

This paper employed a spatial multi-level model to analyze child nutrition data from Nepal. Four levels corresponding to child, household, cluster and district were used. Data from various sources such as NDHS, NLSS, NDVI, rainfall, agriculture production and storage, transportation, and health infrastructure were combined for the analysis. I estimated eight different models that included variables at different levels (child, mother, household, cluster, and district). Spatial lags for some of the district-level variables were created and incorporated in the regressions. As a robustness test, I dropped the urban sample and repeated the regressions at the district level with and without agriculture related variables. I also dropped the rural sample and agriculture variables, and repeat the regression at the district level.

The first objective of this study was to identify factors or variables that are strongly correlated with the child nutrition outcomes in Nepal. I identified a number of variables influencing WHZ and HAZ. Variables that are statistically significant at five percent level of significance or greater were considered as strongly correlated with child nutrition outcomes. The independent variables that are (a) highly robust, (b) strongly correlated with the long-term nutrition outcomes (HAZ), and (c) important from a policy perspective are twin status, mother’s employment status, ethnicity, mother smoking, mother’s education, total children ever born in the family, place of delivery, use of smoke-producing fuels, percentage of households with a bank account in a cluster, food deficit status of a district, bridge density, and presence of pediatrician in a district hospital. The independent variables that are (a) highly robust, (b) strongly correlated with the short-term nutrition outcomes (WHZ), and (c) important from a policy perspective are season of birth (autumn), twin status, presence of diarrhea and fever, mothers working on farm, husband away from home, electricity facility, percentage of households with refrigerator, mean crop yield, district food deficit, percentage of households producing eggs, public food storage capacity, roads, vacant posts of doctors, health facilities that are equivalent of zonal hospital, and number of private hospitals in a district. Especially in this critical period of aftermath of earthquakes, all of these results provide insights into potential policies to reduce current suffering in form of acute (short-term) malnutrition and improve long-term child nutrition outcomes in Nepal.

The second objective of this study was to assess what factors might account for the observed improvements in average outcomes between 2006 and 2011. The strong statistical evidence of improvements in Z-scores over time is largely explained by changes occurring in higher level variables, underscoring the importance of changes occurring at the cluster and district level.

I provide some policy implications based on the results that may be especially important for targeting nutrition intervention programs. Since children born as twins have lower HAZ and WHZ (by 0.73 and 0.48), child nutrition programs targeted for twin children may help to improve nutrition outcomes. A one percent increase in the number of vaccines given to a child can increase HAZ by 11%, encouraging vaccination efforts to reach all children. Kids suffering from diarrhea and fever have lower WHZ, underscoring that efforts to prevent and treat diarrhea will help to improve short-term child nutrition outcomes. The mother-level variables were found to be very important for child nutrition outcomes. For example, a one percent increase in mother’s years of education is likely to increase HAZ by 8% and WHZ by 6%. Government programs that promote mother’s education encourage mothers to quit smoking, provide incentives to deliver babies at hospitals will help to improve child nutrition outcomes. An increase of one percent of the number of children in a household is associated with a 6% decrease in the HAZ of her children. Given such a statistics, awareness programs such as importance of family planning and importance of female education will create greater consciousness for mothers and may help to improve child nutrition outcomes. Child nutrition programs can be targeted to children from Unprivileged and Brahmin families. As Brahmin families avoid meat and meat products, programs like substitution of animal protein with plant protein may be very important to improve child nutrition outcomes in Brahmin communities. Programs that lead to substitution of smoke-producing fuels to smokeless fuels, encouraging savings through bank accounts, building sanitation facilities, and reducing poverty helps to improve child nutrition outcomes. Higher rainfall is found to improve WHZ at the cluster level. This finding likely points to the importance of water availability for agriculture in short-term child nutrition and supports the expansion of irrigation facilities in the country.

Child nutrition outcomes in food deficit districts were found to be lower than in food surplus districts. Thus if government launches agricultural programs in food-deficit districts that lead to food surplus districts, child nutrition outcomes are likely to be improved. Some of these agricultural programs that helps to boost total agricultural production and productivity can be through constructing irrigation facilities, distribution of improved seeds and good quality fertilizers in a timely manner, promoting use of farm machinery equipment, and stabilizing output prices. Districts with a higher percentage of households producing eggs have higher WHZ. Programs that lead to small scale egg and poultry production may be helpful in improving short-term child nutrition outcomes. Investments in public food storage facilities are likely to support child nutrition not only locally, but also in neighboring districts. The lowest HAZ is mainly from the mountainous and hilly districts while the lowest WHZ is mainly from the Terai district. Any public interventions related to the improvement of the long-term nutrition outcomes and short-term nutrition outcomes can be prioritize to the hilly and mountainous districts, and the Terai districts, respectively. Random intercept plots at the district-level identify the districts with the lowest average HAZ and WHZ. In terms of launching nutrition intervention programs, more priority may be given to those districts that have the worst child nutrition outcomes.

Based on these findings, higher densities of roads and bridges in a district can help to improve the short- and long-term child nutrition outcomes, respectively, emphasizing the importance of transport investments. The mean distance to a hospital in minutes by foot is negatively correlated with short-term child nutrition outcomes, underscoring the importance of quick access to hospitals. Government policies to create the pediatrician position in government hospitals in all district of the country can help to improve long-term child nutrition outcomes. Similarly government polices to quickly fill empty post of doctors will help to improve short-term child nutrition outcomes. If the government builds more zonal hospitals or health facilities equivalent to zonal hospitals, and encourages construction of private hospitals, short-term child nutrition outcomes are likely to improve, underscoring the importance of health infrastructure in supporting child health and nutrition.

Although I tried my best in terms of selecting model and including all relevant variables, this study fails to include some of the important variables especially at the child level. Variables such as the type and amount of food consumed by a child, feeding interval, and birth spacing are not available or available for only a small portion of the children sampled. It was hard to find suitable instruments to make causal statement for many variables; thus limiting us from casual interpretation of these coefficients. Due to the unavailability of the GPS coordinates at the household level, I was not able to account for spatial dependency occurring at the child level. Furthermore, I was also not able to take account of spatial error correlation due to the complexities owed by introducing spatial error component in the multi-level model. These remains future work.

CHAPTER 4. INFRASTRUCTURE AND CHILD NUTRITION IN NEPAL

4.1. Introduction

Poor nutrition is a major problem in low income countries.[19] In 2010, about 30% of the population of low-income countries was undernourished and about 42% of children under age of five in those countries were stunted (WB 2010).[20] Poor nutrition not only hinders personal and social development but also affects national development as a whole (Boyden and Dercon 2012). According to the World Bank (2015):

> Undernutrition is one of the world's most serious but least addressed public health challenges. Its human and economic costs are enormous, falling hardest on the very poor and on women and children.

Given the importance of nutrition, donor agencies and governments are actively exploring various options for improving nutrition outcomes to reduce suffering and promote human development.

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[19]The low income countries, as indicated by the World Bank, are Afghanistan, Bangladesh, Benin, Burkina Faso, Burundi, Cambodia, Central African Republic, Chad, Comoros, Dem. Rep of Congo., Eritrea, Ethiopia, Gambia, Guinea, Guinea-Bissau, Haiti, Kenya, Dem. Rep of Korea., Liberia, Madagascar, Malawi, Mali, Mozambique, Myanmar, Nepal, Niger, Sierra Leone, Rwanda, Somalia, Tajikistan, Tanzania, Togo, Uganda, and Zimbabwe.

[20] Undernourishment is calculated as percentage of the population whose food intake is insufficient to meet dietary energy requirements continuously.

One salient feature of low-income countries is the ubiquity of poor transportation infrastructure, especially outside core urban areas. A majority have road densities of less than 15 km/100 km^2 (WB 2010).[21] Nepal's situation is characteristic of this pattern. For example, although Nepal and Switzerland have similar topographies, Switzerland has a total road density of 173, compared with 14 for Nepal (IRF 2010). In countries with low road densities, many areas are economically and geographically isolated. An overall shortage of infrastructure is widely perceived as impeding access to markets, employment opportunities, and health and educational facilities, and as undermining agricultural development and social progress more generally. According to the World Bank (2010), transport is a crucial driver of economic growth, poverty reduction, and attainment of the Millennium Development Goals, (MDGs) all of which are closely connected to child nutrition and health.[22] However, it is somewhat surprising that very little attention has been devoted to assessing the impact of roads on child nutrition outcomes. While this neglect may in part reflect a perspective that the connection between infrastructure and nutrition is indirect, and therefore that the associations and contributions are likely to be weak, it also just as likely reflects a shortage of data in most settings where one might wish to explore the spatial and temporal linkages between infrastructure and nutrition

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[21]As a comparison, according to the International Road Federation and World Road Statistics, in 2010 the United States, the United Kingdom, and Japan had road densities of 67, 172 and 89 km/100 km^2, respectively.

[22]The MDG's have five pillars: (i) eradicating extreme poverty and hunger, (ii) reducing child mortality, (iii) improving maternal health, (iv) achieving universal primary education, and (v) empowering women.

outcomes. In this study, I compile and combine data for Nepal that allow us to study these linkages. The primary research question motivating this study is whether improvements in infrastructure lead to improvements in child nutrition outcomes. I make both empirical and methodological contributions to the literature on infrastructure and child nutrition.

This analysis is especially important given Nepal's high prevalence of child malnutrition (WB 2010), and the widespread perception that many of the country's problems can be blamed on poor infrastructure. The issue can be best visualized using figures 21 and 22. Figure 21 shows the countrywide distribution of the strategic road network in 2013/14. Figure 22 shows the nationwide probability of child stunting. A comparison of these maps illustrates that the probability of a child being stunted is much higher in hilly and mountainous regions of the country where road networks are limited (and roads are mostly gravel or earthen), compared with the Terai, which has an extensive and well-developed road network (and a much larger proportion of black-topped roads). One might reasonably ask whether the nutrition outcomes displayed in Figure 22 are correlated with the road data displayed in Figure 21 and, more importantly, whether observed local changes in the road network over time have been clearly associated with improvements in local nutrition outcomes. Undoubtedly, other factors such as education, health facilities, and agricultural potential of the local areas may affect child nutrition outcomes, and may themselves be correlated with transport infrastructure. Although this complicates efforts to clearly identify the causal impacts of roads, in this analysis I control for as many of these factors as possible in an attempt to isolate the impact of roads on child nutrition outcomes and move closer to establishing evidence of causality.

The importance of road infrastructure has been widely underscored by the April and May 2015 earthquakes in Nepal.[23] One of the biggest challenges for search and rescue teams has been difficulty of getting to affected areas. In remote locations, immediate search and rescue of those trapped in the rubble was not possible. Injured people were not able to quickly reach health centers; foods stored by households were buried; nearby markets were closed; and immediate food assistance was not possible. In addition, timely delivery of key agricultural inputs, such as seeds and fertilizers, has been undermined, placing future food security at risk. Child nutrition outcomes in regions affected by the earthquakes will likely be severely affected as children and their mothers suffer both short-term and longer-term food security.

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[23]A 7.8 magnitude earthquake struck on 25th April 2015 resulting in approximately 8,000 deaths and 14,000 injuries. A second quake of 7.3 magnitude hit on 12th May 2015, resulting in additional deaths.

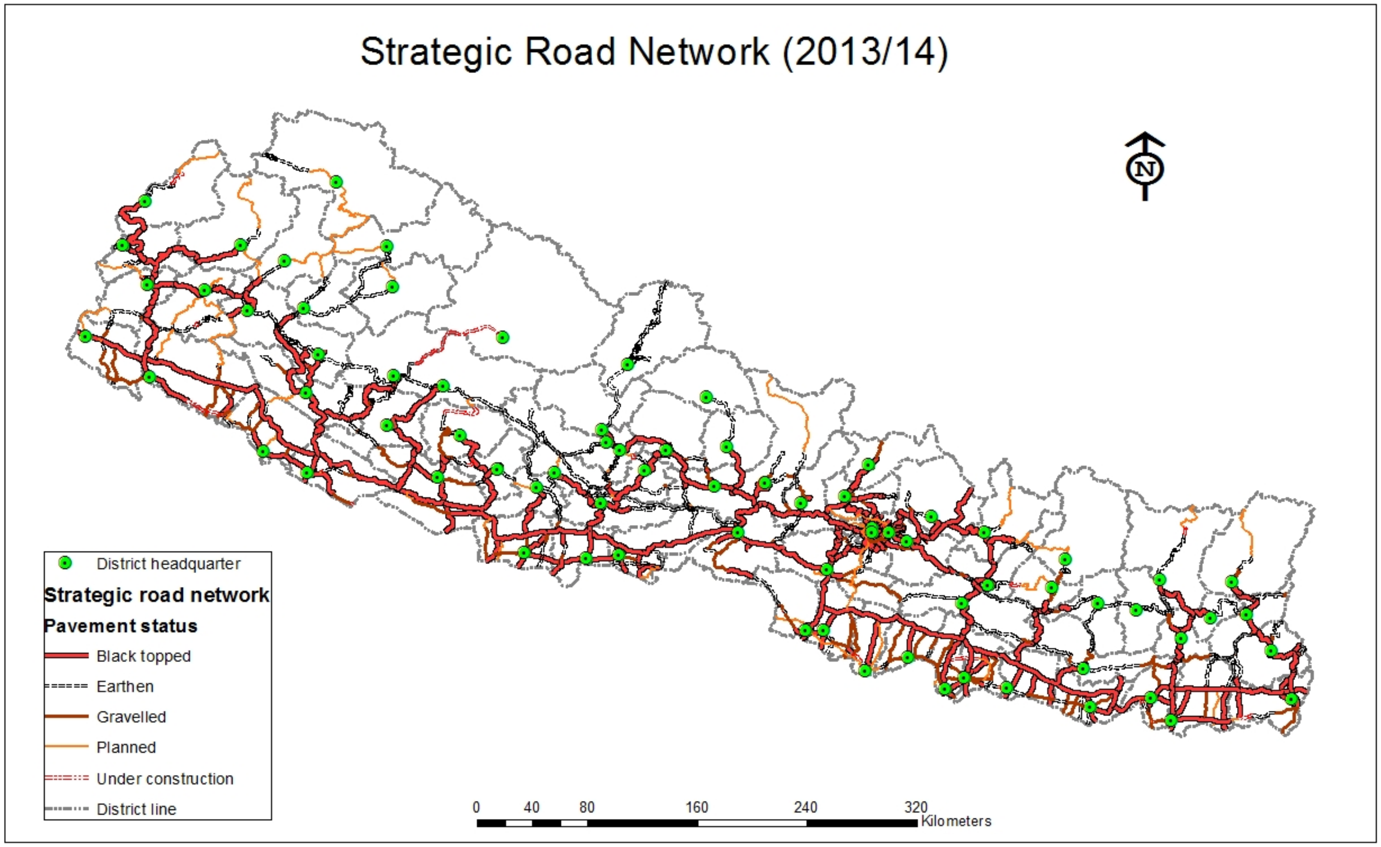

Figure 21. Strategic Road Network (2013/14), Source: Department of Road, Nepal

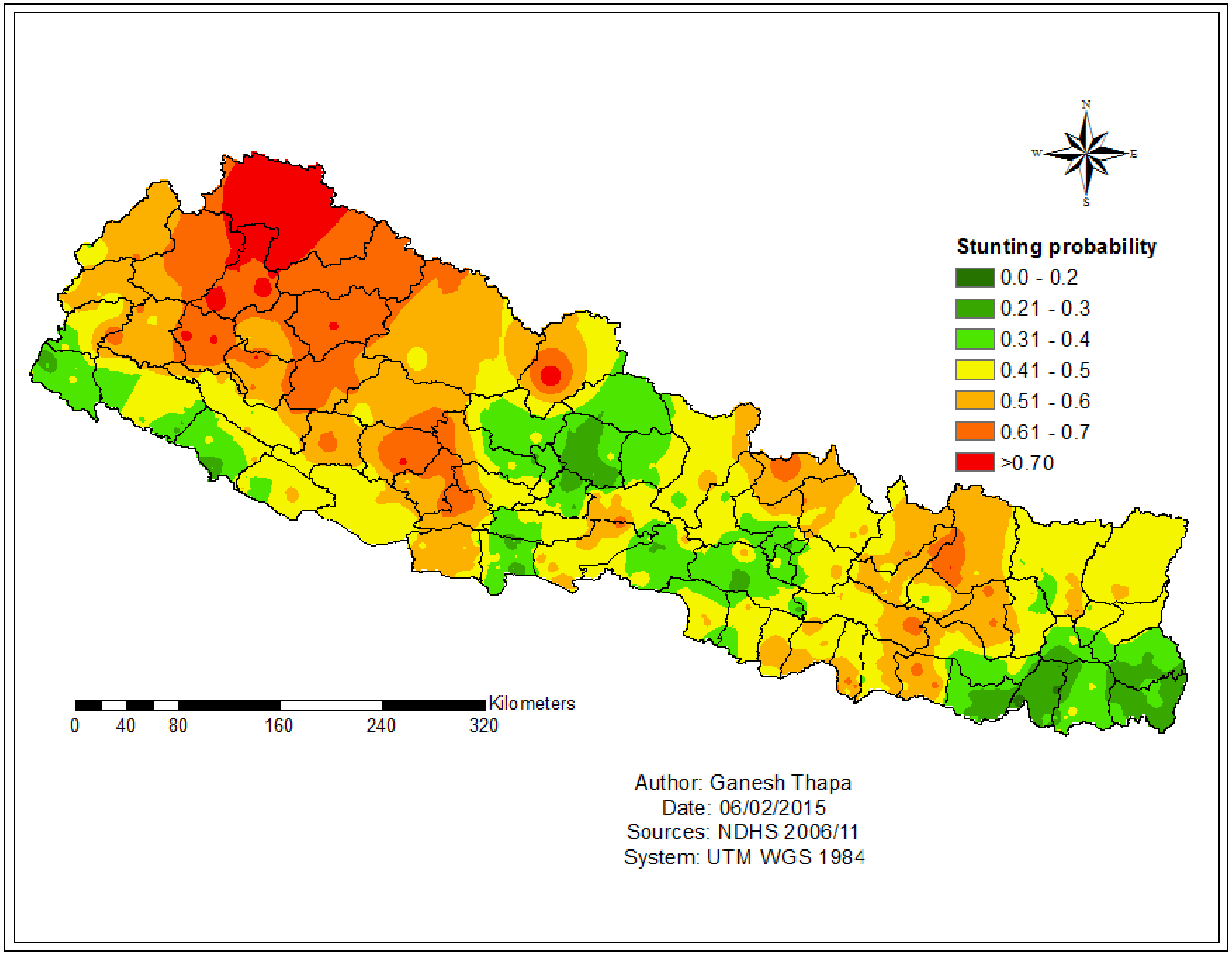

Figure 22. IDW Interpolation-Probability of Child Stunting in Nepal

Previous studies have assessed the impact of roads on indicators that could affect child nutrition indirectly. For example, Khandker et al. (2009) examined the poverty alleviation impacts of rural road projects using household-level panel data from Bangladesh. They argue that public investment in rural roads reduces poverty through higher agricultural production, higher wages, higher output prices, and lower input and transportation costs. Stifle and Minten (2008) find an inverse relationship between isolation and agricultural productivity in Madagascar. One reason, they argue, is the high transportation-induced transaction costs in such isolated areas. Mu and Van de Walle (2014) assessed the impacts of rural roads on local market development in Vietnam and found a significant average impact on the development of local markets. Jalan and Ravallion (2002) argue that higher road density reduced poverty in rural China. Duran-Fernandez and Santos (2014) found that road infrastructure led to higher industrial production in Mexico. The difference in infrastructure endowments was able to partially explain the regional gaps in industrial worker productivity (Duran-Fernandez and Santos 2014). Fan et al. (2002, 2004) argue that road investments led to the growth of agriculture and the non-farm sector in China and Thailand. Past studies have found that an upgrade in road quality is associated with significant improvements in household welfare indicators and other metrics. For example, Bell and van Dillen (2014) studied the effects of all-season rural roads in Orissa, India, and report that, after gaining access to all-weather rural roads, households received higher prices for output (5% higher or more), reported higher school attendance, and received more frequent and timely hospital treatment. Dercon et al. (2009) found that access to all-weather roads reduced poverty by

6.9% and increased consumption growth by 16.3% in Ethiopia. Olsson (2009) found a substantial benefit from road improvement such as lower transportation cost and delivery times, access to larger markets, minimize post-harvest loss, higher productivity and production, and higher market demand in the rural Philippines. Warr (2008) found large effects of all-weather access roads on poverty reduction in Laos. A study from Rwanda found statistically significant negative relationship between travel time to health facilities and height-for-age Z-scores and concluded that improved access to health facilities could be a potential pathway to reduce stunting in Rwanda (Aoun et al. 2015). Moss et al. (2007) found mobility to be a crucial aspect for accessing and retaining jobs by rural people in Northern Ireland.

