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Household Food Security in Developing Countries: Understanding the Role of Dynamic Natural and Social Systems

Steven Archambault

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Household Food Security in Developing Countries: Understanding the Role of Dynamic Natural and Social Systems

by

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DISSERTATION

Submitted in Partial Fulfillment of the
Requirements for the Degree of

**Doctor of Philosophy
Economics**

The University of New Mexico
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Dedication

To my love and companion, Mara,

And to Dominic my joy.

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Abstract

The lack of consistent and reliable levels of nutritious food may be one of the most brutal results of poverty. Beyond the human suffering, the lack of food security has damaging economic consequences, making it difficult for communities to break poverty cycles. This dissertation studies the various decisions made by households, governments, and the international community that impact household food security. Food security, the long-term availability of nutritious foods, is essentially achieved through a trade-off of consumption and investment in assets and capital to ensure future availability of food.

Chapter 2 builds an optimal control model to analyze the trade-offs between stocks of primary forest and agricultural production. This study highlights the role of ecosystem services provided by stocks of forests, which include protection from flooding and erosion, maintenance of soil quality, and contributions to healthy watersheds. The model developed analyzes food production and consumption decisions in the context of sufficient and consistent access to food, particularly represented by changes in the stock of natural capital, in this case primary forest, which is utilized by the population for various reasons, including being cleared to create room for agriculture production. The case study of forest stocks in Nepal demonstrates the cost reductions achieved in the agriculture sector due to the presence of forest stock. The analysis determines optimal levels of per capita agriculture land for the three geographic belts of Nepal: Terai, Hills, and Mountain regions. Steady states in the model are reached beyond 200 years.

Chapter 3 employees data from a World Food Program household survey carried out in 2005, analyzes the role of natural capital, social capital, coping strategies, and levels of violence in determining household food security levels. Using remotely sensed data of two time points--Thematic Mapper (TM) of 1990 and Enhanced Thematic Mapper (ETM+) of 2000, vegetation information was derived for the uses of mapping of vegetation quality, the study uses two-stage ordinary least squares and non-linear spatial modeling econometric techniques to analyze the data. The results indicate household food security is positively impacted by higher levels of vegetation cover in the village where a household is located, as well as by higher vegetation quality in areas surround the village. Time spent accessing drinking water from improved sources is observed to have a negative relationship with food security. The existence of social networks was seen to positively impact food security, while households identified as members of a lower caste relate negatively with food security. Coping strategies

analyzed include remittances received by the household, access to financial credit, and the receipt of food aid. All of these strategies have a positive impact on the level of household food security. The intensity of violence in the village and surrounding areas throughout the Maoist conflict is observed to have a negative impact on household food security.

Chapter 4 undertakes a dynamic panel analysis of the worldwide distribution of emergency food aid in response to natural disasters and the displacement of citizens due to conflict. This is important, as exogenous shocks have the potential to derail the optimal consumption and investment decisions made by households aiming to ensure long-term food security. The data comes from the United Nations WFP Food Aid Information System (FAIS), which aims to provide reliable crosschecked data on all food aid transactions by countries and NGOs, whether or not the food aid was distributed by WFP. The analysis uses a Generalized Method of Moments system approach, which allows a control of the dynamic nature of the data, as well as potential endogeneity issues. As in previous studies, we show a significant relationship between rapid onset disasters (e.g. floods, hurricanes, and earthquakes) and the international response of food aid. Unique to this study, we demonstrate a lag effect of aid in response to gradual onset disasters (droughts, extreme temperature, and disease). This is a particularly important response when considering the potential for increased gradual onset natural disasters in response to climate change. We also show a highly significant and positive relationship between emergency food aid and displaced people.

The dissertation provides important results for advising government policy makers and non-governmental organizations to further address food security needs in developing countries. This research highlights the importance of natural and social capital quality in determining food security. Policy implications include investing in measures to conserve

natural resources, both in local communities and in surrounding regions. Also, it is important for policies to ensure long-term investment in community groups and networks that improve knowledge transfer and the social safety nets needed by those most at risk. The optimal control model provides insight into the long-term balance between natural capital quality and food production. The combination of spatial information derived from the integration of Geographic Information Systems (GIS) and remote sensing tools with econometric modeling provides an important picture of the relationship between household food security and nearby vegetation quality, and vegetation quality in areas further away. The dynamic panel analysis of shocks and food aid indicates a need for improved strategies in addressing food security in the critical moments of disasters.

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List of Abbreviations

2SLS	Two-Stage Least Squares
AR2	Arellano-Bond
CERF	Central Emergency Relief Fund
FAIS	Food Aid Information System
GIS	Geographic Information Systems
GMM	Generalized Methods of Moments
IDP	Internally Displaced Person
IV	Instrumental Variable
MLE	Maximum Likelihood Estimation
MM	Method of Moments
NGO	Non-governmental Organization
OLS	Ordinary Least Squares
PL480	Public Law 480
USAID	United States Agency for International Development
USDA	United States Department of Agriculture
VDC	Village Development Committee
WFP	World Food Program

Chapter 1: Introduction: Food Security and Hunger

1.1 Global Situation and Food Vulnerability

The lack of consistent and reliable levels of nutritious food may be one of the most brutal results of poverty. There are approximately **925 million people classified as hungry worldwide**, and hunger is thought to kill more people than AIDS, tuberculosis, and malaria combined. There is a gender disparity in hunger, with 60% of those hungry being women. Approximately two thirds of the hungry population lives in Asia and the Pacific region.¹ In 1996 and 2002, global leaders gathered at the World Food Summit to discuss what steps would be necessary to improve the food security of people throughout the developing world, and developed a widely accepted definition of food security saying, 'Food security exists when all people, at all times, have physical and economic access to sufficient, safe and nutritious food to meet their dietary needs and food preferences for an active and healthy life' (Webb et al., 2006). It is important for researchers to use technologically advanced research tools to analyze the root causes of hunger, giving policy makers tools to strengthen food security. This research aims to contribute towards these efforts.

The increase in global population, particularly in the context of climate change, places further strain is placed on the natural and social systems that are relied upon to produce food and distribute it to communities throughout the world. Poorer populations are seen to migrate to fragile ecosystems, which may only provide minimal or short-term resources needed for survival. Growing urban centers require a supply of food from rural areas, which often suffer from a shortage of labor and the sophisticated technology needed to meet the demand for food. Those who purchase food, and do not have direct access to farmland, depend on income sources, as a means of meeting food

¹ United Nations World Food Program, www.wfp.org (accessed June 11, 2012).

needs. Even those with access to farmland must supplement their diet with purchased foods. Poor communities are vulnerable to unsteady economic conditions, particularly with minimal access to liquid assets. Social networking, access to financial capital, and institutional safety nets are needed to ensure the vulnerable members of society have consistent access to those resources required for basic survival.

The growing threat of climate change places a uncertainty on whether food systems will be able to keep up with growing food demands. For instance, soil productivity is linked closely with health forest ecosystems and watersheds. If forest ecosystems are damaged due to climate change, the chance of decreased soil quality is high. Farmers may then need to substitute higher cost production measures including fertilizers and erosion controls. It is necessary for researchers and policy makers to understand how natural and social systems are linked in order to educate communities, strengthen institutions, and put in place those policies that best address the long-term well being of society.

1.2 Understanding Food Security

The concept of food security has evolved from a simple concept of people not having enough food, to questions of people's vulnerability and their ability to consistently access food. Feleke et al. (2005) said that early food security studies focused primarily on the world's supply of food, but by the mid-1970s it became apparent that even with a surplus of food and relatively low prices, there was still widespread starvation in developing countries. This shift in the literature is often credited to the work of Amartya Sen, who turned the food security focus towards demand side factors that limited people's access to food (Baro and Deubel, 2006; Coates et al., 2006; Webb et al., 2006; Feleke et al, 2005). Sen's seminal book, entitled *Poverty and Famines: An Essay on Entitlement*, was published in 1981. The influential concept provided by Sen is that people are not deprived of food

because it is not available in the market, but because their access is constrained by other factors. Prior to Sen, most policy solutions aimed at mitigating famine focused on increasing the food supply. Sen's intuition helped practitioners realize that limiting solutions to agricultural improvements was a narrow approach, whereas more focus was needed on access issues (Webb et al., 2006).