To date, a small number of descriptive and econometric studies have attempted to assess the overall benefits of rural roads in Nepal. The UNDP (2011) conducted a benefit-cost analysis of roads in selected districts and found that roads had positive financial and economic returns. Dillon et al. (2011) used hedonic and panel data approaches to estimate the impact of access to infrastructure and extension services in rural Nepal. Their findings suggest that rural road investments have a strong positive effect on household welfare. Jacoby (2010) estimated the household-level benefits of road projects using the relationship between the value of farmland and its distance to agricultural markets in Nepal. His findings revealed that poor households received higher benefits from the market access provided by roads than did better-off households.

All these findings suggest that, at a broad level of investigation, patterns of transportation infrastructure development may indeed correlate with patterns of malnutrition, due to linkages with market development, education and health. At present, I am unaware of any studies drawing a connection between roads and child nutrition outcomes. While it is clear that establishing a causal impact between road and nutrition outcomes may not be easy, the topic is nevertheless worth exploring in a rigorous manner given the substantial attention devoted to infrastructure and child nutrition by policy makers and donor agencies such as the World Bank and the Asian Development Bank.

I measure the causal impact of roads on child nutrition using data organized at the district level. I choose this level of analysis for the investigation because the benefits of roads are likely to be broad in geographic scope. Furthermore, many policy makers are likely to think of development prospects and interventions at a district-level rather than at a household or individual level. I recognize that road construction is not likely to be exogenous with respect to the outcome variables of interest, either because economically and politically favored districts are more likely to receive attention and public funds and to have less overall deprivation, or because projects may specifically target underdeveloped districts. Van de Walle (2009) discusses some of the sources of endogeneity such as initial characteristics influencing both road placement and outcomes/change in outcomes, and the correlation of time-varying factors with changes in outcomes. She argues that in some cases there may be relevant variables that influence road placement but not outcomes, which might serve as proper instrumental variables. I explore an instrumental variable approach to estimate the causal impact of roads on the child nutrition outcomes using “distance from the capital city to a district headquarter” as an instrument. I argue that distance between the capital and a district headquarters is likely to influence road placement but not child nutrition outcomes. In addition, I use the generalized propensity score estimation (GPS) approach of Hirano and Imbens (2004) to remove bias associated with the purposeful construction of roads where roads are treatment and child nutrition is an outcome.

I use a quality-adjusted index of road density index in 2006 as a treatment for HAZ in 2011, and the change in this index between 2011 and 2006 as a treatment for WHZ in 2011.[24] I estimate the effects of treatment on child nutrition outcomes for children under the age of five and also for two separate age-cohorts of children, those under three years and those between three and five years of age. I do this because child growth can be differentially sensitive to overall conditions at different ages (Aguero 2006; Hoddinott and Kinsey 2001). For example, low WHZ reflects short-term nutritional deficits and low HAZ reflects long-term nutritional deficits. For children above 3 years, low HAZ reflects cumulative effects of past health and nutrition defects (WHO 2002), which suggests a potentially greater importance for historical, rather than contemporaneous, infrastructure patterns. I estimate separate and time-sensitive dose-response functions (DRF) for separate age-cohorts of children as mentioned above.

I also examine the specific impact of all-season roads on child nutrition outcomes. Doing this allows us to check the robustness of our GPS results. One might argue that

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[24] Child nutrition outcomes are measured by comparing anthropometric data such as height-for-age (HAZ) and weight-for-height Z-scores (WHZ) for children under five against the WHO standard (WHO, 1995). The detailed discussion of quality-adjusted index of road density is provided in sub-section 4.1.

roads and road networks can have geographically dispersed effects on social and economic outcomes. This is certainly true in the case of Nepal, where road density is low, and modest additions to the transportation stock could be expected to have wide impacts on opportunities and outcomes, both within a district and in adjacent districts linked by roads.[25] I use a spatial econometric approach to address this issue. A detailed discussion is provided in sub-section 4.3.3.

Our results quantify the causal impact of roads on child nutrition outcomes, and thereby provide information that can be used by the government of Nepal, as well as by other low-income countries and development agencies. Our findings put transportation investment into a larger development context and can inform decision making for investments in the transportation sector.

4.2. Background

4.2.1. Child nutrition and road infrastructure in Nepal

Nepal faces a serious child nutrition problem. Although stunting rates in Nepal decreased by 16 per cent between 2001 and 2011, approximately 41% of children less than five years of age are still stunted (a measure of chronic malnutrition) and 12% are wasted (a measure of short-term malnutrition) (NDHS 2011). The stunting rate is even higher (about 60%) in the mountain region (Figure 23). The stunting prevalence in Nepal

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[25] The strategic road network consists of major roads (national highways, feeder roads, district roads, urban roads) that play an important role in moving people and freight.

is similar to or worse than that of the least developed African countries, including Sudan (40%) and Ethiopia (51%) (UNICEF 2009). Moreover, Nepal ranks 57th out of 88 countries on the global hunger index score (GHI).[26] This ranking is even worse in some specific regions of the country. The mid-western mountain region of Nepal ranks one from the bottom of the 88 countries on the GHI list while the far-western mountain region ranks similar to Ethiopia (Hollema and Bishokarma 2009).

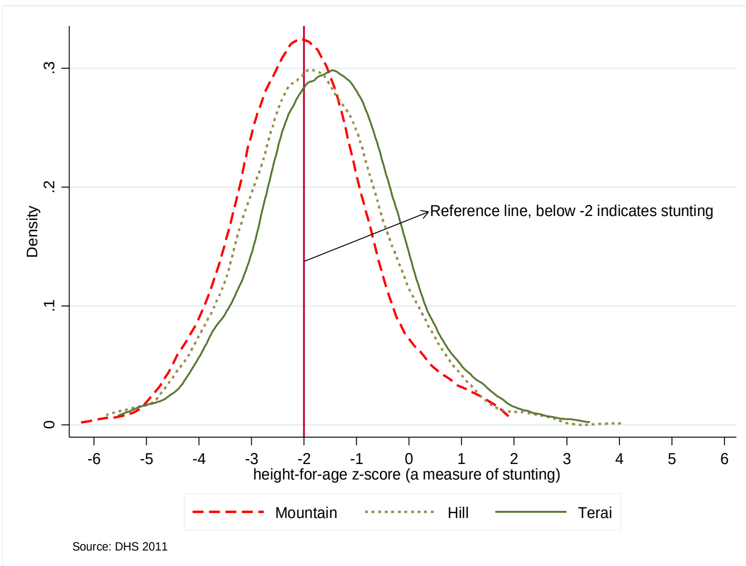

Figure 23. Distribution of HAZ by Agro-ecological Zones in Nepal

Children residing in the mountains and hills face multiple risks in comparison to those in the Terai. Many of these risks stem from poor infrastructure and economic and

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[26]The Global Hunger Index (Wiesmann 2006) is composed of the proportion of the undernourished as a percentage of the population, the prevalence of underweight children under the age of five and the mortality rate of children under the age of five (calculated average, in percentages).

geographic isolation. Mobility is very low and few sources of off-farm income exist (CBS 2011). Agricultural inputs are not available in a timely manner or are very costly. Out of 16 mountainous districts in Nepal, 10 had food deficits in 2011 (NMOAD 2011). Due to the complete lack of roads, or the widespread prevalence of only poor quality roads, transportation costs are very high, resulting in higher food prices than in other areas (FAO/WFP 2007). A majority of the food deficit households in those districts compromise their daily consumption and other basic needs such as child health care and education (FAO et al. 2011). Health, market and road infrastructure are mainly limited to the immediate area around the district headquarters. People living far-away must walk for many hours to receive basic services (CBS 2011). Poor infrastructure undermines community-based and national child nutrition interventions (NMOHP 2011). According to Suvedi et al. (2009), maternal mortality is higher among women from mountain districts. One reason is a shortage or absence of delivery facilities in their vicinities (NMOHP 2011). Well-trained health workers choose not to serve in those regions because of the hardships they face.[27] Out of the total available government posts for doctors in the mountainous districts, only 38% were occupied in 2014. Very few government positions for pediatricians and gynecologists exist in remote districts (NMOHP 2014).

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[27]Remote districts are not easily accessible. There may not be electricity. Daily goods are not easily available or are expensive. All these result in difficult living condition or hardships.

Historically, Nepal has had among the lowest road density in South Asia. In 1998, the total strategic road network length was 4,740 km and the road density was only 3 km per 100 km^2. Within the last decade, there has been substantial improvement in the road network in Nepal. In 2012, the total strategic road network length increased to 11,636 km resulting in an overall national road density of 8 km/100 km^2 (DOR 2012).[28] The country's total road length increased 58% from 16,018 km to 25,265 km, between 2003 and 2013. The length of black-pitched, gravel and earthen roads expanded 129%, 18%, and 47%, respectively over the same period (DOR 2013).

Although Nepal's road network has expanded in recent years (by roughly 5% per year in the first decade of this century), only 43 percent of Nepal's population has access to all-weather roads (CBS 2011). The road network is not well-distributed throughout the country. Road density is very low in the far-western hilly and mountainous regions of the country, and two mountain districts (Humla and Dolpa) remained unconnected with the rest of the country as of May 2015. Most of the black-topped roads are concentrated in either the Terai or the capital. In mountainous districts, all roads are earthen. Lack of a strong road-network in the hilly and mountainous regions reflects high road construction costs, largely due to harsh topography. Moreover, the 2015 earthquakes have led to landslides in many affected areas, compromising the already inadequate road network further.

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[28] The total road density (km of road per 100 sq. km of land area) of Bangladesh, Bhutan, India, Pakistan, Srilanka and Nepal in 2010 were 171, 36, 125, 32, 163, and 14, respectively (Source: WDI online database).

Most of the hilly and mountainous regions of the country are still not easily reached. There are many locations where several hours or days of road travel are required to reach the district headquarters (CBS 2011). In those places, imported goods are often either airlifted or carried by mules and porters. As a result, food prices reflect added transportation costs. Gurung (2010) argues that improved access to roads has lowered food costs in several hilly/mountainous districts of Nepal and provided several other benefits. Sanogo (2008) suggests that better road infrastructure will improve the food security situation of the mid- and far-western districts of Nepal by reducing the time and expense required to move food to deficit areas.

4.3. Conceptual Framework

Undoubtedly, most of the determinants of nutrition outcomes for individual children are established at the child or household level. The following conceptual framework illustrates the pathway by which roads are linked to district child nutrition outcomes. I assume that the government appoints a social planner/administrator to each district (i=1,…, D) who derives utility by improving the district average nutrition outcomes of children (N^i). The social planner in each district maximizes this utility (U^i), subject to a budget constraint.

The utility function of the social planner i can be expressed as:

$$U^i = U(N^i) \tag{34}$$

Here $U(.)$ is twice continuously differentiable, concave, and increasing in its argument. Below, the district superscript is suppressed to keep notation clear. In each district the average nutrition outcome (N) depends on multiple district-level arguments:

$$N = N(C, N_M, M, V, H, S, R) \tag{35}$$

where C is the average amount of food consumed by children in the district, , N_M is the average nutritional outcome of mothers in the district, V indicates total number of vaccinations, S is total money spent on child-related health and nutrition outcomes by the district administrator, M is the average district household income, H indicates the density of health care units (such as health post, sub-health post, hospital etc) and R is the total road density in the district. Food consumption (C) is a function of average agricultural production (A), income (M) and output prices (P):

$$C = C(A, M, P) \tag{36}$$

The district average nutritional outcome of mothers is a function of average years of schooling (E), average working hours (W), and access to health infrastructure (H):

$$N_M = f(E, W, H) \tag{37}$$

Average income in a district is a function of agricultural production, output prices, the literacy rate (L) and total number of non-farm enterprises (F).

$$M = M(A, P, L, F) \tag{38}$$

The average amount of agricultural production is the function of average amount of agricultural input (I) (such as fertilizer, seeds, land, labor, capital) and average rainfall (φ):

$$A = \mathrm{A}(\mathrm{I}, \varphi) \quad (39)$$

The average amount of input application depends on input prices (w):

$$\mathrm{I} = \mathrm{I}(\mathrm{w}) \quad (40)$$

The road density directly influences output prices (P), input prices (w), the literacy rate (L), mother's education (E_M) and non-farm enterprises (F).

$$\mathrm{P} = \mathrm{f}(\mathrm{R}) \quad (41)$$

$$\mathrm{w} = \mathrm{f}(\mathrm{R}) \quad (42)$$

$$\mathrm{E_M} = \mathrm{f}(\mathrm{R}, \mathrm{E}) \quad (43)$$

$$\mathrm{E_M} = \mathrm{f}(\mathrm{R}, \mathrm{E}) \quad (44)$$

$$\mathrm{F} = \mathrm{f}(\mathrm{R}) \quad (45)$$

When maximizing utility, the social planner faces a budget constraint. S/he collects money from the public in the form of a tax and submits it to the government. After receiving foreign aid and taxes from all districts, the government allocates a budget (B^i) to each district. The planner chooses budget allocations such that:

$$\theta_H H^i + \theta_R R^i + \theta_E E^i + \theta_S S^i + \theta_V V^i = B^i \quad 46)$$

where θ_k is the budget share for each activity and $\sum_k \theta_k = 1$. After substituting the value of each argument into the district average child nutrition function (N), equation (34) can be specified as:

$$\mathrm{U} = \mathrm{U}\left(\mathrm{N}\left(\begin{matrix} \mathrm{C}\left(\mathrm{A}\big(\mathrm{I}\big(\mathrm{w}(\mathrm{R})\big), \varphi\big), \mathrm{M}\left(\mathrm{A}\big(\mathrm{I}(\mathrm{w}(\mathrm{R}))\big), \mathrm{P}(\mathrm{R}), \mathrm{L}(\mathrm{R}, \mathrm{E}), \mathrm{F}(\mathrm{R})\right), \mathrm{P}(\mathrm{R})\right) \\ \mathrm{N_M}(\mathrm{E_M}(\mathrm{R}, \mathrm{E}), \mathrm{W}, \mathrm{H}), \mathrm{M}\Big(\mathrm{A}\big(\mathrm{I}\big(\mathrm{w}(\mathrm{R})\big), \varphi\big), \mathrm{P}(\mathrm{R}), \mathrm{L}(\mathrm{R}, \mathrm{E}), \mathrm{F}(\mathrm{R})\Big), \mathrm{V}, \mathrm{H}, \mathrm{S}, \mathrm{R} \end{matrix}\right)\right) \quad (47)$$

The choice variables for each social planner are: θ_H, θ_R, θ_E, θ_S and θ_V. The social planner maximizes utility function (equation 47) subject to the budget constraint (equation 46). This yields a reduced formed equation for the district average child nutrition outcome:

$$N^* = N(R, H, E, S, V, B, \varphi, W) \tag{48}$$

The total effect of road length on child nutrition based on equations (35) and (47) can be decomposed as:

$$\frac{dN}{dR_i} = \frac{\partial N}{\partial R} + \frac{\partial N}{\partial C}\frac{\partial C}{\partial A}\frac{\partial A}{\partial I}\frac{\partial I}{\partial w}\frac{\partial w}{\partial R} + \frac{\partial N}{\partial C}\frac{\partial C}{\partial M}\frac{\partial M}{\partial A}\frac{\partial A}{\partial I}\frac{\partial I}{\partial w}\frac{\partial w}{\partial R} + \frac{\partial N}{\partial C}\frac{\partial C}{\partial M}\frac{\partial M}{\partial P}\frac{\partial P}{\partial R} + \frac{\partial N}{\partial C}\frac{\partial C}{\partial M}\frac{\partial M}{\partial L}\frac{\partial L}{\partial R} + \frac{\partial N}{\partial C}\frac{\partial C}{\partial M}\frac{\partial M}{\partial F}\frac{\partial F}{\partial R} + \frac{\partial N}{\partial C}\frac{\partial C}{\partial P}\frac{\partial P}{\partial R} + \frac{\partial N}{\partial N_M}\frac{\partial N_M}{\partial E_m}\frac{\partial E_M}{\partial R} + \frac{\partial N}{\partial M}\frac{\partial M}{\partial A}\frac{\partial A}{\partial I}\frac{\partial I}{\partial w}\frac{\partial w}{\partial R} + \frac{\partial N}{\partial M}\frac{\partial M}{\partial A}\frac{\partial A}{\partial P}\frac{\partial P}{\partial R} + \frac{\partial N}{\partial M}\frac{\partial M}{\partial L}\frac{\partial L}{\partial R} + \frac{\partial N}{\partial M}\frac{\partial M}{\partial F}\frac{\partial F}{\partial R} \tag{49}$$

where $\frac{dN}{dR_i}$ is the total derivative of the effect of road on child nutrition outcomes. I expect this to be positive. The right-hand side terms are the direct and indirect partial effects of roads on child nutrition outcomes. As indicated by equations (47) and (49), roads influence child nutrition outcomes through various indirect pathways. Road expansion can be expected to decrease agricultural input prices, which will increase application of inputs. Higher input application results in an increase in total agricultural output, which should directly increase child food consumption or increase household income, thereby indirectly increasing food consumption. An increase in consumption translates into better child nutrition outcomes. Road expansion can also be expected to decrease retail food prices by reducing transportation costs. Although a reduction in agricultural prices may hurt net-sellers and their children, I expect that, because a majority of households in Nepal are net-buyers of food and lower food prices boost purchasing power, on average, child nutrition outcomes in a district will benefit from lower food prices. Districts with extensive road networks will have higher literacy rates among mothers, due to improved access to schools (CBS 2011). Higher literacy rates can contribute to higher incomes and better child nutrition outcomes. Similarly higher educational attainment of mothers improves employment, income and empowerment, all of which can contribute to better nutrition outcomes for mothers and their children. Districts with more non-farm enterprises generally have higher employment opportunities and, as a result, higher average incomes. This also translates into better consumption, health and nutrition outcomes.

4.4. Empirical model

4.4.1. Road index

There are three different types of roads in Nepal. Earthen roads are constructed during the initial phase of road construction. Later, earthen roads are transformed into gravel roads and, eventually, into black-topped roads. Black-topped roads are considered all-season roads and are the highest quality. Gravel roads are better than earthen roads in terms of road quality. When properly managed and operated, gravel roads may be suitable as all-season roads. Earthen roads may be passable during the dry season, but may be impassable during the rainy season. Although earthen roads exist in all districts of the country, as of May 2015, some districts in Nepal still did not have gravel or black-topped roads.

To measure the impact of roads on child nutrition outcomes, I first generate a road index using weights that account for different road qualities and the travel times that they imply. I initially assume that a black-topped road is five times faster than a gravel road and fifty times faster than an earthen road. Accordingly, the road index is computed as:

$$\mathrm{I} = 1.0 \times \text{length of blacktopped road} + 0.20 \times \text{length of gravel road} + 0.02 \times \text{length of earthen road} \tag{50}$$

where all values are expressed in km of linear distance. I then convert the index to a density measure, by dividing by district area (in km^2). My goal is to produce a measure of transport infrastructure that combines quantity and quality.[29]

4.4.2. Factors influencing the placement of roads in Nepal

Nepal is landlocked and mountainous. Agro-ecology and elevation can be important factors influencing the placement of roads. The Terai accounts for about 17% of the total land area. Since the Terai is flat, it is much cheaper to construct roads there than in districts of the hills and mountains, where topography makes road construction time and resource intensive. As shown in Figure 24, there is a negative and non-linear (quadratic) relationship between the road index and elevation.

[29] Below, in section 7, I report results from sensitivity analysis that explores the impact of changing the weights in equation 17.

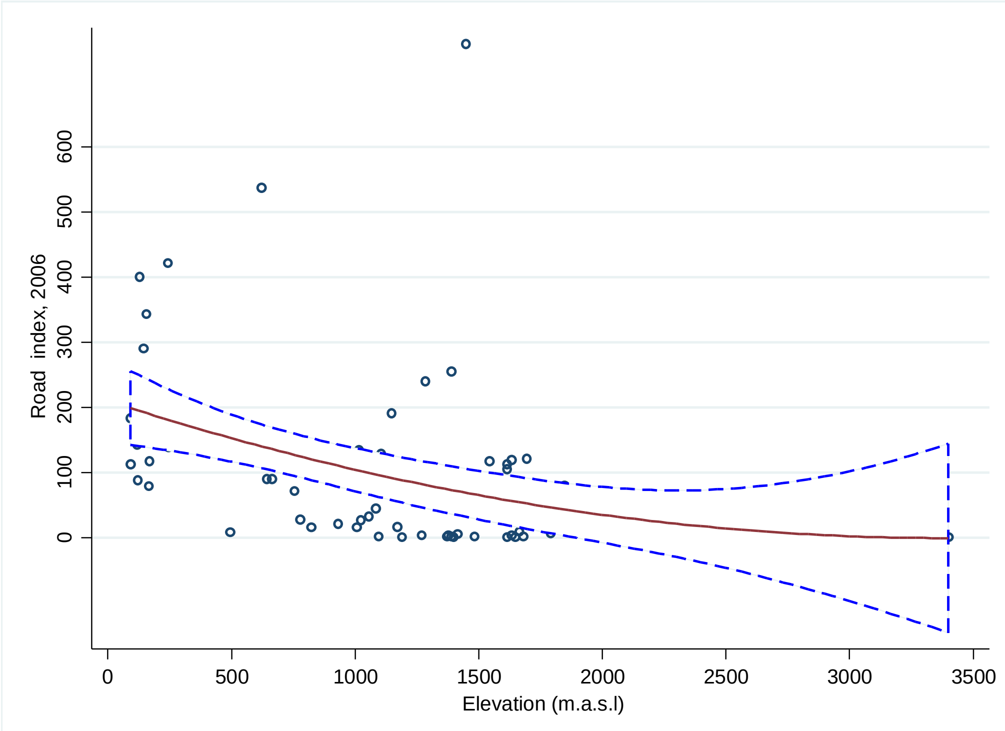

Figure 24. Relationship between road index in 2006 and elevation (m.a.s.l) in Nepal

I hypothesize that districts with strong political influence are likely to have more roads. In this study, I define a district as having strong political influence if at least one of its parliamentary members had been appointed as a minister at some point in the past.[30] During the campaigns, politicians promise constituents a range of development changes.

[30]I use the time period between 1994 and 2008 because major road construction in the country started after 1990. I also do not consider the period after 2008 because between 2008 and 2015, the government changed six times. Since a minister appointed during this period was unlikely to serve for very long, he was unlikely to play an influential role in road placement in his district.

However, some of these agendas are likely to be realized only when an elected official holds a minister-level position.

Districts with high populations may have higher road densities than districts with low populations, either because government is likely to focus development efforts on populous areas or because government receives greater pressure for road construction in such areas, or both. Clearly, our data supports this conjecture. As Figure 25 illustrates, there is a positive correlation between the road index and population, and the graph shows the non-linear (quadratic) relationship. Thus I hypothesize that population is one factor influencing road construction in a district.

I assume that districts close to the capital city are likely to have more roads than remote districts. Those districts have historically been the focus of Nepal’s development. This variable captures the radial structure of the development of the road network with Kathmandu city in the center. According to Figure 26, the road index in 2006 gradually decreases as one move away from the capital. Thus I hypothesize that districts located near the capital city possess more roads than far-away districts.

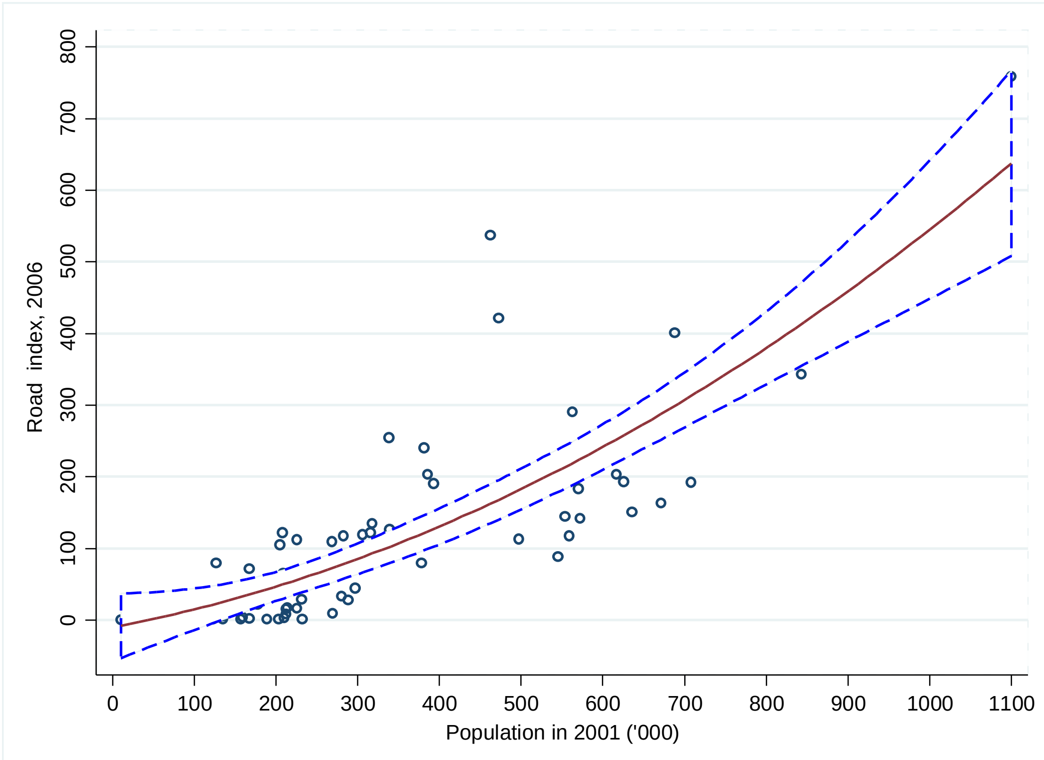

Figure 25. Relationship between Road Index in 2006 and Population (‘000) in Nepal

I exclude Kathmandu district from the non-spatial analysis for both conceptual and practical reasons. Kathmandu is a small and densely populated district with the highest road density in the country and is highly atypical for the country. When estimating the causal impact of road density on child nutrition outcomes using the generalized propensity score approach, there are no districts in the country that are similar enough to Kathmandu (in terms of observed covariates) to serve as a match. However when estimating the spillover effects of roads on child nutrition outcomes, I include Kathmandu district. Excluding Kathmandu distorts the spatial structure, and thus doing so prevents us from correctly estimating the spatial externality effects of roads on child nutrition outcomes.

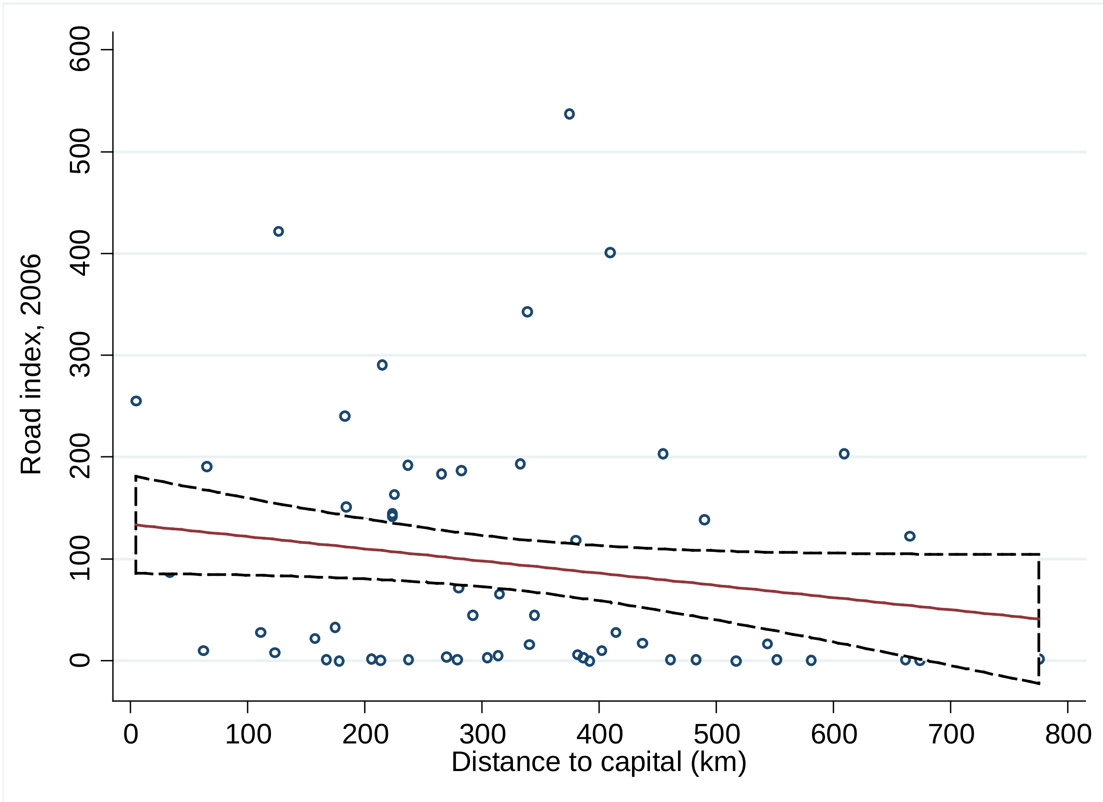

Figure 26. Relationship between Road Index in 2006 and Distance to Capital (km) in Nepal

As discussed above, I assume the district road density index (I) is a function of total district population (N), agro-ecological zone (hills (H), mountain (M)), elevation (E), political influence (P), and distance from the capital to the district headquarters in km (D). I simply use ordinary least squares to estimate the empirical model as follows:

$$\mathrm{I} = \alpha_0 + \alpha_1 \mathrm{N} + \alpha_2 \mathrm{H} + \alpha_3 \mathrm{M} + \alpha_4 \mathrm{E} + \alpha_5 \mathrm{P} + \alpha_6 \mathrm{D} + \varepsilon \tag{51}$$

I also examine the hypothesis of path dependency, by which I mean that changes in the road density index between 2011 and 2006 will be higher for those districts that have a higher initial road density index in 2006. One reason why this hypothesis might hold is that districts with ongoing road construction projects in 2006 were likely to continue for subsequent years. However the hypothesis of path dependency may not hold if districts with poor road infrastructure in 2006 were given priority for road construction between 2011 and 2006. The hypothesis of path dependency is examined using an ordinary least square regression while controlling for agro-ecological effects and elevation as follows:

$$\Delta \mathrm{I} = \gamma_0 + \gamma_1 \mathrm{I}_{06} + \gamma_2 \mathrm{H} + \gamma_3 \mathrm{M} + \gamma_4 \mathrm{E} + \varepsilon_{\mathrm{i}} \tag{52}$$

where ΔI is the change in road density index between 2011 and 2006 and I_{06} is the road density index in 2006.

4.4.3. Estimating the relationship between child nutrition outcomes and roads

One of the contributions of this study is the way it estimates the impacts of roads on child nutrition outcomes. This sub-section discusses the equations and identification strategies used to establish the casual impact of roads on child nutrition outcomes. The equations related to the child nutrition outcomes and roads are:

$$\mathrm{Z}^{\mathrm{H}}_{2011} = \mathrm{b}_0 + \mathrm{b}_1 \mathrm{I}_{06} + \mathrm{b}_2 \mathrm{E} + \mathrm{b}_3 \mathrm{H} + \mathrm{b}_4 \mathrm{M} + \mathrm{b}_5 \mathrm{L} + \mathrm{b}_6 \mathrm{F} + \mathrm{b}_7 \mathrm{N} + \mu \tag{53}$$

$$\mathrm{Z}^{\mathrm{w}}_{2011} = \delta_0 + \delta_1 \Delta \mathrm{I} + \delta_2 \mathrm{E} + \delta_3 \mathrm{H} + \delta_4 \mathrm{M} + \delta_5 \mathrm{L} + \delta_6 \mathrm{F} + \delta_7 \mathrm{N} + \epsilon \tag{54}$$

where Z^{H}_{2011} denotes the district-level average HAZ for children below age five in 2011; Z^{w}_{2011} denotes the district-level average WHZ in 2011; L denotes the district literacy rate in 2001; F denotes whether a district annual agricultural production is able to meet the annual food requirement need of its population; N denotes the total number of health facilities divided by the total population in a district in 2011; and μ and ϵ are error terms with mean zero. $I_{06}, \Delta I, E, H,$ and M are already defined above (see Table 12 for a full list of explanatory variables). The only difference between equations (53) and (54) is that in equation (54), I replace the variable I_{06} with ΔI. I do this because, by definition, WHZ is a short-term measure of nutrition outcomes and is expected to be responsive to short-term changes. Thus ΔI is more likely to influence WHZ while I_{06} is more likely to influence HAZ. I also replace the road density index variables in equations (53) and (54) with variables for the proportion of all-season road.[31] Taking the partial derivative of Z^{H}_{2011} with respect to I_{06} in equation (53) one obtains:

$$dZ^{H}_{2011}/dI_{06} = b_1\epsilon \tag{55}$$

Similarly, for Z^{W}_{2011}, the partial effects with respect to ΔI is δ_1. Evidence that b_1 and δ_1 are positive and statistically significant confirms the hypothesis that roads have a positive long-term and short-term impact on the nutrition outcomes of children.

Although this approach provides an estimate of correlation between child nutrition outcomes and road infrastructure, I am interested in estimating the causal impact of roads on child nutrition outcomes. As discussed above, road placement, especially placement of strategic roads, can be influenced by a range of observable factors. In general, treatment

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[31] This proportion variable is discussed in the data section.

exposure cannot be assumed random, and I need a corrective procedure to isolate the treatment effects. The next sections elaborate on the identification strategies and the spatial econometric approach used to estimate the impact of roads on child nutrition outcomes.

4.4.4. The generalized propensity score

When treatment is binary, the propensity score framework developed by Rosenbaum and Rubin (1983) can be used to estimate the effects of treatment. In many instances, however, treatment is continuous or categorical. The literature on estimating continuous treatment effects has grown recently. The approach has been widely used in medical- and health-related fields to estimate the dose-response function when a drug dosage is continuous (Efron and Feldman 1991). Although Imbens (2000) originally developed a generalized propensity score (GPS) technique for estimating multiple treatments, Hirano and Imbens (2004) developed a generalization of the binary treatment propensity score that can be appropriate for estimating continuous treatment. Given that our treatment, i.e. road density, is continuous, I follow the Hirano and Imbens (2004) approach to estimate the dose-response function, where the “dose” is road density and the “response” is child Z-scores. For HAZ in 2011, the treatment is the road density index in 2006. For WHZ in 2011, the treatment is the change in the road density index between 2011 and 2006.

In Figure 27, WHZ and HAZ in 2011 are plotted against the 2006 road density index. In Figure 28, WHZ and HAZ in 2011 are plotted against the change in the road density index between 2011 and 2006. From these figures, I see that HAZ is highly correlated with the initial condition (road index in 2006) while WHZ is highly correlated with the road index changes between 2011 and 2006. This seems to follow the logic of our dose-response framework because, as a measure of long-term nutrition outcomes, HAZ in 2011 could be expected to respond to infrastructure with a lag. As a short-term measure of nutrition outcomes, WHZ is more sensitive to the short-term changes in infrastructure. This shows up in the figures as a correlation between WHZ in 2011 and the change in the road density index between 2011 and 2006.[32]

The dose-response function model is explained in detail by Hirano and Imbens (2004). Here I briefly review the assumptions of the model and the estimation process, using their notation of Hirano and Imbens (2004). I have a total of 74 districts indexed by $i=1,2,\ldots,74$. For each district i, I observe a $p\times 1$ vector of pretreatment covariates X_i, the treatment received (road density index) T_i, and the outcome variable (Z-score) associated with the treatment Y_i. For the 2006 treatment, the pretreatment covariates are total population, ecological indicators, elevation, political influence, and distance (in km) from the capital to the district headquarters. For the 2011 treatment (change in road index between 2011 and 2006), the pretreatment covariates are road index in 2006, ecological indicators and elevation. The key identification assumption is that conditional on these pretreatment covariates, road placement in different districts is random.

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[32]For some districts, the officially reported road length remained constant between 2011 and 2006. After consulting with engineers of the Nepal Road Department, I increased earthen road lengths of such districts by 5% between 2010 and 2011. In the case of Mugu and Dolpa, where strategic road length was not reported, I used rural road length (earthen) as reported by DOLIDAR in 2011 as the 2011 road length.