One difficulty for food and nutrition researchers and practitioners is developing a measure for food security that are in terms of food access described by Sen. Often the measures used are considered proxies for the larger issues of food security, as they may only directly measure small facets of food security (Webb et al., 2006). Nutritional related measures of food security have been used, including child height-for-age levels (Alderman et al., 2006). Measures have been used that observe when households deplete food stores during non-harvest seasons (Kerr, 2005 and Feleke et al., 2005). Other studies rely on individuals and representatives of households to indicate their food security levels (Martin et al., 2004). Coates et al. (2006) say observing the chronically malnourished and dying is much easier than recognizing those individuals who might not experience hunger on a daily basis, but are at risk for slipping into desperate conditions at any point. Developing the appropriate measures of food security is a crucial step towards developing the policy interventions aimed at avoiding the negative health and economic outcomes that accompany food insecurity.

Using Sen's philosophy of demand side constraints to accessing food, researchers and practitioners have moved further towards developing policy tools to strengthen food security by analyzing the determinants of food security for specific communities and regions. Researchers have explored the correlation between education and better food security (Babatunde et al., 2007; Feleke et al., 2005). Environmental degradation has been shown to be an important factor in weakening food security (Baro and Deubel, 2006; Misselhorn, 2005; Feleke et al., 2005). Kerr (2005) illustrated

the importance of informal labor systems and social networks in Malawi. Shocks such as conflict and drought have shown to correlate with lower levels of food security in sub-Saharan Africa (Alderman et al., 2006 and Baro and Deubel, 2006). Misselhorn (2005) illustrated the linkages between food security levels and market access, as well as how government policy may restrict or support food access. Authors have considered the role of assets, such as animals, in maintaining food security (Feleke et al., 2005). Coates et al. (2006) discussed the role of access to loans as important for achieving food security. Although Sen encouraged researchers to look towards access issues, it was not a call to completely avoid supply concerns. Farm size, access to agricultural inputs, and the production abilities of farms continue to be relevant to the issue of food security (Babatunde et al., 2007 and Feleke et al., 2005)

1.3 Sustainable development

Beyond the human suffering, the lack of food security has damaging economic consequences, making it difficult for communities to break poverty cycles. Those who experience poor nutrition are often found to receive less education, and be less economically productive members of society (Alderman et al., 2006). The Board on Sustainable Development of the National Research Council (in Washington, D.C.) has suggested that transitioning the world towards sustainability requires not only concentrating on preserving natural systems, but also focusing on the reduction of hunger and poverty (Parris and Kates, 2003). Studies have indicated that protecting natural systems and alleviating hunger are not mutually exclusive, but rather food security is strengthened with better-protected natural capital (Feleke et al., 2003; Stein and Shiferaw, 2004). Researchers have also shown links between strong social capital and higher levels of food security (Martin et al., 2004; Alderman et al., 2006). Maintaining the integrity of natural and social capital is often discussed as a means for achieving sustainable development (Costanza and Daly, 1992;

Lehtonen, 2004; Azquetq and Sotelsk, 2007; Prante, et al., 2007). The relationship between food security, natural capital and social capital is a central theme of the research analyses in this dissertation.

Costanza and Daly (1992) explain that natural capital is a flow of benefits from a natural system, for examples, fish used in a stream, or trees in a forest. This may be fish used in a stream, or trees in a forest. Natural capital may also be processes, such as the natural waste processing of ecosystems. Social capital is explained by Portes (1998) as the access to or membership in social networks that provide formal or informal support systems. Some of the food security papers have discussed the importance of natural and social capital. Pender et al. (2004) discussed the links between natural forest capital and food security in Uganda. Kerr (2005) carried out an analysis that highlighted the role of informal labor opportunities in Malawai as an important determinant of food security. Martin et al. (2004) quantified the impact of ‘close knit’ neighborhoods on impacting food security. Many of the food security studies may not explicitly mention natural or social capital, but many of the previous studies consider elements that can be classified as such.

1.4 Economic trade-offs

There have been a variety of studies aimed at understanding the various factors that promote or inhibit food security. These studies often analyze historical data of socio-economic and other explanatory variables that influence a proxy measure of food security, such as the number of calories consumed or levels of childhood malnutrition. These studies often recognize that food consumption decisions made by individuals, households, or communities are constrained by such things as income, education levels, gender, environmental conditions, and social status (including Babatunde et al., 2007; Baro and Deubel, 2006; Alderman et al., 2006; Misselhorn, 2005; Feleke et al., 2005).

The econometric analyses applied often measure the impact that these constraints, or the adjustment of these constraints, have on food security. Often, these studies do not capture the actual

consumption and investment decisions that are made by stakeholders to influence their food security. Several general theoretical dynamic optimization models have been developed to explain the constrained utility maximizing decisions made by stakeholders to maximize their food security (including Stokes and Frechette, 2006 and Barrett, 2002). These models consider the contribution to food security of changing asset stocks, health status, environmental quality, and other variables. Along with choices made by decision makers, the state variables directly and indirectly influence food security.

1.5 Disasters, Food Shocks, and Food Aid

There is strong evidence showing an increase in the frequency of natural disasters such as droughts, storms, forest fires, flooding, and typhoons attributable to a changing climate, with strong consensus among scientists that this will be the new normal. There is also raised concern that climate change will increase migratory pressure and competition for resources, leading to increased violence and conflict (O'Brien et al., 2007). One of the initial emergency concerns when natural and manmade shocks occur is ensuring victims have access to adequate food supplies to maintain food security, in order to prevent further suffering and losses of human capital (Barrett and Maxwell, 2005). Numerous studies have highlighted the short-term gain of maintaining food security through the distribution of emergency food aid, when local food sources are inadequate, and there is a shortfall of financial means to import food (including Marchione, 2002; Quisumbing, 2003; Yamano, et al., 2005). Ensuring a safety net of basic needs is met may increase resiliency to future shocks while laying the foundation for redevelopment and long-term recovery from shocks (Barrett and Maxwell, 2005 and Porter, 2010). With the potential increase in the number of natural disasters and conflicts, it is therefore important to understand the response of humanitarian food assistance when

natural disasters and conflicts do occur, and whether or not there is adequate response to such shocks.

Prior to the 1980s, the majority of food aid was targeted for development assistance, with less available for emergency aid. By 2002 and 2003, emergency food aid was nearly triple that of development food aid (Barret and Maxwell, 2005). In recent years there has been movement of countries to pool resources in emergency assistance funds, such as the Central Emergency Relief Fund (CERF), which gives United Nations (UN) agencies, including the World Food Program (WFP), the ability to remain flexible with the way funds are used, and to respond quickly in times of emergencies (Harvey et al., 2010). Multilateral assistance has been considered a more effective approach for tackling emergency aid distribution than bilateral efforts (Barrett and Heisy, 2002). However, food aid is delivered for reasons reaching beyond the needs of the hungry, with shipments related to political and economic motivations of the assisting countries. Research has shown food aid does flow in times of sudden onset disasters such as floods, earthquakes, and typhoons. However, for gradual onset disasters such as drought, the flow of food aid is more difficult to describe. A primary argument is that there is a greater response to more rapid onset disasters, as these rapid events have been seen to garner greater media attention (Eisensee and Strömberg, 2007). It is important to understand the ability of countries to respond the international food aid response to disasters, to ensure emergency resources are allocated as efficiently as possible.

1.6 Contributions of this Dissertation

This research conducts three types of analyses of food security focusing on the trade-offs between current consumption of food and investments and preservation of natural capital; the impact of social capital and other community and household characteristics on household food security; and the impact and response of manmade and natural exogenous shocks. The analyses are

presented in the following three chapters (Chapter 2, Chapter 3, and Chapter 4). Conclusions and discussions are presented in Chapter 5. An overview of the contributions of each of these chapters is presented in this section.

Chapter 2 develops an optimal control model to illustrate the trade-offs from utilizing natural capital stock in order to produce more food. In this case, forest cover is considered the natural capital stock. It is harvested, in part, to convert additional lands to agriculture production. In the case study presented, the ecosystem services of the stock of primary forests in Nepal are seen to cause reductions in agriculture costs. The optimal control model is calibrated to give optimal starting values and steady state values for per capita agriculture and forest cover levels.

Chapter 3 employees data from a World Food Program household survey carried out in 2005, to analyze the role of natural capital, social capital, coping strategies, and levels of violence in determining household food security levels. Using Geographic Information Systems (GIS) mapping of vegetation quality, the study uses two-stage ordinary least squares and non-linear spatial modeling econometric techniques to analyze the data. The results indicate household food security is positively impacted by higher levels of vegetation cover in the village where a household is located, as well as with higher vegetation quality in areas surround the village. Time spent accessing drinking water from improved sources is observed to have a negative relationship with food security. The existence of social networks was seen to positively impact food security, while households identified as members of a lower caste relate negatively with food security. Coping strategies analyzed include remittances received by the household, access to financial credit, and the receipt of food aide. All of these strategies have a positive impact on the level of household food security. The intensity of violence in the village and surrounding areas due to Nepal's Maoist conflict is observed to have a negative impact on household food security.

Chapter 4 undertakes a dynamic panel analysis of the worldwide distribution of emergency

food aid in response to natural disasters and the displacement of citizens due to conflict. This is important, as exogenous shocks have the potential to derail the optimal consumption and investment decisions made by households aiming to ensure long-term food security. The data comes from the UN WFP Food Aid Information System (FAIS), which aims to provide reliable crosschecked data on all food aid transactions by countries and NGOs, whether or not the food aid was distributed by WFP. The analysis uses a Generalized Method of Moments (GMM) system approach, which allows control of the dynamic nature of the data, as well as potential endogeneity issues. As in previous studies, we show a significant relationship between rapid onset disasters (e.g. floods, hurricanes, and earthquakes) and the international response of food aid. Unique to this study, we demonstrate a lag effect of aid in response to gradual onset disasters (droughts, extreme temperature, and disease). This is a particularly important result considering the potential for increased gradual onset natural disasters in response to climate change. We also show a highly significant and positive relationship between emergency food aid and displaced people.

The dissertation provides important results for advising government policy makers and non-governmental organizations to further address food security needs in developing countries. This research highlights the importance of natural and social capital quality in determining food security. The optimal control model provides insight into the long-term balance between natural capital quality and food production. The combination of GIS and remote sensing tools with econometric modeling provides an important picture of the relationship between household food security and nearby vegetation quality, and vegetation quality in areas further away. The dynamic panel analysis of shocks and food aid indicates a need for improved strategies in addressing food security in the critical moments of disasters.

Chapter 2: Trade-offs Between Food Production and Natural Capital Stocks: A Dynamic Optimal Control Model

2.1 Introduction

This section builds an optimal control model to analyze the trade-offs between stocks of primary forest and agricultural production. This study highlights the role of ecosystem services provided by stocks of forests, which include protection from flooding and erosion, maintenance of soil quality, and contributions to healthy watersheds. The model developed analyzes food production and consumption decisions in the context of sufficient and consistent access to food, particularly represented by changes in the stock of natural capital, in this case primary forest, which is utilized by the population for various reasons, including being cleared to create room for agriculture production. We demonstrate the cost reductions achieved in the agriculture sector due to the presence of forest stock. The analysis determines optimal levels of per capita agriculture land for the three geographic belts of Nepal: Terai, Hills, and Mountain regions.

This chapter proceeds as follows. First, relevant background information is presented. This is followed by the development of the dynamic model. Next, the case study data for Nepal is presented, including econometric analysis results of the various components of the optimal control model. Then, the results of the optimal control analysis are presented under varying parameters. Finally, discussions and conclusions are presented.

2.2 Background

2.2.1 Deforestation, Frontier Lands and Food Security

The growth in population and resulting increased demands for food is a leading factor in the growth in the conversion of forests to agricultural lands in developing countries. In many

developing countries, the conversion of forest lands into agricultural lands occurs from internal migration, as rural residents move within a country searching for the most productive resource rich lands (Lucas, 2007; Carr, 2009; Fonner, et al, 2012). Ironically, the destruction of forests threatens the long-term sustainability of food supplies and rural development (Carr, 2004), often perpetuating a cycle of poverty. Barbier (2005) discusses the frontier expansion hypothesis, related to the resource-development paradox, whereby resource-dependent countries see rapid land expansion in biologically fragile areas typically occupied by the poorest populations. The hypothesis suggests that the rural poor, while seeking out better opportunities, exploit open access resources in an unsustainable manner. Often, there is limited reinvestment in other productive sectors in society to generate sustained economic growth, instead continuing the cycle of unsustainable conversion of frontier lands. The social impact frontier land conversion, particularly forests, includes decreased food security, violent conflicts, increased inequity among gender, ethnic groups, and social castes (Vilet et al., 2012).

The benefits of forest resources for food security are many, through both the direct consumption of products, recreation and passive uses, and through the indirect benefits of forest ecosystem services. Forests are sources of food, fuel, construction material, and other products that are consumed directly, and provide the income needed to buy other food products and welfare improving goods. Forest ecosystem services include stabilizing landscapes; maintaining moisture and nutrients in soil; buffering against the spread of disease and pests; regulating the water quality and quantity of watershed flows preventing both floods and droughts; regulating climate at the local, regional, and global levels; and serving as stores of greenhouse gases; and maintaining stores of biodiversity (including Myers, 1997; Thomas, et al.; and Dessie and Klemen, 2007).

Meyfroidt and Lambin (2011) discuss slowdowns in deforestation between 2000-2010, with some trends in reforestation seen. Drivers of reforestation include industrialization and growth in service and other non-extractive sectors of society, and the intensification of agriculture in areas most suitable for food production in a country. Understanding the value of forest ecosystems is critical for policy makers attempting to achieve long-term protection of habitats critical for conservation, and for economic development. The seminal article by Costanza et al. (1997) attempted to put a total monetary value on forest ecosystem services. Chiabai et al. (2011) analyze the incremental value of ecosystem services provided by forest biomes, measuring the cost to society when these services are no longer available.

2.2.2 Forests and agricultural productivity

Several studies have specifically looked at the role of forests, and deforestation, and agricultural productivity. Zhang et al. (2007) provide a complete discussion of the benefits to agricultural production of ecosystem services, such as pollination and maintenance of soil quality, and also discuss potential ecosystem disservices, such as animal pests that feed on crops.

Ehui and Hertel (1989) analyzed the dynamic relationship between deforestation and agricultural production in the Ivory Coast, with an econometric analysis showing immediate benefits to production from deforestation. However, these benefits are seen to diminish as forest stocks are depleted. A further study showed a 10% increase in the stock of forested land resulted in a 26.9% decline in aggregate agriculture yields (Ehui and Hertel, 1992).

Bulte et al. (2001) used an optimal control model to determine the optimal level of deforestation in Costa Rica, assuming benefits go to both forestry and agriculture production. The determination was that the total benefit of forest stock is heavily dependent on the value placed on

carbon storage, and the ability for the Costa Rican government to be compensated for this externality. The model does not include the direct benefits of forested land to the agricultural sector.

Hassan et al. (2009) used an optimal control model to measure the benefits of forest stocks for agricultural production, and the benefits of deforestation for energy consumption. This model considered the benefits of forest stock to agriculture to be increasing at a decreasing rate. The model was particularly interested in finding optimal investments to be made for reforestation, and the need to optimally price firewood to encourage less deforestation.

This analysis aims to draw on previous studies of the impact of forest ecosystems on agricultural productivity. We econometrically measure the impacts of forests on agricultural productivity, and control for the feedback of agriculture production on stocks of forest. The developed model is then applied to several districts in Nepal, providing insight into optimal forest stock and agricultural lands.

2.3 Optimal Control Model Development

The goal of this model is to highlight the trade-offs between increased consumption today and the long-term ability to maintain food security levels. The essence of food security is such that an adequate quantity of food is available in the present time period, while those resources that will provide food in the future are cultivated and preserved. We choose the optimal control methodology to account for the impact on the stock of natural capital, in this case forests, as households bring lands into agricultural production. The level of forest stock, a state variable, in turn influences the performance of the farm. This trade-off highlights the food security problem, where current consumption decisions impact future consumption potential.

It is important to keep in mind that the nature of modeling requires making simplifying assumptions. This is particularly the case when applying real world data to the model. In some

instances, relaxing or varying certain assumptions will change the conclusions. Therefore, we incorporate a sensitivity analysis within our model. The various components of the model, and the initial simplifying assumptions, will be presented in this section.