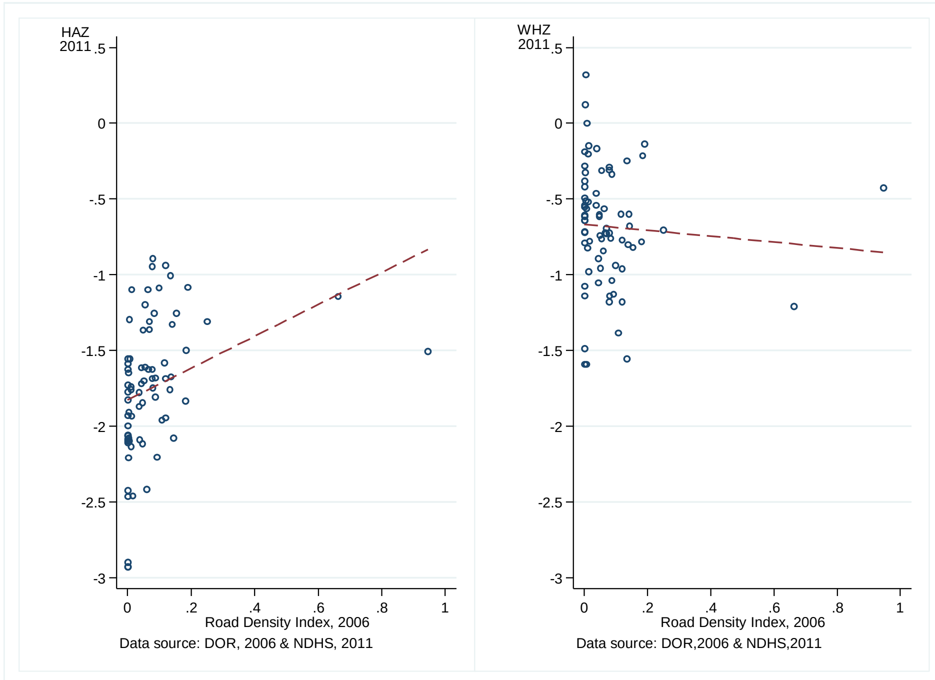

Figure 27. Road Density Index and Child Nutrition in Nepal, 2006

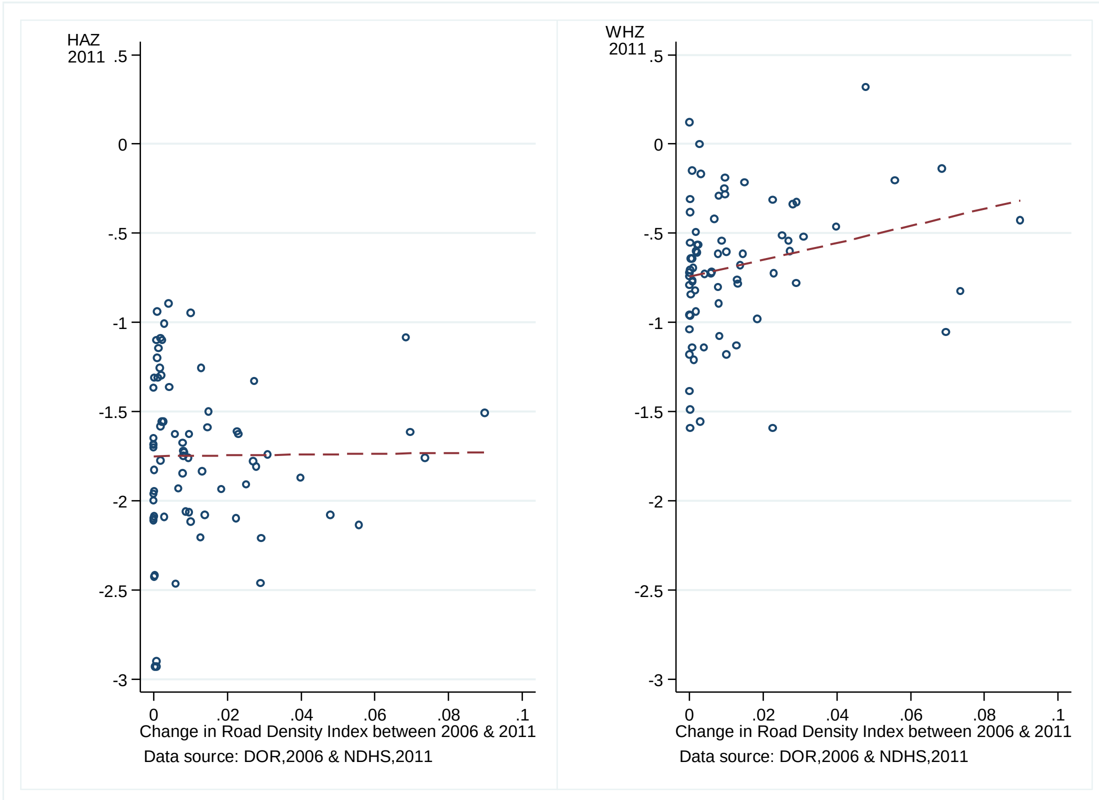

Figure 28. Change in Road Density Index between 2011 and 2006 and Child Nutrition in Nepal

I use the counterfactual framework where unit *i* has a set of potential outcomes, defined as $\{Y_i(t)\}_{t\in\tau}$, *i=1,2,…,74* and τ is a set of continuous treatment values. Here $\{Y_i(t)\}_{t\in\tau}$ is the unit-level dose-response function. I am interested in estimating the average dose-response function $\hat{\mu}(t) = E\{Y_i(t)\}$. Although the parametric model assumes a normal distribution of the treatment variable, I observe a conditional distribution of the road density index that is highly skewed. Thus I use a logarithmic transformation of T_i to correct for non-normality. I implement a normal linear model for the conditional distribution of treatments given the covariates:

$$g(T_i)|X_i \approx N(\beta_0 + \beta_1 X_i, \sigma^2) \tag{56}$$

where $g(T_i)$ is a logarithmic transformation of the treatment variable. The regression model is estimated using maximum likelihood, where $g(T_i)$ is the dependent variable, and the independent variables are X_i. The estimated regression coefficients are used for calculating the GPS. To estimate the GPS, I must choose a treatment level t_i. I divide the sample into sub-classes and use the median ln(T) within each class to estimate the sets of GPSs. The GPS is defined as the conditional density of the treatment given the covariates, and is calculated as:

$$\widehat{R}_i = \frac{1}{\sqrt{2\pi\widehat{\sigma}^2}} \exp\left(-\frac{1}{\sqrt{2\widehat{\sigma}^2}}(g(T_i) - \widehat{\beta_0} - \widehat{\beta_1}X_i)^2\right) \tag{57}$$

The GPS has a balancing property similar to the balancing properties of the propensity score for binary treatments. Hirano and Imbens (2004) prove two theorems related to the balancing property of GPS: (1) weak unconfoundedness given the GPS, which implies that the GPS can be used to remove any bias associated with differences in the observed covariates X; and (2) bias removal with GPS. For the data and model, the balancing property is satisfied at a 0.01 test level. The balancing test assures that, within strata and with the same value of $r(T_i; X_i)$, the probability that T_i=t_i does not depend on the value of X_i so that differences in the set of covariates X in the comparison and treatment groups are removed. Once the balancing test is met, the conditional expectation of the child nutrition outcome as a function of two scalar variables, the treatment level T_i and the R_i, $\widehat{gps}$, is estimated as:

$$\mathrm{E}[\mathrm{Y_i}|\mathrm{T_i} = \mathrm{t_i}, \mathrm{R_i} = \mathrm{r_i}] = \mathrm{E}[\mathrm{Y_i}(\mathrm{t})|\mathrm{r_i}(\mathrm{t}, \mathrm{X}) = \mathrm{r}] = \beta_\mathrm{i}(\mathrm{t}, \mathrm{r}) \tag{58}$$

A regression of Y_i on the treatment T_i and R_i includes all second-order moments of treatment and pscore as follows:

$$\beta_\mathrm{i}(\mathrm{t}, \mathrm{r}) = \mathrm{E}[\mathrm{Y_i}|\mathrm{t_i}, \mathrm{r_i}] = \mathrm{b_0} + \mathrm{b_1 t_i} + \mathrm{b_2 r_i} + \mathrm{b_3 t_i^2} + \mathrm{b_4 r_i^2} + \mathrm{b_5 r_i} \times \mathrm{t_i} \tag{59}$$

The estimated coefficients of equation (59) do not have a direct interpretation. However, Hirano and Imbens (2004) assert that testing whether all coefficients equal zero can be interpreted as a test of whether the independent variables introduce any bias. Given the estimated parameters in equation (59), the average potential outcome, $\hat{E}[Y_i]$, can be estimated.[33] This is known as the dose-response equation, and is:

$$\hat{\mu}(\mathrm{t}) = \hat{\mathrm{E}}[\mathrm{Y_i}] = \frac{1}{\mathrm{N}}\sum_{\mathrm{i}=1}^{\mathrm{N}}\left(\hat{\mathrm{b}}_0 + \hat{\mathrm{b}}_1\mathrm{t} + \hat{\mathrm{b}}_2\hat{\mathrm{r_i}} + \hat{\mathrm{b}}_3\mathrm{t}^2 + \hat{\mathrm{b}}_4\hat{\mathrm{r_i}}^2 + \hat{\mathrm{b}}_5\hat{\mathrm{r_i}} \times \mathrm{t}\right)\mathrm{t_i} \tag{60}$$

I compute $\hat{\mu}(t)$ to get an estimate of the entire dose-response function. The function is mean-weighted by each different calculated *r*, estimated in correspondence of that specific treatment *t*. To compute standard errors and confidence intervals, I use a bootstrapping technique, taking into account the estimation of the beta parameters and GPS. Finally I compute a non-constant effect of treatment on the treated by differencing between the average and the benchmark level of treatment as follows:

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[33]Adding higher-order polynomials in treatment (t) and pscore (r) adds little additional explanatory power to the model.

$$\hat{\theta}(t) = \hat{\mu}(t) - \hat{\mu}(\tilde{t})\ \forall t \epsilon T \tag{61}$$

where $\tilde{t}$ is a benchmark road density index, here the lowest road density index recorded in the data.

4.4.5. Instrumental variable approach

If the road density index variables are exogenous to child nutrition outcomes, coefficient b_1 from equation (53) represents the average treatment effects (ATE) of roads on HAZ in 2011, and δ_1 from equation (54) represents the average treatment effects (ATE) of roads on WHZ in 2011. However these coefficients are likely to be inconsistent if the road-related variables $(I_{06}, \Delta I)$ are correlated with unobservables (μ, ϵ). As mentioned above, road placement in a district could be correlated with unobserved factors that affect child nutrition outcomes.

I used an instrumental variable (IV) approach to deal with the potential correlation between road-related variables and unobservables. Potential candidates for suitable IVs are political influence, elevation, and distance to the capital. In order to be a suitable instrument, a candidate variable should first be correlated with the road density index, i.e. it should meet a relevance criterion. Second, a candidate variable should be uncorrelated with the unobservables, i.e. it must meet an exclusion restriction. Among possible candidates, political influence may not be a good instrument because ministers with influence may, in addition to building roads, launch projects that could directly influence child nutrition outcomes. Our second candidate, elevation may be correlated with soil fertility and may therefore influence nutrition outcomes through effects on agricultural production. Our third candidate, distance to the capital seems like a good instrument. As discussed above, districts that are close to Kathmandu have historically been the focus of Nepal's development and thus are likely to have higher road density (thereby meeting the relevance criterion) but cannot be argued to be correlated with the child nutrition outcomes (thereby meeting the exclusion restriction). Fernandez and Santos (2014) also used "distance to Mexico City" as an instrumental variable to estimate the causal impact of road infrastructure on the industrial average product of labor in Mexico. Here the identifying assumption is that distance to the capital is uncorrelated with ε_1 in equation (62):

$$Z^{H}_{2011} = b_{01} + b_{11}\hat{I}_{06} + b_{21}E + b_{31}H + b_{41}M + b_{51}L + b_{61}F + b_{71}N + \varepsilon_1 \qquad (62)$$

where $\hat{I}_{06}$ is the predicted value of I_{06} obtained from the first-stage regression of road density index in 2006 on distance to capital and all the control variables in equation (63) such that:

$$Z^{H}_{2011} = b_{01} + b_{11}\hat{I}_{06} + b_{21}E + b_{31}H + b_{41}M + b_{51}L + b_{61}F + b_{71}N + \varepsilon_1 \qquad (63)$$

$$I_{06} = b_{02} + b_{12}D + b_{22}E + b_{32}H + b_{42}M + b_{52}L + b_{62}F + b_{72}N + \varepsilon_2 \qquad (64)$$

where D is the distance to capital (km), ε_2 is an error term with mean zero. The standard error for the instrumented variable ($\hat{I}_{06}$) in the second stage is corrected. The remaining variables are defined as above. According to Angrist and Pischke (2009), the coefficient b_{11} can be considered as the local average treatment effects (LATE) of roads on child nutrition outcomes, given validity of our instrument (distance to capital).

One might also like to use the distance to capital (km) as an instrument for the changes in road density index between 2011 and 2006, in addition to instrumenting the road density index in 2006/11. However each endogenous variable requires its own instrument (Woolridge 2002, p.236). Since I have only one instrument available, the empirical results on the impacts of change in the road density index between 2011 and 2006 and proportion of changes in the all-season roads between 2011 and 2006 for Z_{2011}^{W} cannot be claimed to be causal.

Lastly, one might argue that omission of control variables like food prices and incomes in equations (62) could affect the identification of the causal impact of the roads on child nutrition outcomes. However the effects of these variables are likely to be captured by the agro-ecological fixed effects, since the mountain districts have high food prices and low incomes and the Terai districts have low food prices and high incomes (CBS 2011).

4.4.6. Spatial econometrics approach

I can find no reason to argue that the average child nutrition outcome in one district would influence the average child nutrition outcome in a neighboring district. I therefore put aside considerations of employing a spatial lag model. However, I have reasonable arguments to support the use of spatial error and cross-regressive models.

As discussed above, roads and road networks not only have potential impacts locally but also potentially have impacts on outcomes in adjoining locations where roads connect to extended networks. Thus there are externalities from one district with rich road infrastructure to another adjacent district with poor road infrastructure or where two districts are linked by the same road. Fernandez and Santos (2014) found significant spatial spillovers from road infrastructure to the manufacturing sector in Mexico. Even after addressing endogeneity issues in equations (62), spillover effects may remain because the GPS approach is not able to account for spatial externalities.

I use a cross-regressive spatial econometric model to account for potential district-level spillover effects. Estimating this spatial econometric model requires a *75 × 75* spatial weights matrix (W) to account for the structure of neighbor relations. Our weight matrix consists of binary entries, where $w_{ij} = 1$ when *i* and *j* are neighbors (sharing a common border or edge), and $w_{ij} = 0$ when they are not. The diagonal elements $w_{ii} = 0$. To facilitate interpretations, I create a row-standardized first-order queen weight matrix. I modify equations (54) and (62) to represent the cross regressive model (also called the spatial Durbin model) by adding average-neighbor values of the roads related variables as follows:

$$Z^{H}_{2011} = b_{11} + W\hat{I}_{06}b_{12} + b_{22}E + b_{32}H + b_{42}M + b_{52}L + b_{62}F + b_{72}N + b_{82}\hat{I}_{06} + \varepsilon_2 \quad (65)$$

$$Z^{w}_{2011} = \delta_{11} + W\Delta I\delta_{12} + \delta_{22}E + \delta_{32}H + \delta_{42}M + \delta_{52}L + \delta_{62}F + \delta_{72}N + \delta_{82}\Delta I + \epsilon_2 \quad (66)$$

where the coefficients b_{12} and δ_{12} represent the indirect effects or local spatial spillover effects, and b_{82} and δ_{82} represent the direct effects of road-related variables on Z-scores. Equations (63) and (65) can be estimated using OLS.

Since our data are observed at the district level, autocorrelation in the stochastic disturbances of equations (64) and (65) cannot be ruled out. Errors are likely to be correlated if spatially correlated variables are omitted. Also, any natural shocks (such as drought) that occur in some geographically close districts of the country could introduce spatial autocorrelation. For example, a disease/pathogen outbreak in one district could spread to a neighboring district, thereby influencing Z-scores. If errors are correlated, some or all the off-diagonal elements of the variance-covariance matrix will be non-zero, violating the assumption of OLS. Testing for spatial autocorrelation among OLS residuals from (64) and (65) using Moran's test reveals the presence of significant spatial autocorrelation for most implementations of our models. To account the spatial autocorrelation of errors, I modify the error terms of equations (64) and (65) as follows:

$$\mathrm{\varepsilon}_2 = \mathrm{\rho W \varepsilon}_2 + \mathrm{v} \quad (67)$$

$$\epsilon_2 = \mathrm{\tau W} \epsilon_2 + \mathrm{u} \quad (68)$$

with v and u assumed to be normal with $E(v) = 0, E(u) = 0, E(vv') = \sigma_v^2 I$, and $E(uu') = \sigma_u^2 I$. Here, ρ and τ are the scalar spatial autoregressive coefficients with absolute values less than one. Solving for the error specification for ε_2 and ϵ_2, I find $(I - \rho W)\varepsilon_2 = v$ or $\varepsilon_2 = (I - \rho W)^{-1} v$ and $\epsilon_2 = (I - \tau W)^{-1} u$. Now I can write $E(\varepsilon_2) = 0, E(\varepsilon_2 {\varepsilon_2}') = \sigma^2 (I - \rho W)^{-1} (I - \rho W)^{-1}$=$\sigma^2 \Omega$, a formulation that considers both heteroskedastic and auto-correlated error terms. W is assumed to satisfy the condition that $(I - \rho W)$ is nonsingular for all $|\rho| < 1$. The parameters are estimated using the maximum likelihood estimation method.

4.5. Data

I use child nutrition data from the 2006 and 2011 Nepal Demographic and Health Surveys (NDHS). A total of 5,237 children were included in the 2006 survey, and 2,335 were included in the 2011 survey. The NDHS data were collected by trained enumerators under the supervision of the Ministry of Health and Population (MOHP) Nepal. This is a comprehensive and nationally representative geo-referenced household survey where samples are selected using a stratified two-stage cluster design. I calculated the unweighted district average HAZ and WHZ for each survey year. I procured annual time series data on total length (km) of earthen, gravel and black pitched roads constructed in each district from the Department of Roads, Ministry of Physical Planning and Works, Nepal. I created the road index for 2006 and 2011 by summing the length of different roads after adjusting for road quality as discussed above. The detailed data on length of road and our constructed road index are provided in Appendix A.1. I converted the road index to a density by dividing it by district area (in km^2). This serves as our continuous treatment. Also in an addition to the road density index, I created the proportion of all-season roads in the district by diving total length of black-topped and gravel roads by the total length of strategic roads in each district. Also, the distance from the capital city (Kathmandu) to each district headquarters was calculated through network analysis in ArcGIS 10.1. These distances are reported in Appendix A.2. Population and literacy rate data come from Nepal Central Bureau of Statistics. Elevation data come from the Nepal Department of Hydrology and Meteorology under the Ministry of Environment, Government of Nepal. I created the variable “Political Influence.” This is a binary variable that takes the value 1 if any member of a district held a ministerial position in the government between 1994 and 2008. The lists of ministers formed in each change of government were compiled and combined using newspaper sources and the Nepal Home Ministry official website. The detailed list is provided in Appendix A.3. The data on district food sufficiency in 2011 comes from the Ministry of Agriculture (NMOAD), Nepal. The NMOAD considers a district to be food sufficient if its annual agricultural production is able to meet the annual food requirement of its population. The number of health facilities existing in a district in 2014 come from the Nepal Ministry of Health and Population (NMOHP).

The descriptive statistics of variables used in the analysis are provided in Table 12. The mean road index increased from 95.4 to 115 between 2011 and 2006 and the average change in the road index was 20. The distributions shifted to the right between 2011 and 2006 (Figure 29). In fact, the total strategic road length increased roughly 13% between 2011 and 2006, from 21,464 km to 24,655 km (DOR 2012).[34] The average proportion of all-season roads in a district increased from 0.38 to 0.43 between 2011 and 2006, indicating an upgrade in road quality from unpaved to paved roads. The minimum change in all-season roads between 2011 and 2006 is negative, indicating increasing attention toward constructing new unpaved roads rather than upgrading road quality. The average district population in Nepal increased from 298,300 to 336,200 between 2001 and 2011.

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[34] If I include rural roads defined as those constructed in rural communities and are mainly unpaved in nature, then the percentage increase is higher. The World Bank reports about 5% annual increase, on average, in the total road length in Nepal.

Nepal has made significant progress in increasing district literacy rates. These rose, on average, from 57% to 68% between 2001 and 2011. The maximum literacy rate reported for district was 84% in 2011. Sixty percent of districts in Nepal had a full-minister and eighty percent had either a full or state minister between 1994 and 2008. Sixty percent of districts were reported to be food sufficient in 2011. The maximum distance to the capital is 776 km. The mean HAZ and WHZ of children below five years improved between 2011 and 2006. The mean HAZ and WHZ in 2011 for children below 3 years of age were higher than those of children between 3 and 5 years of age. Average WHZ was higher than average HAZ, indicating the seriousness of Nepal's long-term nutrition problems.