2.3.1 Value function from agriculture production

The goal of our model is to measure the aggregate social benefits from agriculture land (A) to the population (n) under production minus the costs of that production, which is impacted by A , and the quantity of forest stock (F_S). The model developed is in per capita terms, where the individual is representative of the society. When the benefits are maximized for an individual, they are maximized for society. Agriculture land per capita is defined as $a = \frac{A}{n}$, and forested land per capita is defined as $f = \frac{F_S}{n}$. We use the general unconstrained dynamic social welfare function as follows.

$$V = \int_0^T B[a(t), n(t)] - C[a(t), f(t), n(t)] dt \quad (2-1)$$

Where $B[a(t), n(t)]$ represents dynamic aggregate social benefits $\forall t = 1, \dots, T$, of agricultural land under production, while $C[a(t), f(t), n(t)]$, represents the dynamic social costs $\forall t = 1, \dots, T$.

We begin considering the benefits society receives from agriculture production. There are difficulties placing a monetary value on agricultural output in societies with a large subsistence population, as much of the food produced is not sold in a market place. Ignoring this value, though, can distort economic analyses (Chibnik, 1978, Kamanga, et al. 2009). Therefore, we assume all

agricultural production has a market price (p_i^f) whether or not the food is sold. Considering Φ food types, total agricultural value per household, B , is given the following formulation.

$$B = \sum_{i=1}^{\Phi} p_i^f Q_i \quad (2-2)$$

The term Q_i is the quantity of i food types produced. With a large variety of crops produced by subsistence level farmers, it is difficult to track the necessary market values of each individual crop produced. In our model, we are most interested in the marginal decision to put land into production. It is therefore convenient to follow Shalit and Schmitz (1982) and, and consider v to be a function of the household agricultural land in production (a). Individual farmers are considered price takers, choosing an optimal a to maximize their production value given a rate of return per land area, P^a , which is set by the market. The value function is rewritten as follows.

$$B = B(a, P^a) \quad (2-3)$$

The return received per area of land in production is assumed exogenously determined by the demand for agriculture products, and the existing supply of farmland in production. We provide a relationship for P^A as follows.

$$P^A = P^A(A, n, \mathbf{X}) \quad (2-4)$$

Where \mathbf{X} is a vector of market characteristics.

2.3.2 Costs of production

To develop the cost function we consider the static household production function of

subsistence level farmers. In addition to the land under production, households in rural developing countries often do not use inputs beyond household labor, seeds, and manure as fertilizer (Godfray, et al., 2010). Instead, subsistence farmers rely heavily on the quality of ecosystem services, which impacts soil quality, soil erosion, flooding, and irrigation. Any additional inputs utilized will be related to the quality of ecosystem services available. Similarly, labor availability is impacted by the availability of forest ecosystem services, which provide the household with firewood and improved drinking water sources (Millennium Ecosystem Assessment, 2005, p. 86). With better access to such resources, more of the household labor may be diverted to agriculture production. To highlight this effect, we consider the following household production function.

$$q = y(a, w(f), \mathbf{I}(f)) \quad (2-5)$$

Where household agricultural output (q) is a function of a , labor ($w(f)$), and a vector of other inputs and uses of capital ($\mathbf{I}(f)$). Both w and \mathbf{I} are functions of the quantity of forest per household (f) in the household's geographic area. We consider (2-5) as a well-behaved twice differentiable function, such that production increases at a decreasing rate with the inputs, $y_a > 0$, $y_{aa} \leq 0$, $y_f > 0$, $y_{ff} \leq 0$, and $y_{af} \leq 0$. We use this production function to develop a welfare maximization approach to analyzing household production.

Individual costs of production are considered a function of both of our inputs, a and f , as well as n , expressed in the following equation.

$$C = C(a, f, n) \quad (2-6)$$

Which is twice differentiable in each of the inputs, with a increasing costs at an increasing rate, such that $C_a > 0$ and $C_{aa} > 0$. We assume the costs of converting forest to agricultural land, and

maintaining agricultural land so it does not return to a natural vegetative state, are part of these production costs. Due to the ecological services of soil productivity, erosion and flood protection, and other benefits discussed above, we expect the cost of production to decrease in f , however these cost saving effects may decline with high levels of vegetation, as more vegetation decreases the overall supply of agricultural land. So, it is expected that $C_f < 0$ and $C_{ff} > 0$. We include n to account for the demand for inputs. It is hypothesized that regions with higher population will cause the price of inputs to go up, increasing the cost of production. There is also the potential for labor costs to go down as population increases, as more labor is available, so it is expected that population will increase costs of production at a decreasing rate, such that $C_n > 0$ and $C_{nn} < 0$. It is expected that the cross effect of production inputs will be such that $C_{af} \leq 0$. This suggests that marginal costs of agriculture go down with more f available, and up with less f available.

2.3.3 Forest stock

The stock of forest (F_S) is the state variable in this dynamic optimal control model. We use a simple linear form similar to Hassan et al. (2009), who considered the stock of forests as a function of natural growth, harvesting and reforestation. In our model, vegetation, which includes mature forest growth and other natural vegetation (not to include degraded land and agriculture land), is primarily impacted by the conversion of land to agriculture at a rate of the growth in population (\dot{n}) multiplied by a . The impact on forest stock of per person agriculture land may not be in a one to one ratio. The term ω is defined as the rate of impact of agriculture land. Additionally, d is the natural growth rate of F_S . We consider growth to occur as a growth rate multiplied by the percentage of land that is forested ($\frac{F_S}{L}$, where L represents the total land area). As discussed by

Brown and Lugo (1990), Schulz et al. (2010), and others, the impact of secondary vegetation growth on forest stocks must also be considered. The conversion of forested land into secondary vegetation and other non-agriculture land uses, and the potential re-growth of this land into forested land, is included. The term s is the impact of this land on F_S . Finally, ref is reforestation that occurs through government, community, and other investments into the natural capital stock. We make the assumption that additional conversion of F_S . The following equations summarize the relationship of the combined terms.

$$\dot{F}_S = d \frac{F_S(t)}{L} + n a(t) \omega + s[L - F_S(t) - A(t)] + ref, \quad (2-7)$$

where $\omega < 0$, $d \begin{matrix} < \\ \equiv \\ > \end{matrix} 0$, $s \begin{matrix} < \\ \equiv \\ > \end{matrix} 0$, and $ref > 0$.

To keep the notation in per capita terms, (2-7) becomes

$$\dot{F}_S = d \left(\frac{f(t) \cdot n(t)}{L} \right) + \omega \dot{n}(t) a(t) + s[L - (f(t) \cdot n(t)) - (a(t) \cdot n(t))] + ref \quad (2-8)$$

The change in \dot{F}_S will be negative if

$d \cdot f(t) \cdot n(t) \cdot L^{-1} + ref < \omega \dot{n}(t) a(t) + s \cdot (L - f(t) \cdot n(t) - a(t) \cdot n(t))$, which is the intuitive result, as a growing population is likely to increase pressure on forest stocks. However, larger investments in replanting may offset the negative impacts of population growth. For simplicity, we keep ref constant in our model.

2.4 Constrained Welfare Maximization

Combining the value function and the F_S state equation, gives us the following dynamic maximization problem, where a community or social planner in a location is interested in maximizing the value of agriculture production at a sustainable level, given an initial number of people in the community ($n_0 = n(0)$). The goal of the community is to choose the optimal quantities of farmland and forest stock, per capita, to maximize future benefits from food consumption. Based on the area of study we can adjust the model parameters to account for regional differences, namely the demand for agricultural land and the dynamics of the forest stock.

$$\text{Max}_{a(t)} V = \int_0^{\infty} e^{-rt} [B(a(t), n(t), P^M(n(t) \cdot a(t), \mathbf{X})) - C(a(t), f(t), n(t))] dt$$

s.t.

$$\dot{F}_S = d \cdot f(t) \cdot n(t) \cdot L^{-1} + \varpi \dot{n} a(t) + s[L - f(t) \cdot n - a(t) \cdot n] + ref \quad (2-9)$$

$$0 \leq n(t) \cdot [f(t) + a(t)] \leq L$$

$$n(0) = n_0$$

$$\text{With } \frac{A(t)}{n} = a(t), \quad \frac{F_S(t)}{n} = f(t)$$

The term e^{-rt} is the discount factor, and $0 \leq n(t) \cdot [f(t) + a(t)] \leq L$ ensures the combination of agriculture land and forested land does not exceed the total land size of the geographic area under consideration. The time horizon is infinite, given the assumed goal of sustainability. It should be noted that this problem ignores the direct benefits and costs of uses of land area beyond agriculture production.

The present value Lagrangian to solve the social planner's problem is as follows.

$$\mathcal{L} = e^{-\pi} [B(a, n) - C(a, f, n)] + \lambda (d \cdot f \cdot n \cdot L^{-1} + \dot{\omega} n a + s [L - f \cdot n - a \cdot n] + r f) + \mu (L - f \cdot n - a \cdot n) \quad (2-10)$$

Now, the first order conditions are as follows.²

$$\mathcal{L}_a = e^{-\pi} [B_a - C_a] + \lambda (\dot{\omega} n + s) - \mu \begin{matrix} < \\ = \\ > \end{matrix} 0 \rightarrow \begin{matrix} a = 0 \\ a = \frac{L}{n} - f \\ 0 < a < \frac{L}{n} - f \end{matrix} \quad (2-11)$$

$$-\mathcal{L}_f = e^{-\pi} [C_f] - \lambda (d \cdot n \cdot L^{-1} + s \cdot n) + \mu \cdot n = \dot{\lambda} \quad (2-12)$$

$$\mathcal{L}_\lambda = \dot{f} \quad (2-13)$$

indicates the marginal value of the Hamiltonian with respect to the change in the marginal shadow value is equal to the state equation.

$$\mathcal{L}_\mu = L - na - nf = \dot{\mu} \quad (2-14)$$

$$\lim_{t \rightarrow \infty} \lambda(t) = 0 \quad (2-15)$$

indicates the transversality condition for a free terminal state as the time goes to infinity (Chiang, 1992, p. 240).

$$\dot{\mu} = 0, \mu \geq 0, L - fn - an \geq 0, \mu (L - fn - an) = 0 \quad (2-16)$$

² Time arguments are dropped for simplification, and partial derivatives, such as the Lagrangian with respect to f is \mathcal{L}_f .

provides the complementary slack conditions, along with the assumption that the marginal value of the fixed stock of land is assumed not to change.

2.4.1 Interpretation of first order conditions

The term λ is the marginal shadow value of the resource stock, in this case the stock of vegetation. The value of λ at $t = 0$ (given the use of a present valued Hamiltonian) will increase as the stock of resource depletes in future time periods, meaning each unit of remaining stock becomes more valuable. The term μ is the marginal shadow value of the total land area. We have defined this value to be constant throughout the horizon of the problem through (2-16).

Equation (2-11) governs the optimal agricultural land per person, including the Kuhn-Tucker conditions, which indicate several potential scenarios. First, if $a = 0$, then the marginal benefits of the value function of using land for agriculture, are less than the marginal shadow costs of converting land for agriculture use.

$$e^{-rt}B_a - e^{-rt}C_a + \lambda(\dot{\omega}_{n+s}) < \mu \quad (2-17)$$

Second, if a reaches the upper boundary of the constraint, $a = \frac{L}{n} - f$, then the marginal benefits of a outweigh the marginal costs of a .

$$e^{-rt}B_a > e^{-rt}C_a + \mu - \lambda(\dot{\omega}_{n+s}) \quad (2-18)$$

Third, if a is an interior solution, we can equate the marginal benefits of a with the marginal costs of a . The shadow value of the total land area is 0, as the constraint is not binding.

$$e^{-rt}B_a = e^{-rt}C_a - \lambda(\dot{\omega}_{n+s}) \quad (2-19)$$

We are not bound to an interior solution for a or for f . However, we assume an interior solution here, to further explain the trade-offs between maintaining vegetation stock and increasing the amount of land under production. In other words, at any time period, we now assume $na + nf < L$. An expression for λ , the marginal user cost (MUC) of turning vegetation into agriculture land, is then

$$\lambda = \frac{e^{-rt}[B_a - C_a]}{-(\dot{\omega}_{n+s})} \quad (2-20)$$

where $\lambda > 0$, with $R_a - C_a > 0$ (assuming $B_a > C_a$), and $(\dot{\omega}_{n+s}) < 0$ (assuming positive population growth and $\omega < 0, s < 0$, as defined previously). Therefore, the opportunity cost of using a unit of vegetation stock is positive. A basic economic principle suggests the optimal amount of agriculture land put into service should be where the marginal benefits (MB) are equal to the marginal costs (MC). Ignoring MUC of turning forest into agricultural land would give a sub-optimal quantity of agricultural land put into service. Further rearranging (2-20) gives the correct maximization rule to be considered by the social planner.

$$e^{-rt}B_a = -\lambda(\dot{\omega}_{n+s}) + e^{-rt}C_a \quad (2-21)$$

where $e^{-rt}B_a$ = Marginal Benefits and $-\lambda(\dot{\omega}_{n+s}) + e^{-rt}C_a$ = Marginal Costs

Assuming an interior solution, we can re-write (2-12) (from the first order conditions) to analyze the expression of the change in user costs.

$$\dot{\lambda} = e^{-rt}[C_f] - \lambda(d \cdot n \cdot L^{-1} + s \cdot n) \quad (2-22)$$

Our previous assumption of $C_f < 0$ suggest the user costs will be decreasing if $\dot{f} > 0$, and user costs will be increasing if $\dot{f} < 0$, as expected.

The optimal time path for a is found by differentiating (2-11) (with $H_a = 0$ for the interior case) with respect to time. After rearranging terms, and substituting in the state equation, (2-20) for λ , and (2-26) for $\dot{\lambda}$, \dot{a} is as follows.

$$\dot{a} = \frac{1}{-(B_{aa} - C_{aa})} \left[\begin{array}{l} -r(B_a - C_a) - C_{af} [dfL^{-1} - \omega \dot{n} a - s(\frac{L}{n} - a - f + \frac{ref}{n})] \\ -(\frac{n[B_a - C_a]}{\dot{\omega} n}) [(\ddot{\omega} n) - (d + s)(\dot{\omega} n + s)] - (C_f)(\dot{\omega} n + s) \end{array} \right] \quad (2-27)$$

Using our expressions for \dot{F}_S and \dot{a} , we can find a combination of per person forest and agricultural land that is a steady state. This will only be possible if population change is also at a steady state level. This may be realistic if we consider reaching a carrying capacity level for the geographic region in question. Alternatively, one could choose a variety of per capita steady state values for potential population sizes. Either way, the mathematical definition of a steady state requires $\dot{a} = \dot{F}_S = \dot{n} = 0$. In our numerical application that follows, we will assume a policy goal of sustainability, on the path for reaching the steady state.

2.5 Agricultural Land Use and Deforestation in Nepal

To operationalize the optimal control model to use in the case study, we allow the model to take a form similar to that of an indirect profit function. A functional form for the $B(\cdot)$ component of the model is as follows.

$$B(\cdot) = a(t) \cdot P^m(a(t), n(t), \mathbf{X}) \quad (2-28)$$

We also consider a linear cost function that meets our model requirements of $C_a < 0$ and $C_{aa} \geq 0$; $C_f < 0$, and $C_{ff} \geq 0$; and $C_{fa} \leq 0$. The parameters for the function forms of P^m , $C(\cdot)$, and the state equation (2-15) were estimated econometrically. Our methodology, discussion of the data used, and the econometric results are presented in this section.

We use household agriculture production data from rural areas of Nepal, collected through the Nepal Living Standard Surveys, from 1995-1996 and 2003-2004. We incorporate land cover data using GIS information from 1990 and 2000 derived from the analysis of remotely sensed imagery in a GIS platform. This gives us baseline forest data for the areas in which the households are carrying out agricultural activities. Population data comes from the Nepal Census Bureau.

To calculate per hectare revenue data and agriculture cost data, it was necessary to extract the amount of land each household surveyed indicated they owned, or had access to for farming purposes. We include all land that had farming activities occurring. We did not include those lands, which were owned and rented out for agricultural purposes, as the actual costs and revenue from operating these lands was not included in the survey data. Land sizes were reported in different amounts in the data. It was necessary to convert land sizes to common units, hectares.