Table 12. Descriptive Statistics for the Variables used in the Analysis

Variable	Obs	Mean	Std. Dev.	Min	Max
Road index in 2006	74	95.4	110.2	0.0	537.1
Road index in 2011	74	115.0	116.7	0.5	575.8
Change in road index (between 2011 and 2006)	74	19.6	27.9	0.0	151.8
Proportion of all-season road in 2011	74	.43	.26	0	.82
Proportion of all-season road in 2006	74	.38	.28	0	.82
Change in the proportion of all-season road between 2011 and 2006	74	.05	.14	-.08	.76
District population in 2001 (‘000s)	74	298.3	190.8	9.6	843.2
District population in 2011 (‘000s)	74	336.2	234.3	652.7	964.7
Literacy rate (%) in 2001	74	57.22	11.33	30.13	76.76
Literacy rate (%) in 2010	74	67.91	8.70	45.38	84.27
Number of health facilities per million population in 2011[c]	74	28	28	5	214
Hill†	74	0.5	0.5	0.0	1.0
Mountain†	74	0.2	0.4	0.0	1.0
Terai†	74	0.3	0.4	0.0	1.0
Elevation (m.a.s.l.)	74	1126.8	781.9	91.0	3400.0
Political influence (full minister)†	74	0.6	0.5	0.0	1.0
Political influence (full & state minister)†	74	0.8	0.4	0.0	1.0
Food sufficiency status in 2011†	74	0.6	0.5	0.0	1.0
Distance to capital (km)	74	321.1	197.7	4.6	775.7
Height-for-age, 2011 (Kids < 5 years)	74	-1.7	0.5	-2.9	-0.9
Height-for-age, 2006 (Kids < 5 years)	74	-2.0	.4	-3.0	-1
Height-for-age, 2011 (Kids < 3 years)	74	-1.6	0.5	-3.0	-0.4
Height-for-age, 2006 (Kids < 3 years)	74	-1.8	0.5	-3.0	-0.6
Height-for-age, 2011 (Kids 3 to 5 years)	74	-2.0	0.5	-3.0	-0.4
Height-for-age, 2006 (Kids 3 to 5 years)	74	-1.8	0.5	-3.0	-0.6
Weight-for-height, 2011 (Kids < 5 years)	74	-0.7	0.4	-1.6	0.3
Weight-for-height, 2006 (Kids < 5 years)	74	-0.8	0.3	-1.7	-0.1
Weight-for-height, 2011 (Kids < 3 years)	74	-0.7	0.5	-1.9	0.4
Weight-for-height, 2006 (Kids < 3 years)	74	-0.9	0.4	-1.8	0.2
Weight-for-height, 2011 (Kids 3 to 5 years)	74	-0.6	0.5	-2.1	1.3
Weight-for-height, 2006 (Kids 3 to 5 years)	74	-0.7	0.4	-2.0	0.05

Note: Terai is reference category, † indicates a binary indicator, [c]health facilities includes health post, sub-health post, primary health center, private nursing home, district hospital, zonal hospital, and district ayurvedic ausadhalaya.

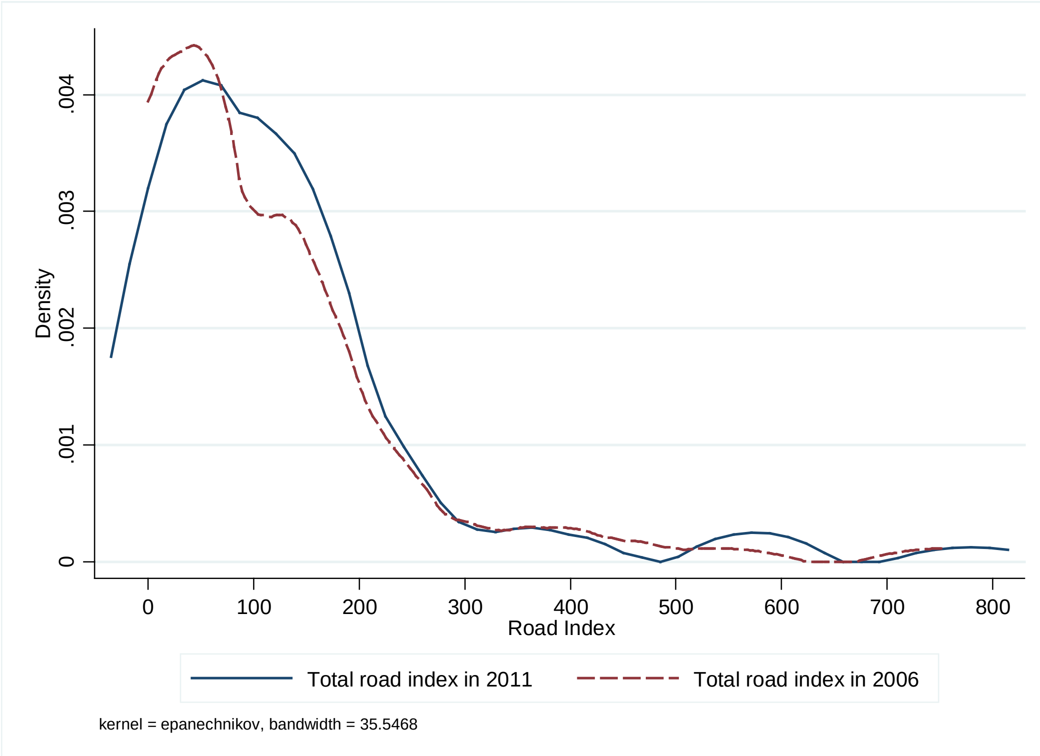

Figure 29. Kernel Density Plot of Road Index in 2006 and 2011 (Black-Topped Road Five times as Effective as Gravel Road and Fifty times Effective as Earthen Road)

4.6. Results

4.6.1 Factors influencing the placement of roads

Regression results for the district road index in 2006 and 2011 are reported in Table 13. Model 1 shows the regression results for the factors influencing road density index in 2006. Model 2 reports the regression results for the factors correlated with the road density index in 2011. The coefficient on population is positive in both models but only statistically significant for Model 2. Surprisingly, the coefficient on elevation is not statistically significant. Model 1 shows that districts with high political influence have a higher road density index than districts with no political influence. The coefficient is weakly significant at a 0.10 level. The coefficient on distance to the capital (in km) is statistically significant and negative, indicating that districts away from the capital have lower road density index values. Variables from Model 1 are used in the estimation of the generalized propensity scores to estimate the causal impact of road density on HAZ 2011.

Table 13. Regression Results for District Road Density Index, 2006 and 2011

Variables	Road density index in 2006	Road density index in 2011
Elevation (meters)	0.00002	0.00003
	(0.00003)	(0.00003)
Population in 2001 ('000s)	0.0001	-
	(0.0001)	-
Population in 2011 ('000s)		0.0003*
		(0.0001)
Political influence[d]	0.064*	0.056
	(0.037)	(0.038)
Distance to capital (km)	-0.0001**	-0.0001*
	(0.0008)	(0.00008)
Constant	0.031	-0.085
	(0.123)	(0.124)
Fixed effect (region k=3)	YES	YES
Observations	74	74
R-squared	0.24	0.26

[d] indicates a binary indicator, Standard errors in parentheses,*** p<0.01, ** p<0.05, * p<0.1

Table 14 reports results on factors explaining change in road density index between 2011 and 2006 and shows evidence of path dependency in road construction in Nepal. Results illustrate that districts with a higher road density index in 2006 had a larger positive change in the road density index between 2011 and 2006. The marginal effect is

0.05 and is statistically significant at the 0.01 test level. The coefficient for elevation is not significantly different from zero.

Table 14. Regression Results for Change in Road Density Index, 2006-2011

Variables	Model 1
Road density index in 2006	0.0457***
	(0.0159)
Elevation (m.a.s.l.)	-0.000015
	(0.0000)
Constant	0.0042
	(0.0045)
Fixed effect (region k=3)	YES
Observations	74
R-squared	0.20

[d] indicates a binary indicator, Standard errors in parantheses, *** p<0.01, **p<0.05, *p<0.1

4.6.2. Results from the dose-response function

As indicated above, the treatment variable for HAZ is the district road index in 2006. The treatment for WHZ is the change in the district road index between 2011 and 2006. No road length was recorded for Solukhombu, Dolpa, and Mugu districts in 2006. For these districts, I assigned the lowest road density observed in the dataset in 2006. After logarithmic transformation of the treatment variable for both models, Kolmogorov-Smirnov tests of normality of the conditional errors are satisfied at the 1% level. For the 2006 treatment: elevation, population, Terai and mountain variables were dropped because of the imbalance of covariates. Tables 15 and 16 present the results of the balance check. Bia and Mattei (2008) presents the “order of magnitude” interpretations of the test statistics.[35] Statistics that show strong to very strong evidence against the balancing property (i.e. *t* statistics greater than 1.96) are in bold and highlighted. After GPS adjustment, *t* statistic show imbalance of covariates based on the *student t* statistics in Table 15 and Table 16. Comparing the value of the t statistic adjusted for GPS with the *t* statistic unadjusted for GPS, I observe that the GPS helped to improve the balancing of overall covariates. I take this as very slight evidence against satisfying the balancing property.

Tables 17 and 18 show the estimates of the first and second stages used to estimate the causal effect of the road density index on HAZ. Tables 19 and 20 show the estimates of the first and second stages to estimate the causal effect of the changes of the road density index on WHZ. The first stage estimates indicate the importance of political influence and the distance from the capital to the district headquarters (in km) in explaining the treatment dose (district road index in 2006) (Table 17). The agroecological (Terai) and elevation (meters) variables are important for explaining the treatment dose (change in road density index between 2011 and 2006) (Table 19). None of the coefficients in Tables 17 and 29 are significant. Since the parameters of the second-stage are insignificant, the independent variables do not introduce any bias (Hirano and Imbens 2004).

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[35] The absolute *t* value of less than 1.282 is considered as evidence supporting the balancing property (BP), absolute t value between 1.282 and 1.645 is considered as very slight evidence against the BP, absolute t value between 1.645 and 1.960 is considered as moderate evidence against the BP, and absolute t value of greater than 2.576 is considered as decisive evidence against the BP (Bia and Mattei 2008).

Table 15. Balance given the Generalized Propensity Score (Treatment is Road Density Index in 2006)

Treatment interval and covariate	Unadjusted t, (unmatched sample)	Adjusted t, (matched sample)
[-9.151, -4.085]		
Full/State minister	3.20	1.61
Hill	-0.50	-0.76
Distance to capital (km)	-2.14	-1.01
[-3.32, 2.005]		
Full/State minister	-1.80	-1.06
Hill	-0.95	-0.76
Distance to capital (km)	-0.84	-0.64
[-1.98, -.055]		
Full/State minister	-1.69	-1.82
Hill	1.66	**2.37**
Distance to capital (km)	1.50	1.67

Note: t-statistics for equality of means, bold t-values indicates strong to very strong evidence against the BP.

Table 16. Balance Given the Generalized Propensity Score, Treatment is the Change in the Road Density Index between 2011 and 2006

Treatment interval and covariate	Unadjusted t, (unmatched sample)	Adjusted t, (matched sample)
[-10.99, -8.12]		
Road density index in 2006	0.60	0.14
Mountain	-1.76	-0.52
Terai	-1.71	-1.66
Elevation	-1.00	-0.07
[-7.86, -6.07]		
Road density index in 2006	-0.62	-0.39
Mountain	1.46	1.04
Terai	-0.14	-0.56
Elevation	-0.25	-0.42
[-5.92, -4.20]		
Road density index in 2006	0.44	0.28
Mountain	-0.94	-0.78
Terai	-0.19	-0.88
Elevation	1.15	1.23
[-3.99,-3.04]		
Road density index in 2006	0.98	1.22
Mountain	1.22	0.99
Terai	1.61	1.37
Elevation	0.53	-0.12
[-2.89,-2.41]		
Road density index in 2006	-2.91	**-2.01**
Mountain	1.21	1.08
Terai	0.35	0.02
Elevation	0.25	0.35

Note: t-statistics for equality of means, bold t-values indicates strong to very strong evidence against the BP.

Table 17. First Stage. MI Estimates of GPS for the Treatment-Road Density Index in 2006

Variables	Model 1
Hilly district[d]	0.57
	(0.50)
Full/State minister[d]	2.09***
	(0.61)
Distance to capital (km)	-0.004***
	(0.001)
Constant	-4.76***
	(0.77)
Observations	74
Wald chi2(4)	25.3
Prob>chi2	0.00

[d] indicates a dummy variable, Standard errors in parentheses,*** p<0.01, ** p<0.05, * p<0.1

Table 18. Second Stage: OLS Estimation of GPS for Outcomes-HAZ

Variables	HAZ, 2011 (Below 5 years)	HAZ , 2011 (3 to 5 years)	HAZ, 2011 (Below 3 years)
treatment (t)[a]	0.23	0.28	0.28
	(0.15)	(0.18)	(0.18)
treatment square (t^2)	0.004	0.01	0.01
	(0.01)	(0.01)	(0.01)
pscore (r)	-6.91	-9.53	-9.53
	(8.82)	(11.20)	(11.20)
pscore square (r^2)	14.08	30.90	30.90
	(26.67)	(33.87)	(33.87)
treatment (t) ×pscore (r)	-0.77	-0.22	-0.22
	(0.63)	(0.81)	(0.81)
Constant	-0.62	-0.63	-0.63
	(0.76)	(0.97)	(0.97)
R-square	0.33	0.24	0.24
Observations	74	74	74

Note:[a] treatment is the road density index in 2006. Standard errors in parentheses, none of the coefficients are statistically significant at less than 0.1 test level.

Figures 30 to 32 plot the road density index response function $\hat{E}[Y_i]$ for HAZ. Figures 33 to 35 plot the road density index response function for WHZ. The dashed lines in the figures show the 95% confidence intervals (calculated using the bootstrap resampling procedure). The confidence interval is much wider at the lower and higher treatment levels reflecting the small number of observations in those treatment levels. The dotted horizontal line is the treatment benchmark and is considered the null treatment estimate, $\hat{\mu}(\tilde{t})$. The treatment benchmark is set at the lowest treatment levels recorded in the data i.e. $\tilde{t}$=-9.15 for HAZ and -10.99 for WHZ. I compare the gains in HAZ and WHZ from receiving the different doses of roads against receiving a “small” dose (treatment benchmark).

As shown in Figure 30, the solid line is the dose-response function estimated using the core model parameters reported in Table 18 and Table 20. The expected outcome (HAZ for children below 5 years) continuously increases as the treatment level increases and does not cross the treatment benchmark. Higher levels of treatment are associated with better expected outcomes. After a treatment level of around -6.5 (corresponding to a road density index value of .001), the threshold level of stunting (HAZ less than -2) is exceeded. The contribution of additional roads on HAZ is higher in the districts with the lower road density (-10 to -6) and higher road density (>-2) than the districts with the moderate road density (-6 to -2). Eighteen districts have road density index values of lower than .001 of which 13 of are from mountainous districts and five are from hilly districts.

Table 19. First Stage: ML Estimation of GPS for the Treatment-Change in Road Density Index between 2011 and 2006

Variables	Coefficient
Road density index in 2006	2.27
	(1.74)
Terai district[d]	-3.56***
	(0.78)
Mountainous district[d]	-0.04
	(0.72)
Elevation (meters)	-0.002***
	(0.001)
Constant	-2.99***
	(0.72)
Wald chi2(4)	25.38
Prob>chi2	0.00
Observations	74

[d] indicates a dummy variable, Standard errors in parentheses,*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 20. Second Stage: OLS Estimation of GPS for WHZ Outcomes

Variables	WHZ, 2011 (Below 5 years)	WHZ, 2011 (3 to 5 years)	WHZ, 2011 (Below 3 years)
treatment (t)[a]	0.09	0.08	0.04
	(0.19)	(0.24)	(0.22)
treatment square (t^2)	0.004	0.01	-0.002
	(0.01)	(0.02)	(0.02)
pscore (r)	3.47	-0.20	4.74
	(6.00)	(7.30)	(6.94)
pscore square (r^2)	-12.08	3.77	-24.68
	(19.87)	(24.20)	(22.99)
treatment (t) ×pscore (r)	0.09	-0.03	-0.09
	(0.39)	(0.47)	(0.45)
Constant	-0.47	-0.39	-0.61
	(0.57)	(0.70)	(0.66)
R-square	0.08	0.15	0.11
Observations	74	74	74

Note:[a] treatment is the change in road density index between 2011 and 2006. Standard errors in parentheses, none of the coefficients are statistically significant at less than 0.1 test level.

As discussed earlier, the response of child nutrition outcomes to roads may be different for children below and above 3 years. Therefore I estimate separate dose-response functions for these age groups. Figures 31 and 32 clearly illustrate the distinct dose-response function for children below three years and those between three and five years of age. In case of the HAZ for children between three and five years of age, the expected HAZ decreases as treatment increases to the level of -6 (Figure 31). After this point, an increase in treatment leads to a continuous increase in the expected outcome. Only at a treatment level of around -4 (corresponding to a road density index of .02), is a positive treatment effect observed. Thirty-nine districts have road density indexes lower than .05. However for children below three years, the expected outcomes increase continuously as the treatment level increases (Figure 32). The threshold level of stunting is exceeded at a treatment level of -8 (corresponding to a road density index of .0003). All eight mountainous districts (Mugu, Dolpa, Solukhumbu, Humla, Bajura, Manang, Mustang and Jumla) have road density index values lower than .0003.

Our treatment for WHZ is the logarithmic transformation of change in the road index between 2011 and 2006. A positive treatment effect is observed for children below five years of age beyond the change in road index of -10 (Figure 33). Beyond this treatment level, expected outcomes lie above the treatment benchmark and are increasing across the entire treatment range.

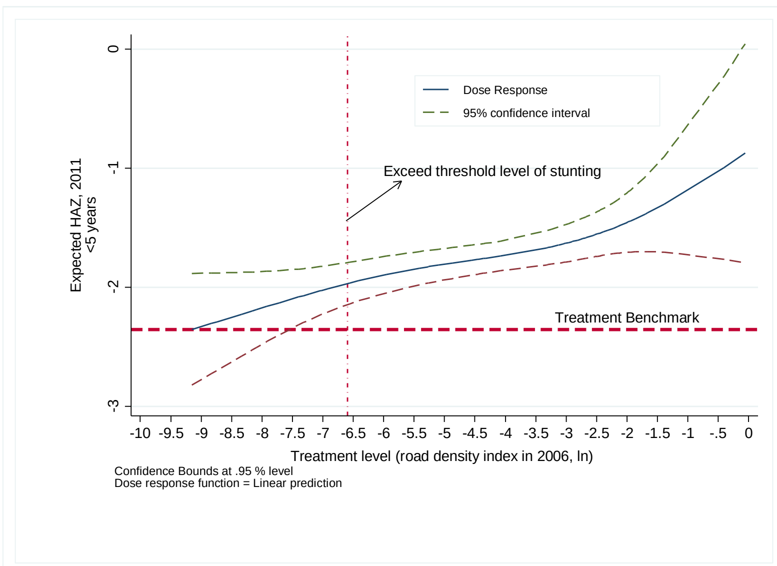

Figure 30. District Road Index Response Function for HAZ of Children Below 5 Years

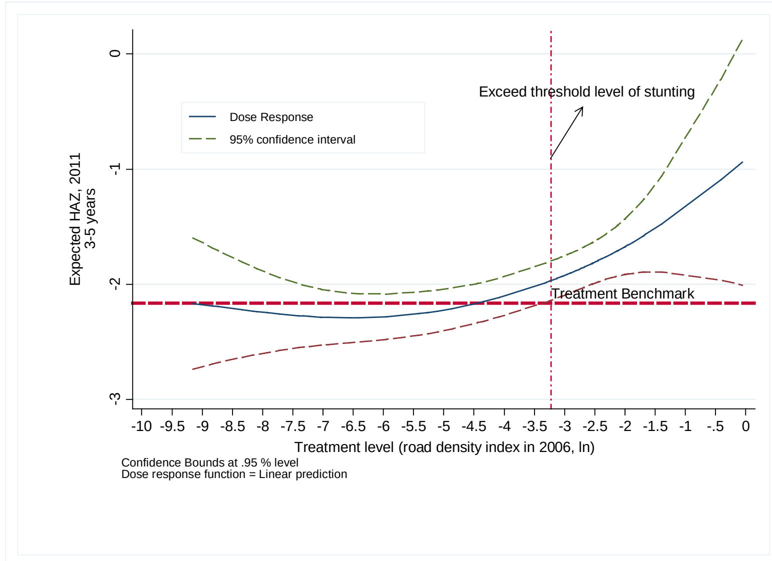

Figure 31. District Road Index Response Function for HAZ of Children between 3 and 5 Years