The quantity of each crop produced, whether sold or not, was included in the data. The revenue earned for each quantity of each crop produced and sold in the market was also reported. In the many instances that crops were not sold, the crop value had to be calculated. To do this average market prices $\bar{P}_{i,j}$ were calculated for each crop type, i , by district, j . After adjusting the measurement units of the crops produced, it was possible to calculate crop values for each individual crop type. Then we summed the value of all crops sold and not sold, to get the revenue per household, b . The survey data did not indicate exactly how much acreage was devoted to each crop, but we were able to calculate the overall revenue per hectare of land farmed by the household. The average revenue per hectare per district is used for the exogenous P^m term in (2-4). While exogenous, we do expect P^m to change dynamically, and therefore estimate P^m in this section.

The costs specific to each crop were not provided. However, the overall costs used for labor, inputs, equipment and other expenses per household were provided. Although provided, we did not include land rental costs for those who did not own the land being farmed, as there would be a potential distortion between those who paid and did not pay rent.³ Also, it was reported which district each plot of land was located in. In some cases, the district where the land was located was not the home district of the household being surveyed. We merged the survey data with population and land cover by each district.

The land use categories include mature forest, secondary vegetation, degraded, agriculture use, and bare land. There is also land area not defined in any of these primary categories due to snow and cloud cover at the time the images were captured by satellite. A small percentage of the data is defined as unidentified. We included the sq. hectares of mature forest stock (F_S) in each of the 75

³ It should be noted that including rental data did not overly distort the regression results, however we elected not to include this data as a cost.

districts in Nepal in our analysis. Also, we included the aggregate measure of agricultural land (A) in each of the districts. The dates of remote sensing data collection of 1990 and 2000 did not match with the NLSS survey period. To deal with this problem, we calculated the ten-year change for F_S and A in each district, dividing by 10 to get the average annual change in both. The average annual change was then multiplied by 3, and added to the 2000 data to give 2003 data. Likewise, the average annual change was multiplied by 4, and subtracted from the 2000 data to give 1996 data. Although this approach is not the most ideal situation, it is assumed more precise than trying to align known 1990 and 2000 vegetation data directly with 1996 and 2003 data. Similar data misalignments occurred for the population data, which were corrected in a similar manner. We took the average annual growth rate for the population data points available, 1981, 1991, and 2001, and used 2001 data to find the population for 2003 and 1996. This gave us the required data needed to carry out ordinary least squares regressions to estimate our revenue and cost functions. All data is summarized in table 2-1.

2.5.1 Econometric Analyses

First, we econometrically estimate the relationship of P_j^m with A_j , n_j , and L_j , where (j) represents district level data. We used a panel regression approach, as we had two years of data for each of the districts in our study.⁴ This allows us to control for unobserved heterogeneity in geographic areas. The econometric model is as follows.

$$P_{jt}^m = \beta_0 + \beta_1(A_{jt}) + \beta_2 n_{jt} + \beta_3 L_j + u_j + \delta_t + \epsilon_{jt} \quad (2-29)$$

⁴ We excluded observations for Humla, which were outliers in the model. Inclusion of this observation caused all regression results to be insignificant.

The Hausman test indicated that the random effects model was acceptable so we report these regression results below.⁵ We also considered potential endogeneity effects of A_{jt} .

Endogeneity tests indicated it was not necessary to instrumentalize A_{jt} .

$$P_{jt}^m = -2.44 A_{jt} + 0.430 n_{jt} + 0.526 L_{jt} + 100533.8 \quad (2-30)$$

(1.169) (0.110) (0.357) (60064.0)

(robust s.e.), R-squared=0.115, n=142, Hausman=5.77, (P=0.0558)

The linear cost function is estimated using all of the total cost data provided from the NLSS survey as the dependent variable. The NLSS data includes the cost of operating farms, and the size of these household farms ($size_j$). It is assumed the relationship between hectares of farmland and costs of production will hold regardless if the measure of agriculture land is in per person terms or per household terms. Therefore, we equate $size_j$ with a in the optimal control model. We choose a cubic form, to ensure the second derivative of the cost function is positive. Assuming a long-run cost curve, we do not include a constant, or dummy variables, the econometric model estimated is as follows.⁶

$$C(a, f, n)_i = \alpha_1 a_i + \alpha_2 a_i^2 + \alpha_3 a_i^3 + \alpha_4 f_i + \alpha_5 f_i^2 + \alpha_7 n_i + \epsilon_i \quad (2-31)$$

The regression was carried out using robust standard errors. The results, are indicated below. All coefficients were statistically significant in the regression.

$$C(a, f, n) = 6311.9 a - 572.373 a^2 + 12.388 a^3 - 2269.510 f + 231.820 f^2 + 0.007 n \quad (2-32)$$

(370.375) (58.551) (1.944) (311.081) (63.026) (0.0004)

⁶ Regressions with dummy variables and the constant do not greatly impact the value of model parameters.

(robust s.e.), $N=4969$, $R\text{-squared}=0.323$, $F\text{-test}=262.48$

The results indicate consistency with the theory we developed. Marginal cost, $C_a > 0$, as expected.

We see that for individual farm sizes beyond 15.4 Ha, then $C_{aa} > 0$.

Our third econometric regression was for the state equation. The model estimated is as follows.

$$\dot{F}_s = \beta_0 + \beta_1 \frac{F_s}{Land} - \beta_2(n \cdot a) - \beta_3[(L - F_s - A)_j] - \beta_4 mnt + \beta_5 hil + \beta_6 ter \quad (2-33)$$

We used the change in mature forest cover from 1990 to 2000 as our dependent variable. This gave us one observation for each district. The included F_s data on the right hand side of the equation was the 1990 F_s value for each district. We created a corresponding 1-year population change term (dividing a known 10 year population growth value by 10), and multiplied this by the a value for 1990. The $(L - F_s - A)$ term was also taken from 1990 data. We suspect an endogeneity issue with the $(L - F_s - A)$ in this equation. We also considered potential endogeneity problems with our explanatory variables. Using instruments, and carrying out endogeneity tests showed endogeneity not to be an issue. Finally, we also account for regional characteristics by including dummy variables for the primary geographic belts of Nepal Mountain (*Mnt*), Hills (*Hil*), and Terai (*Ter*). We created an additional dummy for the three districts that make up the Kathmandu Valley, in order to control for the economic power. These three districts were not included in *Hil* belt. In our econometric analysis, the *Kat* dummy was excluded. The aggregate of the dummies and the constant correspond with the *ref* term in (7). The regression was carried out using robust standard errors. The regression results of (2-32) are presented below.

$$\begin{aligned} \dot{F}_s = & -10441.63 \frac{F_s}{Land} - 0.028 \dot{n} a - 0.013 (L - F_s - A) \\ & (2647.8) \quad (0.010) \quad (0.007) \\ & + 3675.35 + 1271.02 \text{ bil} - 478.76 \text{ ter} + 541.77 \text{ mnt} \quad (2-34) \\ & (968.8) \quad (651.13) \quad (529.51) \quad (973.80) \end{aligned}$$

(s.e.), $N=75$, $R\text{-squared (centered)}=0.549$; $F\text{-test}=9.94$;

The results in (2-29) and (2-31) can be used to populate the Benefit and Cost functions in equation (2-7). We rewrite terms to maintain per capita notation for $a(t)$, recalling $A(t) = a(t) \cdot n(t)$ and $F_s(t) = f(t) \cdot n(t)$.⁷ Suppressing time notation, our optimal control components with parameters are as follows.

$$B(a, n) = a(-2.44 a \cdot n + 0.430 n + 0.526 L + 100533.8) \quad (2-35)$$

$$C(a, f, n) = a(6311.9 - 572.4 a + 12.4 a^2) - f(2269.5 - 231.8 f) + 0.007 n \quad (2-36)$$

$$\begin{aligned} \dot{F}_s = & -10441.63 \frac{nf}{L} - 0.028 \dot{n} a - 0.013 (L - nf - na) \\ & + 3196.6 \text{ ter} + 4217.2 \text{ mnt} + 4946.37 \text{ bil} \quad (2-37) \end{aligned}$$

The final equation of motion that we must consider is the population growth equation. We use a Verhulst logistic equation (Clark, 1990, p. 11), which allows the population to grow at rate g , and then taper off to the carrying capacity (k), as follows.

$$\dot{n} = gn \left(1 - \frac{n}{k}\right) \quad (2-38)$$

⁷ It is important to note that the state equation was estimated in its aggregate form, which must be considered when carrying out the optimal control analysis.

One of the limitations of (2-38) is that the growth rate is constant over the time horizon of the optimal control analysis. The 2011 growth data show a 1.4% annual population growth in Nepal (Nepal Census), while the World Bank reports a 1.8% growth rate in 2010.⁸ However, Kathmandu had a 4.8% growth in population.

The Nepal Country Profile presented by the UN at the Johannesburg Summit in (2002)⁹ suggested a realistic future population limit in Nepal to be 60 million people. This is approximately double the 2012 population estimated by the World Bank. According to the 2000 data, approximately 7.2% of Nepal's population lived in the districts of the Kathmandu Valley. The remaining Hill districts included 37.1% of the country's population, the Terai districts contained 48.6% of the population, and the Mountain region contained, 7.1% of the population. With a trend towards urbanization, we expect a larger share of the future population to be located in the Kathmandu Valley. In our regional optimal control analysis that follows, we consider several regional growth rates and carrying capacity values. Table 2-2 gives population and land size characteristics for each of the three regions of Nepal.

2.6 Optimal Control Analysis

We carryout our analysis for the three primary geographic belts mentioned in the econometric model. These include the Mountain region, Terai region, and Hill region (excluding the three districts in the Kathmandu Valley). We use a discount rate of 15%, which is very similar to a recent paper by Das and Bauer (2012), who developed a bio-economic control model of soil quality in an area of Nepal. We also adjust our carrying capacity, k , as discussed below.

⁸ World Bank. 2012. World Development Indicators. <http://data.worldbank.org> (accessed 25 May 2012)

⁹ www.un.org/esa/agenda21/natlinfo/wssd/nepal.pdf (accessed 25 May 2012)

We considered a low k of 150% beyond current population (based on the estimated 30 million country wide population), and a high k of 200% of the current population for non-Kathmandu districts. We consider a low, 1.4% growth rate, and a high 1.8% growth rate for the (non-Kathmandu) districts. It should be kept in mind that these growth rates and carrying capacities are held constant through the time horizon of the model. We carry out the analysis using differing population growth rate and carrying capacity combinations 1) Low k and High g , 2) Low g and Low k , 3) High g and High k , and 4) High g and Low k .

2.6.1 Optimization of the model

The optimal paths for a and f are found using a backward shooting method, where imposed end values (at time = T) of the problem can be used as the starting values. These imposed end values are the steady state of the model, which is also the point where the population is at its imposed carrying capacity. To use the backward shooting method, the system of ODEs is solved in reverse by multiplying the ODEs by -1, and setting the final time period equal to the initial value in reverse, $T = t_0^{reverse}$. The result gives numerical optimal paths that move backwards towards the desired starting values. In the case of this model, that starting point is when the population level reaches the starting population values. The end point in reverse ($T^{reverse}$) now becomes the actual t_0 . The optimal path for each of the variables is then known from $t_0 \rightarrow t_0^{reverse}$ (for more details see Judd, 1999 and Naevdal, 2003).

2.7 Optimal Control Results

Visual results of our analysis are seen in Figures 2-1 through 2-3. There is a clear declining impact for both a and f for all of the models considered. This corresponds with negative differential equations developed for the model. These are generally expected in models where a

variable of value, in this case a and f , are part of a benefit function with a discount factor declining over the time horizon of the analysis. Sensitivity analyses using discount rates within 5-10% above and below the 15% did not noticeably change the per capita results, and are therefore not included in the results. In the analyses pertaining to the Terai Belt and the Hills Belt, the starting values for a and f under the different scenarios considered are close to identical. There is a slight deviation in starting values among the scenarios in the Mountain Belt. As expected, the steady states for the lower steady state population cases have higher steady state values for both a and f . The scenarios with higher growth rates see a and f declining more rapidly to the steady state values. In all cases, the model results do not indicate reaching the binding land constraints outlined in the previous section.

2.7.1 Magnitude of Results

While the trends of the analysis are identical among the different geographic belts, we do see differences in the magnitudes of the results between the belts. The Mountain Belt indicates the highest optimal a and f levels, while the Terai Belt indicates the lowest a and f levels. The results are largely shaped by the population of the regions, which one might expect to be linked back to the productivity of the areas. In the Terai there is a much higher population density, as seen in Table 2-2. This is driving a and f lower than the other two regions. These results and the distribution of population are not surprising. The Terai Belt is considered the breadbasket of Nepal, so it would be expected there would be a high level of per hectare productivity in the area. One might imagine more agriculture output can be achieved in a smaller area in this region. In the Mountain Belt, achieving optimal per capita production requires larger areas of farmland, per person. This lower productivity, and harsher terrain, is also likely to keep the population at lower

levels. The results for the Hills Belt is between both the Mountain and Terai belts, but appears to be more similar to the Terai.

A summary of the optimal starting values and steady state values for each of the scenarios is presented in table 2-3. This table also includes the actual values of a and f observed in the spatial data utilized. Although the observed data is ten years older than the starting point of the calibrated model, these values are important for providing context to the model results. The same relative distribution of a and f between the belts are seen in 2000 as are calculated as the starting values in the optimal control model. This provides a level of validation to the model. Compared to the 2000 levels, the optimal starting values for a are lower in each of our scenarios compared to the 2000 levels. This results in higher starting values for f in each of our scenarios. This is not a surprising result, as the marginal cost of agriculture production with respect to f is negative. We might expect the optimal values of f to be greater if the direct benefits of f were incorporated into the value function. This is further discussed in the discussion and conclusion section.

2.8 Population Effect

The per capita optimal time paths may be a bit misleading, as both agriculture land and forest land are declining. Presumably, forested land is being converted to agriculture land, which is not represented by the optimal time paths. Therefore, the optimal time path results for the aggregate levels of agriculture land and forested land were created, and are presented in Figures 2-4 through Figures 2-6. The results do show an increase in agriculture land over time, while the aggregate forest land is declining to the steady state value.

2.9 Discussion and Conclusions

This model is important for illustrating the trade-offs that often occur between consumption in the current period and long-term protection of capital stocks, whether these are natural capital stocks or otherwise. In the case study presented, we have incorporated the particular ecosystem services of a stock of natural capital. The data analyses provided show a direct relationship between declining agriculture production costs and increased forest stocks. Although we have not explored the exact contribution of forest stocks to production, it is hypothesized that the physical benefits include erosion and flooding control, maintenance of soil quality, and protection of watersheds, among others. A further study should analyze the substitutability between forest stock and agricultural inputs. We may also expect that labor is more productive in locations with higher forest stocks, as firewood, freshwater, and other products and services relying on forests are more easily accessible to the local population. Less time has to be spent collecting forest related products. A further study may also more directly analyze the trade-off between labor availability and forest stock.

One weakness of the model developed is the limited incorporation of forest value. The model only incorporates the value of forests in terms of the costs of production. It would be expected that forests provide direct benefits to society. There may be some difficulty in directly observing these benefits though, as much like subsistence agriculture, many of the forest benefits may arise from goods and services that cannot be measured in a functioning market. Benefits could be measured in a non-market approach. Other benefits, including those from tourism, could be directly observed. Further, the model does not incorporate the benefits of secondary vegetation, which may have some of the same land protection features as primary forests. A further model should incorporate this.

While the costs and benefits from forests are important for producers, the entire economy would be expected to benefit from the protection of forests. By taking a regional approach to the analysis, we generate a general picture of the optimal levels of agriculture land in production. This policy suggestion is to protect more forest. But, the model does not say where that forest should be located. A further analysis could calibrate the model for specific districts or village level. The difficulty with a smaller scale analysis is that the benefits received from forests do not stop at the boundary of the forest. Perhaps an even more precise study would look at the optimal agriculture land by watershed.