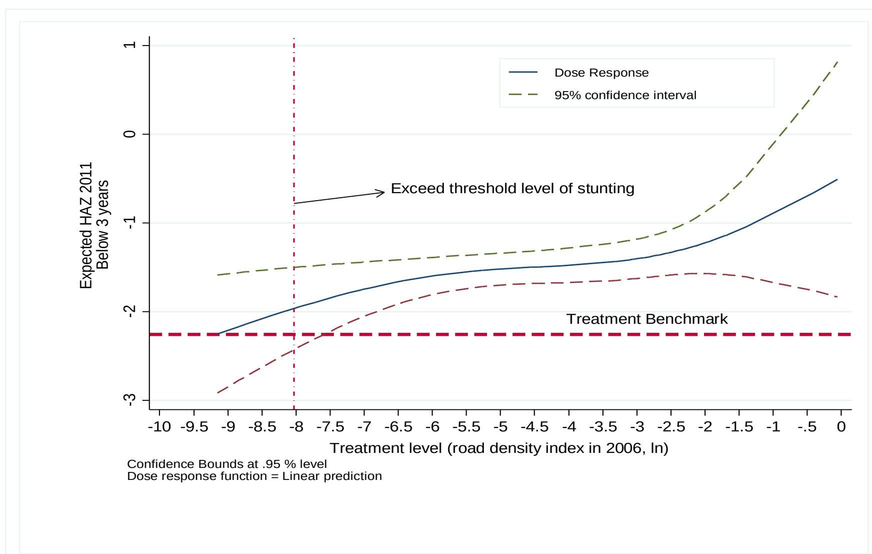

Figure 32. District Road Index Response Function for HAZ of Children below 3 Years

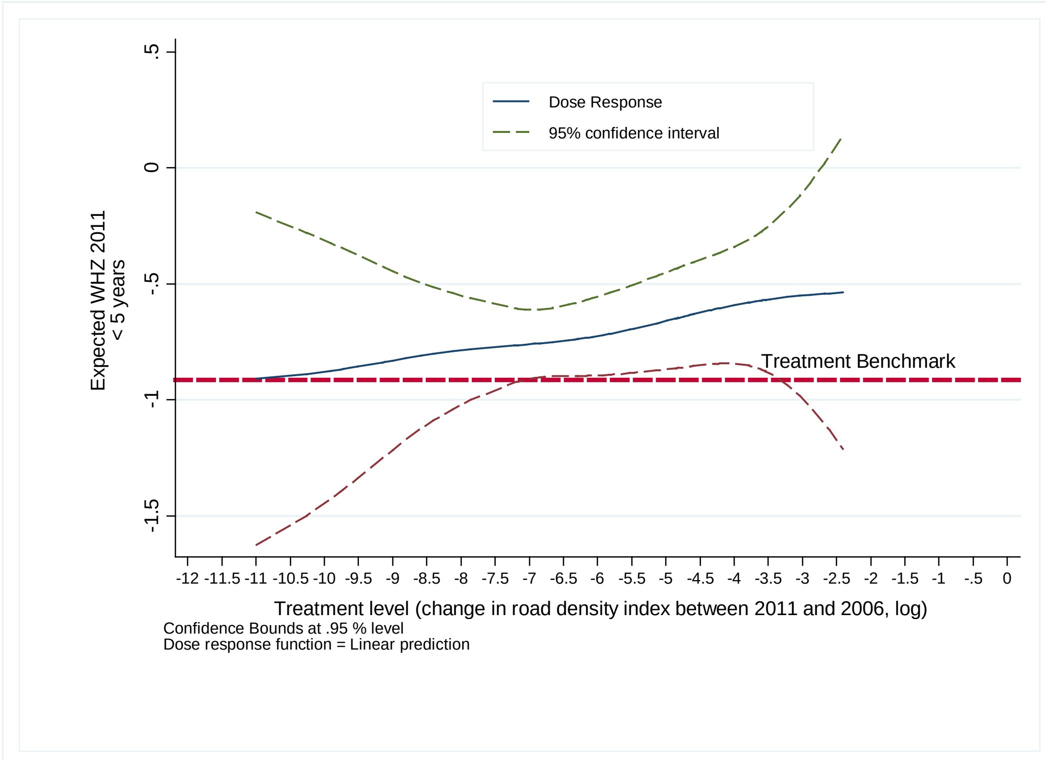

Figure 33. District Road Index Response Function for WHZ of Children below 5 Years

Similar to HAZ, I also estimate separate dose-response functions for children below 3 years and those between 3 and 5 years. Figures 34 and 35 show the dose-response functions for the different age groups. Expected outcome (WHZ) for children between three and five years of age are not responsive to treatment. The expected outcome decreases as treatment level increases up to a level of around -7 (Figure 34). Beyond a treatment level of -7, the expected outcome slightly increases and levels off. However expected outcomes for children below three years of age increase with treatment (Figure 35). The treatment effects are greater in the treatment interval between -11 and -8 than in other treatment intervals. It seems that at a treatment level of approximately -2, the expected outcome reaches -0.4 and then tends to stabilize.

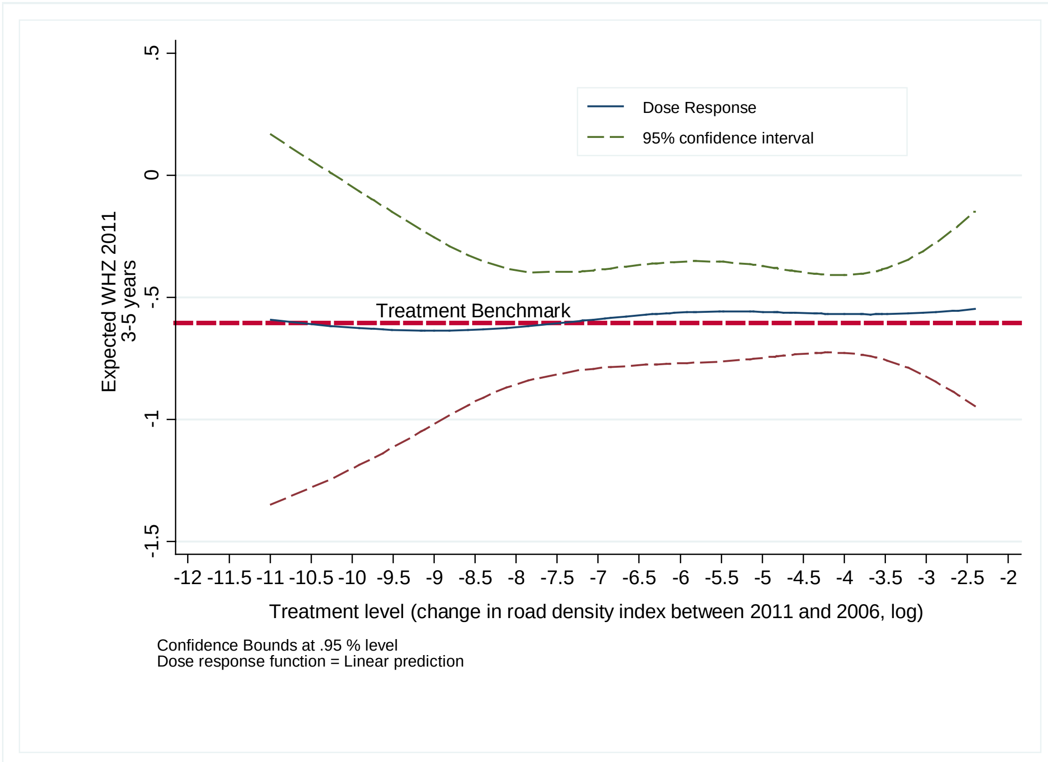

Figure 34. District Road Index Response Function for WHZ of Children between 3 and 5 Years

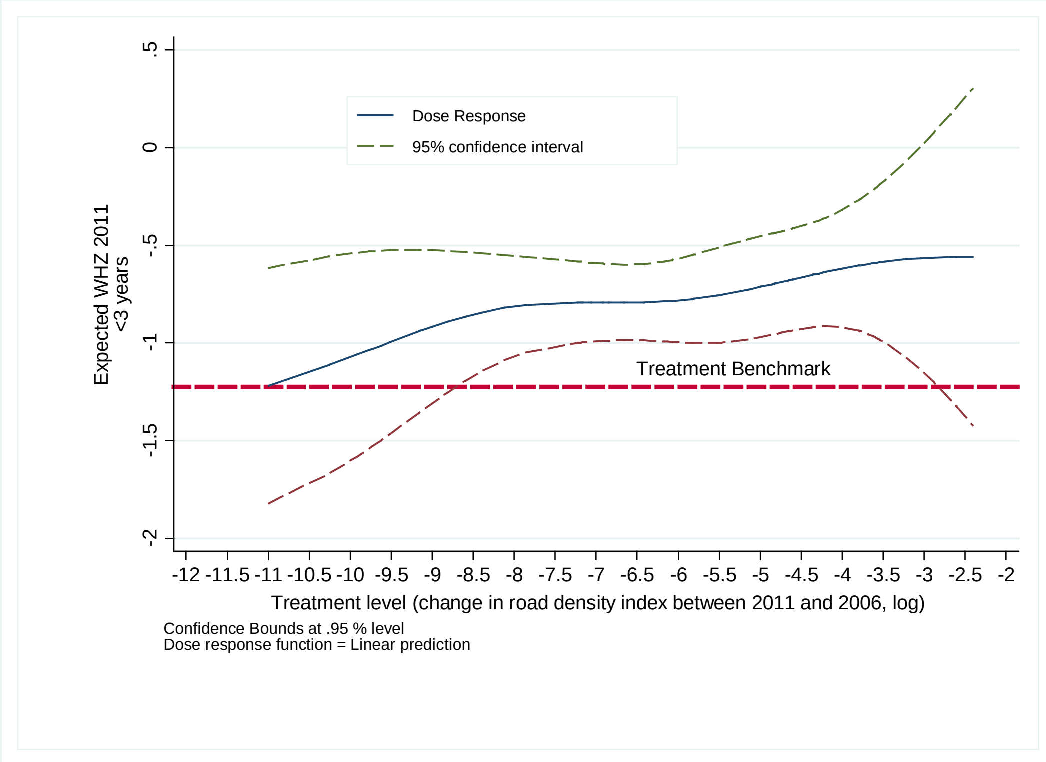

Figure 35. District Road Index Response Function for WHZ of Children below 3 Years

4.6.3. Results from the instrumental variable approach

Before discussing results obtained from estimating equations (53) and (54), I use a nonparametric approach to assess the extent to which roads and child nutrition outcomes are correlated. As mentioned above, figures 27 and 28 plot the average HAZ and WHZ in 2011 against the change in the road density index between 2011 and 2006, and the road density index in 2006. The HAZ in 2011, an indicator of long-term nutrition outcomes, is highly correlated with the road density index in 2006, and the WHZ in 2011 is highly correlated with the change in the road density index between 2011 and 2006. However these figures do not control for various confounding factors. Results from tables 21 to 24 control for confounding factors by including controls for the elevation, agro-ecology, education, food sufficiency status of a district, and health infrastructure in a district, while making a causal statement regarding roads and nutrition outcomes by instrumenting the road density index and the proportion of all-season roads in 2006 and 2011 using the distance from a district headquarter to the capital. When the road density index is used as an independent variable, the under-identification test reveals that the IV is relevant, meaning it is correlated with the endogenous regressor for the HAZ models. Similarly, a weak identification test, i.e. the F version of the Cragg-Donal Wald statistic values, exceed Stock-Yogo weak ID test critical values at 15% maximal IV size, suggesting our instrument is strong. As recommended by Angrist and Pischke (2009) and Chernozhukov and Hansen (2008), I run a diagnostic regression of the long-term child nutrition outcomes on the IV variable (distance from a district headquarter to the capital). The coefficient is statistically significant at less than a 10 percent test level indicating evidence in favor of a causal relationship flowing from distance to capital to the long-term child nutrition outcomes (Table A.4).

Table 21. Instrumental Variable Regression Results for HAZ in 2011 (road density index in 2006 treated as endogenous)

Variables	Model A			Model B		
	Below 5	Between 3 and 5	Below 3	Below 5	Between 3 and 5	Below 3
Road density index in 2006	2.83**	3.59**	2.43*	1.73*	2.26*	1.12
	(1.23)	(1.50)	(1.43)	(1.06)	(1.36)	(1.32)
An average altitude of a district (meters)				-0.00	-0.00*	-0.00
				(0.00)	(0.00)	(0.00)
Hilly district[d]				0.05	-0.01	0.05
				(0.23)	(0.29)	(0.28)
Mountainous district[d]				0.03	-0.06	-0.01
				(0.30)	(0.38)	(0.37)
Literacy percentage in 2010				0.01	0.01	0.01
				(0.01)	(0.01)	(0.01)
Food sufficient in 2011[d]				0.29**	0.21	0.34**
				(0.13)	(0.17)	(0.17)
Health facilities per capita				-53.98	762.33**	-43.86
				(262.05)	(334.09)	(325.70)
Constant	-1.96***	-2.29***	-1.74***	-2.42***	-2.67***	-2.44***
	(0.11)	(0.13)	(0.13)	(0.50)	(0.63)	(0.62)
Observations	74	74	74	74	74	74
Underidentification test (Anderson canon. Corr. LM statistic)	9***			9.35***		
Weak identification test (Cragg-Donald Wald F statistic)	10			9.54		

Note: [d] indicates a dummy variable (=1), Standard errors in parentheses,*** p<0.01, ** p<0.05, * p<0.1

Table 22. Regression Results for HAZ (proportion of all-season road in 2006 treated as endogenous)

Variables	Model A Below 5	Model A Between 3 and 5	Model A Below 3	Model B Below 5	Model B Between 3 and 5	Model B Below 3
Proportion of all-season road in 2006	1.72**	2.18**	1.47*	1.34	1.75	0.87
	(0.71)	(0.95)	(0.80)	(0.83)	(1.13)	(0.97)
An average altitude of a district (meters)				-0.00	-0.00	-0.00
				(0.00)	(0.00)	(0.00)
Hilly district[d]				0.32	0.35	0.23
				(0.38)	(0.51)	(0.44)
Mountainous district[d]				0.27	0.26	0.15
				(0.42)	(0.58)	(0.49)
Literacy percentage in 2010				0.00	0.00	0.01
				(0.01)	(0.02)	(0.01)
Food sufficient in 2011[d]				0.33**	0.25	0.36**
				(0.15)	(0.21)	(0.18)
Health facilities per capita				-62.40	751.35**	-49.31
				(262.42)	(356.92)	(306.64)
Constant	-2.40***	-2.84***	-2.11***	-2.92***	-3.33***	-2.76***
	(0.28)	(0.37)	(0.31)	(0.36)	(0.49)	(0.42)
Observations	74	74	74	74	74	74
Underidentification test (Anderson canon. Corr. LM statistic)		5.4***			7.063***	
Weak identification test (Cragg-Donald Wald F statistic)		5.66			6.96	

Note: [d] indicates a dummy variable (=1), Standard errors in parentheses,*** p<0.01, ** p<0.05, * p<0.1

Results from a parsimonious model (Model A in Table 21) illustrate that a higher road density index in 2006 causes better long-term nutrition outcomes (higher HAZ) in 2011 for all age categories. However when I control for other covariates (Model B), the positive and statistically significant results are obtained only for children below five years, and between three and five years. More health facilities per capita is associated with a higher average HAZ for children between three and five years of age. Except for children between three and five years of age, food self-sufficiency in 2011 is correlated with higher HAZ.

I also regressed HAZ in 2011 on the proportion of all-season roads in 2006, after instrumenting with the same variable, i.e. the distance from district headquarter to the capital city of the country (Table 22). Although the coefficient on proportion of all-season road in 2006 is statistically significant for all age categories in Model A, I find the coefficient to be statistically significant at only a 11 percent level for the children below 5 in Model B. For rest of the variables, I note similar sign and significance with a slight change in the magnitude of coefficients in comparison to the regression results reported in Table 21. The results, especially from parsimonious models, indicate that an improvement in road quality in 2006 leads to higher HAZ in 2011.

Table 23 reports regression results for WHZ, where none of the variables are treated as endogenous. The coefficient on the change in the road density index between 2011 and 2006 is statistically significant for children below five years and below three years of age

Table 23. Regression Results for WHZ (change in road density)

Variables	Model A Below 5	Model A Between 3 and 5	Model A Below 3	Model B Below 5	Model B Between 3 and 5	Model B Below 3
Change in road density index between 2011 and 2006	4.77*	0.09	6.01**	4.38	-0.18	5.13*
	(2.46)	(2.17)	(2.95)	(2.72)	(2.88)	(3.08)
An average altitude of a district (meters)				0.00**	0.0001	0.0002**
				(0.00)	(0.00)	(0.00)
Hilly district[d]				0.05	0.13	-0.01
				(0.13)	(0.19)	(0.14)
Mountainous district[d]				-0.07	-0.00	-0.14
				(0.19)	(0.23)	(0.21)
Literacy percentage in 2010				-0.003	-0.004	0.003
				(0.01)	(0.01)	(0.01)
Food sufficient in 2011[d]				0.37***	0.25**	0.38***
				(0.09)	(0.11)	(0.11)
Health facilities per capita				-522.86**	-181.43	-526.13**
				(224.49)	(172.03)	(238.43)
Constant	-0.74***	-0.57***	-0.82***	-0.82**	-0.64	-1.27***
	(0.05)	(0.07)	(0.06)	(0.37)	(0.44)	(0.41)
Observations	74	74	74	74	74	74
R-squared	0.06	0.01	0.07	0.31	0.11	0.30

Note: [d] indicates a dummy variable (=1), Robust standard errors in parentheses,*** p<0.01, ** p<0.05, * p<0.1

in Model A. However, when other covariates are included, only the relationship for children below three is statistically significant at a 10 percent level in Model B. This result shows that roads matters to the short-term nutrition outcomes, especially for younger children.

I also regressed WHZ in 2011 on the change in the proportion of all-season roads between 2011 and 2006 (Table 24). The estimates of the change in the proportion of all-season road between 2011 and 2006 on the WHZ is non-significant in Model A. However after controlling for other covariates, the coefficient is statistically significant at a 14 percent level for the children below age of five years. This suggests that a positive change in the proportion of all-season roads between 2011 and 2006 is weakly associated with higher WHZ for children below five in 2011.

Table 24. Regression Results for WHZ (change in the proportion of all-season road)

	Model A			Model B		
Variables	Below 5	Between 3 and 5	Below 3	Below 5	Between 3 and 5	Below 3
Change in the proportion of all-season road between 2011 and 2006	0.22	0.27	0.08	0.47	0.40	0.43
	(0.34)	(0.35)	(0.35)	(0.32)	(0.43)	(0.36)
An average altitude of a district (meters)				0.0002**	0.0001	0.0002*
				(0.00)	(0.00)	(0.00)
Hilly district[d]				0.02	0.06	-0.03
				(0.15)	(0.22)	(0.17)
Mountainous district[d]				-0.19	-0.12	-0.25
				(0.23)	(0.31)	(0.26)
Literacy percentage in 2010				-0.0006	-0.003	0.01
				(0.01)	(0.01)	(0.01)
Food sufficient in 2011[d]				0.36***	0.26**	0.36***
				(0.09)	(0.11)	(0.11)
Health facilities per capita				-539.4**	-189.59	-542.89**
				(231.96)	(177.04)	(247.60)
Constant	-0.69***	-0.58***	-0.75***	-0.95**	-0.70*	-1.39***
	(0.05)	(0.06)	(0.06)	(0.39)	(0.42)	(0.43)
Observations	74	74	74	74	74	74
R-squared	0.02	0.05	0.00	0.30	1.45	0.28

Note: [d] indicates a dummy variable (=1), Standard errors in parentheses,*** $p<0.01$, ** $p<0.05$, * $p<0.1$

4.6.4. Results from the spatial econometrics approach

I first specify all models with intercept only as an independent variable. After estimating these models using OLS, I predict residuals. A Moran's test is then conducted to assess whether residuals are spatially auto-correlated or not. The Global Moran's I for regression residuals for HAZ of children below five years, between three and five years, and below three years are 0.35, 0.33, and 0.26, respectively. These Moran's I statistics are statistically significant at less than a 1 percent level of significance. Similarly, the Global Moran's I for regression residuals for WHZ of children below five years, between three and five years, and below three years are 0.11, 0.03, and 0.15, respectively. These Moran's I am only statistically significant at less than a 5 percent level of significance for WHZ of children below five years and below three years. To ensure convergence I dropped the elevation variable from equation (67) and the health per capita variables from equations (66) and (67).

Table 25 presents results for HAZ of children in 2011. The spatial autoregressive coefficient (Rho) was statistically significant in Model A (HAZ of children below five years). However after controlling for other district-level variables, spatial autoregressive coefficients are not found to be significant. For both models A and B, the direct effect of road density index in 2006 is not statistically significant. The spillover effects are positive and statistically significant in Model A for all ages, but after controlling for other variables, the coefficient is statistically significant only for children between three and five years. These results show that constructing roads in one district not only influences long-term child nutrition outcomes in that district but also influences long-term child nutrition outcomes in neighboring districts.

Table 26 presents the results for WHZ in 2011. The spatial autoregressive coefficient (tau) is statistically significant in Model A (WHZ of children below five years and below three years). However, spatial autoregressive coefficients are not found to be significant in Model B. For both the models A and B, the direct effects of the change in road density index between 2011 and 2006 are positive and statistically significant at less than 5 percent level for the WHZ of children below five years and below three years. The spillover effects are not found to be significant in all models.

As an alternative to the road density index I also created another form of a road variable that measures the quality of roads prevailing in a district, i.e. the proportion of all-season roads in a district. Table 27 presents the causal estimates of the proportion of all-season road on the long-term child nutrition outcomes. The parsimonious Model A indicates that the direct effects of proportion of all-season roads on long-term nutrition outcomes is positive and statistically significant for children between three and five years of age. The indirect effect of the proportion of all-season road on HAZ between three and five years is not significant, although significant for children below three. After controlling for other covariates as in Model B, I find that only the average proportion of all-season road in neighboring districts matters for children below five and three years. Table 28 presents results of the proportion of all-season roads on short-term child nutrition outcomes. None of the coefficients on the road-related variables are significant.

I do not find significant effects of the proportion of all-season roads on short-term child nutrition outcomes in Nepal.

Table 25. Coefficient Estimates for HAZ in 2011 (road density index in 2006 treated as endogenous and accounting its spillovers)

Variables	Model A			Model B		
	Below 5	Between 3 and 5	Below 3	Below 5	Between 3 and 5	Below 3
Road density index in 2006 (direct effects)	0.335	0.3308	0.1243	-0.0182	-0.8301	-0.5668
	(0.38)	(0.4720)	(0.4912)	(1.0386)	(1.3860)	(1.2930)
Average road density index in neighboring districts in 2006 (indirect/spillover effects)	1.76***	2.3174***	1.7924**	0.9370	1.9841**	1.1890
	(0.58)	(0.6631)	(0.7257)	(0.6672)	(0.8486)	(0.9033)
An average altitude of a district (meters)				-0.0002	0.0000	-0.0001
				(0.0001)	(0.0001)	(0.0001)
Hilly district[d]				-0.1421	-0.5424*	-0.1754
				(0.2150)	(0.2880)	(0.2604)
Mountainous district[d]				-0.1945	-0.5592	-0.2944
				(0.2863)	(0.3824)	(0.3491)
Literacy percentage in 2010				0.0191	0.0297	0.0237
				(0.0138)	(0.0188)	(0.0162)
Food sufficient in 2011[d]				0.1262	-0.0247	0.1006
				(0.2050)	(0.2769)	(0.2447)
Constant	-2.0***	-2.3***	-1.7443	-2.92***	-3.73***	-2.9***
	(0.084)	(0.0772)	(0.0954)	(0.70)	(0.9616)	(0.8354)
Observations	75	75	75	75	75	75
Log-likelihood	-32.95	-46.33	-51.43	-19.35	-37.31	-41.89
Rho	0.33**	0.08	0.22	0.13	0.23	-0.10

Note: [d] indicates a dummy variable (=1), Standard errors in parentheses,*** p<0.01, ** p<0.05, * p<0.1

Table 26. Coefficient Estimates for WHZ in 2011 (change in the road density index between 2011 and 2006 and accounting its spillovers)

Variables	Model A Below 5	Model A Between 3 and 5	Model A Below 3	Model B Below 5	Model B Between 3 and 5	Model B Below 3
Change in the road density index between 2011 and 2006 (direct effects)	5.908*** (2.2148)	1.151 (2.694)	7.068*** (2.5796)	5.151*** (2.2041)	0.4052 (2.7735)	5.8535** (2.568)
Average change in the road density index between 2011 and 2006 in neighboring districts (indirect/spillover effects)	-0.4368 (5.2127)	-3.693 (6.052)	4.3239 (6.1127)	-2.4775 (4.6320)	-5.7137 (5.6838)	2.2924 (5.5026)
Hilly district[d]				0.1840* (0.1045)	0.2850** (0.1264)	0.1121 (0.1251)
Mountainous district[d]				0.0671 (0.1168)	0.2188 (0.1369)	-0.0291 (0.1433)
Literacy percentage in 2010				0.0001 (0.0053)	-0.0003 (0.0063)	0.0047 (0.0064)
Food sufficient in 2011[d]				0.287*** (0.0873)	0.1995* (0.1064)	0.2965*** (0.1036)
Constant	-0.74*** (0.1013)	-0.52*** (0.106)	-0.88*** (0.1210)	-0.987*** (0.3280)	-0.81** (0.4422)	-1.383*** (0.4000)
Observations	75	75	75	75	75	75
Log-likelihood	-32.21	-47.16	-43.50	-26.64	-43.503	-38.19
Tau	0.29*	0.07	0.33**	-0.24	-0.16	0.05

Note: [d] indicates a dummy variable (=1), Standard errors in parentheses,*** p<0.01, ** <0.05, * p<0.1

Table 27. Coefficient Estimates for HAZ in 2011 (proportion of all-season roads in 2006 treated as endogenous and accounting its spillovers)

	Model A			Model B		
Variables	Below 5	Between 3 and 5	Below 3	Below 5	Between 3 and 5	Below 3
Proportion of all-season road in 2006 (direct effects)	0.3870	0.844**	-0.0646	0.1216	1.545	-1.1501
	(0.2697)	(0.3428)	(0.3533)	(1.0484)	(1.531)	(1.2047)
Average proportion of all-season road in neighboring districts in 2006 (indirect/spillover effects)	1.238***	0.6430	1.763***	0.914**	0.195	1.636***
	(0.4088)	(0.5170)	(0.5245)	(0.4320)	(0.577)	(0.5748)
An average altitude of a district (meters)				-0.0001	0.000	-0.0002
				(0.0001)	(0.000)	(0.0001)
Hilly district[d]				0.0042	0.182	-0.3102
				(0.3998)	(0.588)	(0.4484)
Mountainous district[d]				0.0182	0.215	-0.2966
				(0.4424)	(0.649)	(0.4975)
Literacy percentage in 2010				0.0182	0.005	0.0304*
				(0.0145)	(0.021)	(0.0164)
Food sufficient in 2011[d]				0.1639	0.406	0.0403
				(0.1871)	(0.272)	(0.2143)
Constant	-2.35***	-2.57***	-2.17***	-3.244***	-3.475**	-3.3863
	(0.1167)	(0.1458)	(0.1417)	(0.3619)	(0.505)	(0.4361)
Observations	75	75	75	75	75	75
Log-likelihood	-28.24	-45.97	-47.35	-18.06	-39.84	-38.84
Rho	0.16	0.15	0.09	0.18	0.30	-0.03

Note: [d] indicates a dummy variable (=1), Standard errors in parentheses,*** p<0.01, ** p<0.05, * p<0.1

Table 28. Coefficient Estimates for the WHZ in 2011 (change in the proportion of all-season roads between 2011 and 2006 and accounting its spillovers)

	Model A			Model B		
Variables	Below 5	Between 3 and 5	Below 3	Below 5	Between 3 and 5	Below 3
Proportion of all-season road in 2006 (direct effects)	0.3299	0.1510	0.1696	0.3784	0.4053	0.288
	(0.3534)	(0.2694)	(0.4113)	(0.3412)	(2.7735)	(0.395)
Average proportion of all-season road in neighboring districts in 2006 (indirect/spillover effects)	-0.5460	-3.693	-0.4066	-0.1425	-5.7138	0.271
	(0.8092)	(6.052)	(0.9624)	(0.7610)	(5.6839)	(0.899)
Hilly district[d]				0.1921*	0.285**	0.120
				(0.1129)	(0.1265)	(0.134)
Mountainous district[d]				0.0044	0.2189	-0.114
				(0.1344)	(0.1369)	(0.163)
Literacy percentage in 2010				0.0026	0.0003	0.009
				(0.0055)	(0.0063)	(0.007)
Food sufficient in 2011[d]				0.2609***	0.1996*	0.262**
				(0.0883)	(0.1064)	(0.105)
Constant	-0.66***	-0.52***	-0.71***	-1.109***	-0.811**	-1.56***
	(0.0698)	(0.105)	(0.0865)	(0.3523)	(0.388)	(0.425)
Observations	75	75	75	75	75	75
Log-likelihood	-35.16	-47.163	-43.50	-28.72	-43.50	-38.19
Tau	0.27	0.07	0.33**	-0.02	-0.16	0.05

Note: [d] indicates a dummy variable (=1), Standard errors in parentheses,*** p<0.01, ** p<0.05, * p<0.1

4.7. Discussion and sensitivity analysis for index weights

Evidence suggests that political leaders, appointed as ministers, positively influenced the placement of roads in their residence districts. However, I find no significant influence on road placement in 2011. Since the government was highly unstable from 2006-11, many ministers appointed during this period just served for a brief period, and were not able to exert much political influence. The literature on political economy also suggests that politicians favor their birthplace, ethnicity, and connections. Nguyen et al. (2012) find that towns in Vietnam whose officials were promoted to higher ranks of government witnessed positive effects on local infrastructure (such as roads to villages, marketplaces, sanitation, irrigation, etc.) compared with other towns in Vietnam. Fishman (2001) indicates that politically well-connected firms in Indonesia have larger valuations and higher profitability. Khwaja and Mian (2005) find that politically connected firms in Pakistan borrow more than non-political firms and have a higher default rate than non-political firms. Districts that are close to the capital city have more roads than remote districts which supports the radial structure of the development of the road network of Nepal. In the context of road construction, a hypothesis of path-dependency seems to hold in Nepal. Evidence suggests that road expansion between 2011 and 2006 was not prioritized for districts with low existing road densities, but rather took place at a faster pace in districts with pre-existing roads.

The increase of the road density index in 2006 clearly leads to the improvement of HAZ in 2011 (Figure 30). Beyond the treatment level of around -6.5 (corresponding to a road density index value of .001) exceeded the stunting threshold (HAZ less than -2). I found this low value of road density index because the road density index value is expressed in terms of highest quality roads (black pitched). The dose response function for HAZ looks distinct for the children below and above 3 years confirming the different responses of child nutrition outcomes to roads in different age categories (Figures 31 and 32). Although children below 3 positively responded to an immediate increase in treatment, the children above 3 responded positively only after a treatment level of -4 (corresponding to a road density index of .02). Similarly, the threshold level of stunting was exceeded only at a higher treatment level for the children above 3 than children below 3. These results suggests that the chance of stunting for children above three is higher than for the children below 3 in a district with poor road network. Hoddinott and Kinsey (2001) also find different impacts of income treatment (created by drought) on child nutrition outcomes for different age categories. Aguero et al. (2006) find the impact of the child support grant (CSG) treatment on HAZ scores to be higher and positive for children less than 12 months than the older aged children.

One hypothesis of this study was that a change in the road network over time would translate into improved child nutrition outcomes. Figure 33 explicitly shows that an increase in the road density index in a district between 2011 and 2006 led to a higher average WHZ in that district. Districts with larger changes in the road density index between 2011 and 2006 witnessed larger positive changes in WHZ in 2011. Similar to HAZ, I found distinct dose-response functions for children below 3 years and those between 3 and 5 years. I find WHZ to be more sensitive to the treatment at an earlier age (below 3) than at a later age (above 3). A modest increase in treatment led to a higher response than a larger increase of treatments for the children below 3. To improve short-term nutrition outcomes of the children below 3, road construction activities can be targeted to districts with low road densities.

In addition to the GPS approach, I also implemented an instrumental variable approach to estimate the causal impact of the roads on the child nutrition outcomes. The impact of roads on long-term nutrition outcomes is significant and larger for children between three and five in both models (Table 21). However the impact is insignificant for children below 3 after controlling for confounding factors. These findings are in accordance with the GPS results. Districts with a higher proportion of all-season roads in 2006 had higher average HAZ for children below five (Table 22). This underscores the importance of road quality for child nutrition outcomes.

Results confirm that districts with larger changes in the road density index between 2011 and 2006 had higher WHZ for children below 3, similar to the GPS results. Given the geographically dispersed effects of roads, I accounted spillovers of roads on child nutrition outcomes. I found significant spillover effects, especially for children between three and five. Such a high magnitude and significance of spillover effects on long-term nutrition outcomes underscores the importance of government and donor efforts on building transportation infrastructure. Although I witnessed a significant direct effect of the change in the road density index between 2011 and 2006 for children below three years, the indirect effects was insignificant (Table 26). I also estimated the spillover effects of all-season roads on child nutrition outcomes. I found a significant impact on nutrition outcomes for children below 3 (Table 27). This suggests that improvements in road networks lead to HAZ improvements for children below 3.

This study did not measure the pathways by which higher road densities and higher quality of roads lead to improved child nutrition outcomes. That is beyond the scope of this study. Some of the pathways through which extensive and improved road network leads to improved nutrition outcomes may be through higher agricultural production, higher wages, higher output prices, lower input and transportation costs, lower delivery time, increased access to health facilities and development of local markets.

One concern in this analysis is how sensitive results might be to changes in the weights used for creating our road index. To assess this, I assign different weights by assuming that black-topped roads are ten/twenty times more effective than gravel roads and forty/sixty times more effective than earthen roads. Figures 36 and 37 show the kernel density plots for the probability distributions of these different road indexes. The t-test and Kolmogorov-Smirnov test suggests that the mean and the distribution of the road index doesn’t change significantly when the underlying weights are adjusted in this way. I conducted robustness checks by conducting separate regressions of HAZ and WHZ with these different definitions of the road density index (Tables A.5 and A.6). Overall, the regression results for HAZ and WHZ are highly robust to changes in the weights used to construct the road index. I expect that the changes in the supply of health-related public goods are not spuriously correlated with road density, thus ruling out potential bias of the treatment effects on the child nutrition outcomes. The data support this conjecture. For example, when I construct an index consisting of the total number of health facilities per capita in a district, I find no strong correlation between this variable and the road index (see Figure 38).

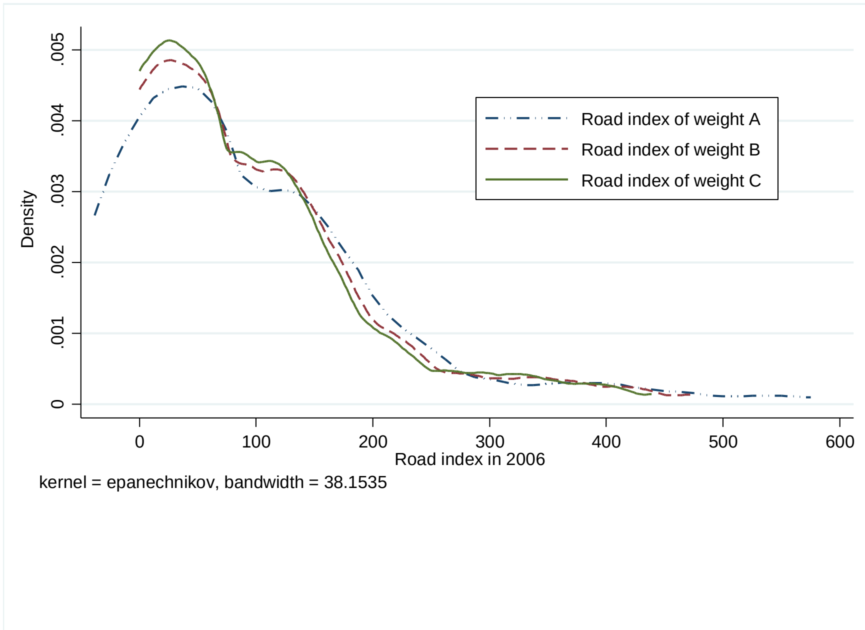

Figure 36. Kernel Density Plot of Road Index of Different Weights in 2006

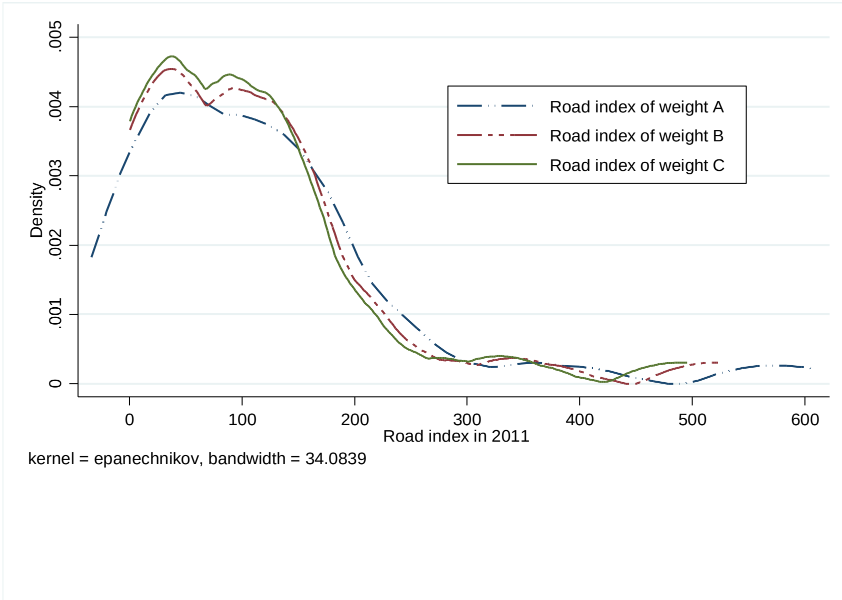

Figure 37. Kernel Density Plot of Road Index of different Weights in 2011

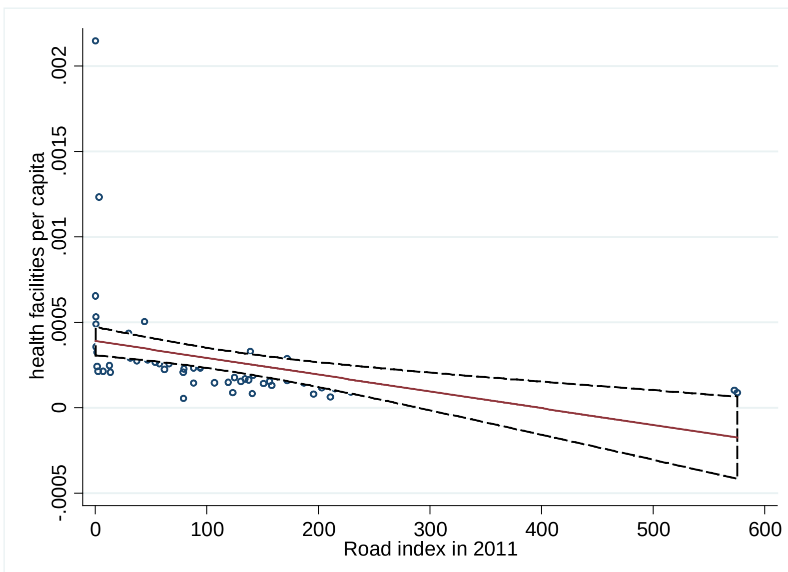

Figure 38. Health Facilities Per Capita and Road Index in 2011, Nepal

4.8. Conclusion

This study rigorously examined the effects of roads on both short- and long-term child nutrition outcomes at the district-level in Nepal. Both the direct and indirect impacts of roads on child nutrition outcomes were estimated. For each district, road index was created by summing the road length, weighting length by quality in terms of black pitched roads. Moreover, I also created a variable for the proportion of all-season roads in a district. To estimate direct effects, GPS and instrumental variable techniques were employed. To estimate spillover effects, a spatial econometrics approach was used.

Exploratory and regression analyses confirm the relationship between child nutrition outcomes and road infrastructure. Political influence and distance from capital to the district headquarter (in km) are correlated with the road index in 2006. I found evidence of path dependency in the road construction process. Changes in the road index between 2011 and 2006 were found to be highly correlated with the road index value in 2006. The dose-response function indicated that road infrastructure improves short-term and long-term nutrition outcomes for children below age 5. The treatment effects on child nutrition outcomes are not same for the children of different age groups. The instrumental variable approach indicated that the marginal effects of roads on long-term nutrition outcomes are higher for children between three and five years of age. However for WHZ, the marginal effects are higher for children below three years of age. I conclude that long-term child nutrition outcomes are more responsive to road infrastructure at later stages of child growth than at earlier stages and a vice-versa in case of short-term child nutrition outcomes. I found that observed local changes in road networks over time have been clearly associated with improvements in short-term nutrition outcomes. I found positive spillovers of roads, especially road quality, on long-term nutrition outcomes for the children below three years.

What policy implications can be provided based on these findings? Based on these findings, the study recommends government and donors on extending road networks and upgrading earthen roads to gravel and black-topped roads. All of this will translate, over time, into better child nutrition outcomes.

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APPENDIX

Table A.1. Length of Strategic Roads (km) and Constructed Road Index in 2006 and 2011

	2006				2011			
District	Black topped	Gravel	Earthen	Road Index	Black topped	Gravel	Earthen	Road Index
Taplejung	1	21	15	5	30	0	29	30
Panchther	31	61	90	45	92	0	124	94
Illam	106	37	252	118	109	50	324	125
Jhapa	341	284	176	401	341	284	185	401
Morang	280	280	316	343	313	257	308	370
Sunsari	145	234	106	194	147	232	111	196
Dhankuta	61	30	202	71	80	46	250	94
Terathum	1	6	57	3	33	0	124	36
Sankhuwasabha	0	11	66	4	48	25	62	54
Bhojpur	0	0	50	1	0	8	109	4
Solukhumbu	0	0	0	0	0	0	37	1
Okhaldhunga	0	0	47	1	9	6	57	11
Khotang	0	0	71	1	13	0	184	17
Udaypur	77	52	120	90	91	62	172	107
Saptari	167	73	97	184	167	93	97	188
Siraha	112	137	118	142	112	137	119	142
Dhanusa	118	187	385	163	128	183	385	172
Mahottari	98	205	251	144	100	264	278	158
Sarlahi	65	415	155	151	65	415	163	151
Sindhuli	26	25	100	33	68	34	222	79
Ramechhap	2	14	160	8	44	0	141	47
Dolkha	87	79	128	105	107	89	128	127
Sindhupalchowk	103	64	150	119	119	85	150	139
Kavre	107	80	269	129	129	60	272	146
Lalitpur	227	131	104	255	227	131	129	256
Bhaktapur	104	40	38	113	114	45	37	123
Kathmandu	714	202	215	758	735	197	212	779
Nuwakot	79	20	222	87	105	11	282	113
Rasuwa	0	41	67	9	41	10	83	44
Dhading	113	53	131	126	115	93	191	137

Table A.1. continued

District	Black topped	Grav el	Earth en	Ro ad Ind ex	Black toppe d	Gravel	Earthen	Road Index
Makwanpur	173	82	92	191	194	101	63	215
Rautahat	76	50	119	88	76	50	124	88
Bara	81	169	127	117	83	169	127	120
Parsa	94	78	188	113	108	91	190	130
Chitwan	326	457	198	421	466	513	235	573
Gorkha	25	3	108	28	27	41	119	37
Lamjung	19	0	129	22	19	1	181	23
Tanahu	111	27	266	122	124	22	286	135
Syangja	132	3	104	135	132	12	121	137
Kaski	229	37	225	240	229	47	225	242
Manang	0	0	18	0	0	0	30	1
Mustang	0	0	43	1	0	0	181	4
Myagdi	0	10	197	6	0	10	201	6
Parbat	26	2	40	27	37	2	49	39
Baglung	6	6	90	9	10	2	142	13
Gulmi	40	4	173	45	45	0	178	48
Palpa	105	4	221	110	109	0	336	115
Nawalparasi	269	101	77	290	292	83	82	311
Rupandehi	158	165	73	192	184	219	101	229
Kapilbastu	168	86	102	187	168	86	107	187
Arghakhanchi	61	2	186	65	61	3	227	66
Pyuthan	0	62	154	16	85	0	152	89
Rolpa	0	0	154	3	38	84	128	58
Rukum	0	0	52	1	0	20	165	7
Salyan	0	71	131	17	46	69	112	62
Dang	402	649	250	537	448	613	251	576
Banke	169	155	139	203	169	155	146	203
Bardiya	117	97	100	139	121	85	122	141
Surkhet	60	139	162	91	138	76	153	156
Dailekh	0	66	135	16	117	36	119	126
Jajarkot	0	0	34	1	0	0	118	2
Dolpa	0	0	0	0	0	0	26	1

Table A.1. continued

District	Black topped	Gravel	Earthen	Road Index	Black topped	Gravel	Earthen	Road Index
Jumla	0	0	36	1	0	0	85	2
Kalikot	0	0	64	1	0	0	77	2
Mugu	0	0	0	0	0	0	33	1
Humla	0	0	30	1	0	0	40	1
Bajura	0	0	16	0	13	0	30	14
Bajhang	0	0	76	2	30	0	48	31
Achham	26	0	113	28	75	0	93	77
Doti	116	23	83	122	116	23	113	122
Kailali	166	175	120	203	171	185	120	211
Kanchanpur	53	122	80	79	53	122	84	79
Dadeldhura	77	2	114	80	77	2	119	80
Baitadi	47	76	225	67	151	78	271	172
Darchula	0	0	71	1	10	50	18	20

Note: Road index, I=1.0×Black-topped+0.2×Gravel +0.002×Earthen. See text for details.

Table A.2. Distance between Kathmandu and District Headquarters in Nepal

District	Length (km)
Taplejung	314
Panchther	345
Illam	380
Jhapa	410
Morang	339
Sunsari	333
Dhankuta	280
Terathum	305
Sankhuwasabha	270
Bhojpur	238
Solukhumbu	179
Okhaldhunga	167
Khotang	206
Udaypur	251
Saptari	266
Siraha	224
Dhanusa	225
Mahottari	224
Sarlahi	184
Sindhuli	175
Ramechhap	123
Dolkha	91
Sindhupalchowk	66
Kavre	26
Lalitpur	5
Bhaktapur	15
Kathmandu	0
Nuwakot	34
Rasuwa	62
Dhading	67
Makwanpur	65
Rautahat	194
Bara	114
Parsa	114
Chitwan	127
Gorkha	111

Table A.2. continued

District	Length (km)
Lamjung	158
Tanahu	133
Syangja	201
Kaski	183
Manang	214
Mustang	279
Myagdi	382
Parbat	415
Baglung	403
Gulmi	292
Palpa	237
Nawalparasi	215
Rupandehi	237
Kapilbastu	282
Arghakhanchi	315
Pyuthan	340
Rolpa	387
Rukum	461
Salyan	437
Dang	375
Banke	455
Bardiya	490
Surkhet	528
Dailekh	544
Jajarkot	662
Dolpa	392
Jumla	483
Kalikot	552
Mugu	517
Humla	581
Bajura	674
Bajhang	697
Achham	620
Doti	666
Kailali	609
Kanchanpur	650
Dadeldhura	675
Baitadi	716
Darchula	776

Table A.3. List of Ministers and their Respective Districts from 1994 to 2008

District	Name of Minister
Acham	Bhim Bahadur Rawal (1998*)
Argakhanchi	Dhundiraj Shastri (1995), Modnath Prashrit (1994)
Baitadi	Lokendra Bahadur Chand (1983*)
Banke	Phatte Singh Tharu (1995*), Shanti Shamsher Rana (1995), Prem B. Bhandari (1997)
Bara	Salim Minya Ansari (1994*), Mukunda Neupane (1997), Rishikesh Gautam (2001)
Bardiya	Bam Dev Gautam (1997)
Bhaktapur	Padmaratna Tuladhar (1994)
Chitwan	Dr. Ganga Dhar Lamsal (1999)
Dadeldhura	Sher Bahadur Deuba (1995*)
Dailekh	Shiv Raj Joshi (2001)
Dang	Khum Bahadur Khadka (1995*)
Darchula	Dilendra Prasad Badu (2001)
Dhading	Buddhi Man Tamang (1997*), Rajendra Prasad Pandey (2006)
Dhankuta	Surya Bahadur Thapa (1963*), Rakam Chemjong (1997)
Dhanusha	Dr.Ram Baran Yadav (1999*), Bimalendra Nidhi (2004*)
Dolakha	Amrit Kumar Bohara (1998), Bhim Bahadur Tamang (1995)
Doti	Siddha Raj Oja (2001)
Gorkha	Chirinjivi Wagle (1995*)
Illam	Subash Nemang (1994*), Jhal Nath Khanal (1997*), Kul Bahadur Gurung (1998)
Jhapa	Chandra Prasad Mainali (1994*), Chakra Prasad Bastola (1995*), Radha Krishna Mainali (1997*), Devi Prasad Ojha (1997), KP Sharma Oli (1994*), Krishna Prasad Sitaula (2001*), Narendra Bikram Nembang (2001*)
Kalikot	Prem B. Singh (1997)
Kanchanpur	Bhoj Raj Joshi (1997), Tarini Datta Chatuat (1999), Ramesh Lekhak (2007)
Kapilbastu	Dip Kumar Upadhaya (Lamichhane) (2004)
Kaski	Tul Bahadur Gurung (1997)
Kathmandu	Man Mohan Adhikari (1994*), Pradip Nepal (1994*), Mrs. Sahana Pradhan (1997), Mrs. Vidya Devi Bhandari (1997), Dr. Bharat Kumar Pradhan (1997), Prakash Man Singh (1999*), Dr Mangal Siddhi Manandhar (2007)
Kavre	Keshav P Badal (1997)

Table A.3. continued

District	Name of Minister
Khotang	Ashok Rai (1997*)
Lalitpur	Siddhilal Singh (1997), Omkar Prasad Shrestha (1999), Raghuji Pant (2004)
Mahottari	Mahendra Raya (1995*), Sarad Singh Bhandari (1999), Ramesh Nath Pandey (1998*)
Makwanpur	Kamal Thapa (1995*)
Manang	Palten Gurung (2001)
Morang	Bharat Mohan Adhikary (1994*), Girija Prasad Koirala (1991*), Yog Prasad Upadhaya (1999*), Mahesh Acharya (1999*), Badri Prasad Mandal (2002*)
Nawalparasi	Hridayas Tripathi (2008*)
Nuwakot	Prakash Chandra Lohani (1995*), Arjun Narsing KC (1995*), Dr. Ram Saran Mahat (1999*)
Okhaldhunga	Bal Bahadur Rai,Gopal Rai
Panchthar	Padma Sundar Lavati (1995*)
Parsa	Rajib Parajuli (1995), Krishna Prasad Bhattari (1990*), Urmila Aryal (2007)
Rasuwa	Ram Krishna Acharya (1995*)
Rautahat	Madhav Kumar Nepal (1994*), Prakash Koirala (2001*)
Rupandehi	Surendra Nath Shukla (1995), Bishnu P. Poudyal (1997), Ram Krishna Tamrakar (2001)
Saptari	Gajendra Narayan Singh (1995*), Jaya Prakash Prasad Gupta (1998)
Sarlahi	Mahanta Thakur (1999*)
Shyanja	Gopal Man Shrestha (2001)
Sindhupalchowk	Pashupati SJBR (1995*), Amrit Kumar Bohra (1998)
Siraha	Chitra Lekha Yadav (2007*), Dharma Nath Prasad Saha (2007)
Sunsari	Bijaya Kumar Gachadar (1995*)
Surkhet	Purna Bahadur Khadka (1998*)
Tanahu	Govinda Raj Joshi (1995*), Ram Chandra Poudel (1991*)

Note * indicates multiple times, year appearing in parenthesis is the first year appointed to cabinet position.

Table A.4. Diagnostic Regression of the Child Nutrition Outcomes on the IV

Variables	HAZ			WHZ		
	Below 5	Between 3 and 5	Below 3	Below 5	Between 3 and 5	Below 3
Distance between Kathmandu (capital city) and district headquarters in km	-0.0007**	-0.0008***	-0.0006*	-0.0001	-0.00002	-0.0003
	(0.0002)	(0.0003)	(0.0003)	(0.0002)	(0.0002)	(0.0003)
Constant	-1.53***	-1.74***	-1.37***	-0.63***	-0.56***	-0.63***
	(0.10)	(0.11)	(0.12)	(0.09)	(0.10)	(0.10)
Observations	74	74	74	74	74	74
R-squared	0.09	0.10	0.05	0.01	0.00	0.02

Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table A.5. Instrumented Variable Regression Results for HAZ in 2011 (road density index in 2006 treated as endogenous, black-topped road is ten times efficient than gravel road and forty times efficient than earthen road)

Variables	Model A			Model B		
	Below 5	Between 3 and 5	Below 3	Below 5	Between 3 and 5	Below 3
Road density index in 2006	2.97**	3.77**	2.55*	1.82*	2.37*	1.18
	(1.29)	(1.57)	(1.51)	(1.12)	(1.43)	(1.39)
An average altitude of a district (meters)				-0.00	-0.00*	-0.00
				(0.00)	(0.00)	(0.00)
Hilly district[d]				0.04	-0.02	0.04
				(0.22)	(0.29)	(0.28)
Mountainous district[d]				0.02	-0.07	-0.01
				(0.29)	(0.37)	(0.37)
Literacy percentage in 2010				0.01	0.01	0.01
				(0.01)	(0.01)	(0.01)
Food sufficient in 2011[d]				0.29**	0.20	0.34**
				(0.13)	(0.17)	(0.17)
Health facilities per capita				-51.65	765.36**	-42.36
				(263.06)	(334.75)	(326.90)
Constant	-1.96***	-2.29***	-1.74***	-2.39***	-2.63***	-2.42***
	(0.11)	(0.13)	(0.13)	(0.51)	(0.65)	(0.63)
Observations	74	74	74	74	74	74

[d] indicates a dummy variable (=1), Standard errors in parentheses,*** p<0.01, ** p<0.05, * p<0.1

Table A.6. Instrumented Variable Regression Results for HAZ in 2011 (road density index in 2006 treated as endogenous, black-topped road is twenty times efficient than gravel road and sixty times efficient than earthen road)

Variables	Model A			Model B		
	Below 5	Between 3 and 5	Below 3	Below 5	Between 3 and 5	Below 3
Road density index in 2006	3.07**	3.89**	2.63*	1.88	2.45*	1.22
	(1.33)	(1.63)	(1.56)	(1.16)	(1.47)	(1.44)
An average altitude of a district (meters)				-0.00	-0.00*	-0.00
				(0.00)	(0.00)	(0.00)
Hilly district[d]				0.03	-0.03	0.04
				(0.22)	(0.28)	(0.28)
Mountainous district[d]				0.01	-0.08	-0.02
				(0.29)	(0.37)	(0.36)
Literacy percentage in 2010				0.01	0.01	0.01
				(0.01)	(0.01)	(0.01)
Food sufficient in 2011[d]				0.29**	0.21	0.34**
				(0.13)	(0.17)	(0.17)
Health facilities per capita				-48.99	768.83**	-40.63
				(264.26)	(335.85)	(328.20)
Constant	-1.96***	-2.28***	-1.73***	-2.37***	-2.61***	-2.41***
	(0.11)	(0.13)	(0.13)	(0.52)	(0.66)	(0.65)
Observations	74	74	74	74	74	74

[d] indicates a dummy variable (=1), Standard errors in parentheses,*** p<0.01, ** p<0.05, * p<0.1

Table A.7. Regression Results for WHZ in 2011 (black-topped road is ten times efficient than gravel road and forty times efficient than earthen road)

Variables	Model A Below 5	Model A Between 3 and 5	Model A Below 3	Model B Below 5	Model B Between 3 and 5	Model B Below 3
Change in road density index between 2011 and 2006	4.73*	0.03	6.05**	4.26	-0.36	5.11
	(2.49)	(2.12)	(2.99)	(2.78)	(2.85)	(3.16)
An average altitude of a district (meters)				0.00**	0.00	0.00**
				(0.00)	(0.00)	(0.00)
Hilly district[d]				0.05	0.13	-0.01
				(0.13)	(0.19)	(0.14)
Mountainous district[d]				-0.07	-0.00	-0.15
				(0.19)	(0.23)	(0.21)
Literacy percentage in 2010				-0.00	-0.00	0.00
				(0.01)	(0.01)	(0.01)
Food sufficient in 2011[d]				0.37***	0.25**	0.38***
				(0.09)	(0.11)	(0.11)
Health facilities per capita				-525.01**	-181.53	-528.54**
				(223.28)	(172.31)	(236.80)
Constant	-0.74***	-0.57***	-0.82***	-0.82**	-0.64	-1.26***
	(0.05)	(0.07)	(0.06)	(0.37)	(0.44)	(0.41)
Observations	74	74	74	74	74	74
R-squared	0.06	0.01	0.07	0.31	0.11	0.29

Note: [d] indicates a dummy variable (=1), Standard errors in parentheses,*** p<0.01, ** p<0.05, * p<0.1

Table A.8. Regression Results for WHZ in 2011 (road density index in 2006 treated as endogenous, black-topped road is twenty times efficient than gravel road and sixty times efficient than earthen road)

Variables	Model A			Model B		
	Below 5	Between 3 and 5	Below 3	Below 5	Between 3 and 5	Below 3
Change in road density index between 2011 and 2006	4.67*	0.05	5.96**	4.18	-0.37	5.01
	(2.48)	(2.09)	(2.98)	(2.79)	(2.83)	(3.18)
An average altitude of a district (meters)				0.00**	0.00	0.00**
				(0.00)	(0.00)	(0.00)
Hilly district[d]				0.05	0.13	-0.01
				(0.13)	(0.19)	(0.14)
Mountainous district[d]				-0.07	-0.00	-0.15
				(0.19)	(0.23)	(0.21)
Literacy percentage in 2010				-0.00	-0.00	0.00
				(0.01)	(0.01)	(0.01)
Food sufficient in 2011[d]				0.37***	0.25**	0.38***
				(0.09)	(0.11)	(0.11)
Health facilities per capita				-526.25**	-181.43	-530.03**
				(222.99)	(172.52)	(236.42)
Constant	-0.74***	-0.57***	-0.82***	-0.82**	-0.64	-1.26***
	(0.05)	(0.07)	(0.06)	(0.37)	(0.44)	(0.41)
Observations	74	74	74	74	74	74
R-squared	0.05	0.01	0.06	0.31	0.11	0.29

Note: [d] indicates a dummy variable (=1), Standard errors in parentheses,*** p<0.01, ** p<0.05, * p<0.1

VITA

VITA

Ganesh was born in the eastern part of the Nepal. Since he grew up in an agrarian society, he decided to pursue his educational career in the field of agriculture. After he completed undergraduate work in agriculture in 2005, he joined the Ministry of Agriculture, Nepal. He worked there as a fisheries development officer for two years. He holds an MS degree in Aquaculture Marketing and Economics from the University of Arkansas at Pine Bluff. He successfully completed the Ph.D. in Agricultural Economics from Purdue University in December 2015. His research interest lies in the fields of child nutrition, poverty alleviation, climate change, price analysis, spatial analysis, and sustainable management of natural resources.