Table 2-1: Optimal Control Data and Descriptive Statistics

Variable (model abbreviation)	Definition	Data Source	Units	Mean	Std. Deviation
Rev per hectare (γ)	Revenue (or value if crops not sold) from crop production and animal production.	Nepal Living Standard Survey (1996 & 2003) ¹	Rupees per hectare ^{a,b}	80244.6	750310.9
Costs (C)	Total cost of agriculture production per household.	Nepal Living Standard Survey (1996 & 2003) ¹	Rupees ^{a,b}	5946.0	12280.6
Farm Size (siz)	Size of farms of those households included in the Nepal Living Standards Survey.	Nepal Living Standard Survey (1996 & 2003) ¹	Hectares ^b	0.802	1.263
Forest (f)	Quantity of mature forest cover.	Based on the analysis of remote sensing imagery	Hectares per capita	0.643	1.708
Ag. Land (a)	Total land used for agriculture production per district.	Based on the analysis of remote sensing imagery	Hectares per capita	0.452	1.322
Land (l)	District land size	Based on the analysis of remote sensing imagery	Hectares	190490.5	107280.0
Population (n)	People living in each district.	Nepal Census Bureau ²	Number	309181.7	200517.3

¹ Nepal Living Standard Survey (1996, 2003)

² Nepal Central Bureau of Statistics, National Population and Housing Census. Government of Nepal. <http://census.gov.np/> (accessed 25 May 2012)

^a1996 Rupees were converted to 2003 Rupees using a conversion of 1.475 (NLSS, 2003)

^bApproximately 30 outliers were excluded. These outliers were several magnitudes larger than the mean land size, average farm revenue, and average costs. It was determined that these variables were not representative of the typical farmland in Nepal. Also, it's possible that survey errors or translation could have created the outliers.

Table 2-2. Variable Definitions

Symbol	Variable Name	Symbol	Variable Name
A, a	Total agriculture land, per capita agriculture land, in hectares	B	Benefits of agriculture land
n	Population	C	Costs of production, in rupees
F_S, f	Total forest stock, per capita forest stock	L, l	Total land area, hectares per capita
p^f	Price of food	ref	Reforestation, in hectares
Q, q	Quantity of food	g	Rate of growth of existing forest
p^A	Return per area of land	ω	Rate of impact of ag. land on forest stock
X	Market Characteristics	s	Rate of impact of non-forest and non-ag. land on forest stock
w	Labor	λ	Shadow value of forest stock
I	Ag. Inputs and Capital	μ	Shadow value of land area
y	Production function	r	Discount rate
k	Carrying capacity		

Table 2-3: Geographic belt characteristics.

Region	2010 Estimated Population (in millions) (source: <i>World Bank</i>)	Land Size (in thousands of km ²) (Based on the analysis of satellite imagery of 1990 and 2000.)	Population Density (2010) (people per km ²)
Mountain	2.2	52.36	42.0
Hill ¹	11.1	60.84	182.4
Terai	14.4	33.95	424.2

¹Not including the Kathmandu Districts

Table 2-4. Optimal Control Results by Region, varying growth rates and carrying capacity. Comparison to 2000 per capita forest land and agriculture land.

Region	2000 Forest Per Capita	2000 Ag. Land Per Capita	Carrying Capacity (g) and Growth Rates (k)	Optimal Starting Values Forest Per Capita (f)	Optimal Starting Values Ag. Land Per Capita (a)	Steady State Values Forest Per Capita, (f)	Steady State Values Ag. Land Per Capita (a)
Mountain	1.14	0.73	g =low, k =high	1.97	0.39	0.99	0.24
	1.14	0.73	g =low, k =low	1.97	0.39	1.35	0.29
	1.14	0.73	g =high, k =high	1.97	0.39	0.99	0.24
	1.14	0.73	g =high, k =low	1.97	0.39	1.35	0.29
Hill	0.26	0.19	g =low, k =high	0.35	0.15	0.14	0.19
	0.26	0.19	g =low, k =low	0.35	0.15	0.24	0.13
	0.26	0.19	g =high, k =high	0.35	0.15	0.14	0.19
	0.26	0.19	g =high, k =low	0.35	0.15	0.24	0.13
Terai	0.04	0.15	g =low, k =high	0.042	0.114	0.06	0.005
	0.04	0.15	g =low, k =low	0.042	0.114	0.08	.057
	0.04	0.15	g =high, k =high	0.042	0.114	0.101	0.005
	0.04	0.15	g =high, k =low	0.042	0.114	0.06	0.057

Figure 2-1. Optimal time paths, Mountain Belt, per capita.

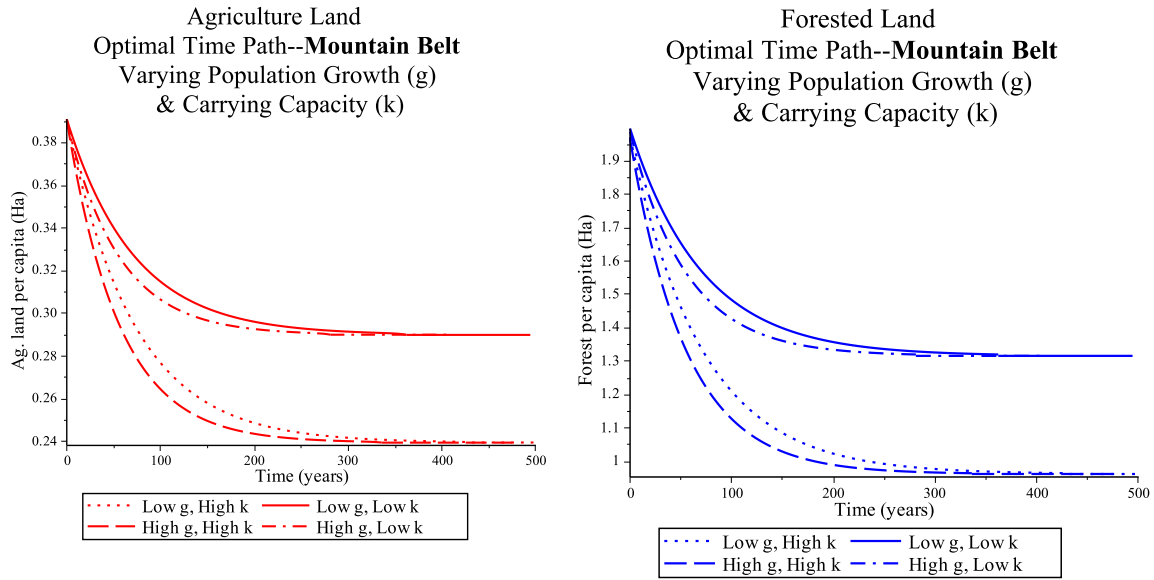


Figure 2-2. Optimal time paths, Hills Belt, per capita.

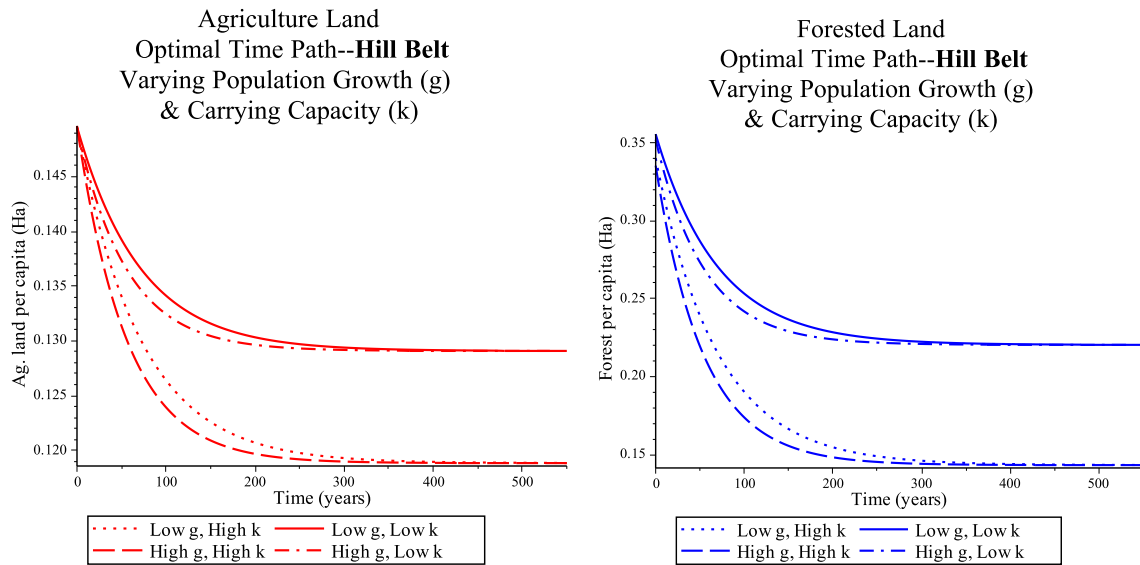


Figure 2-3. Optimal time paths, Terai Belt, per capita.

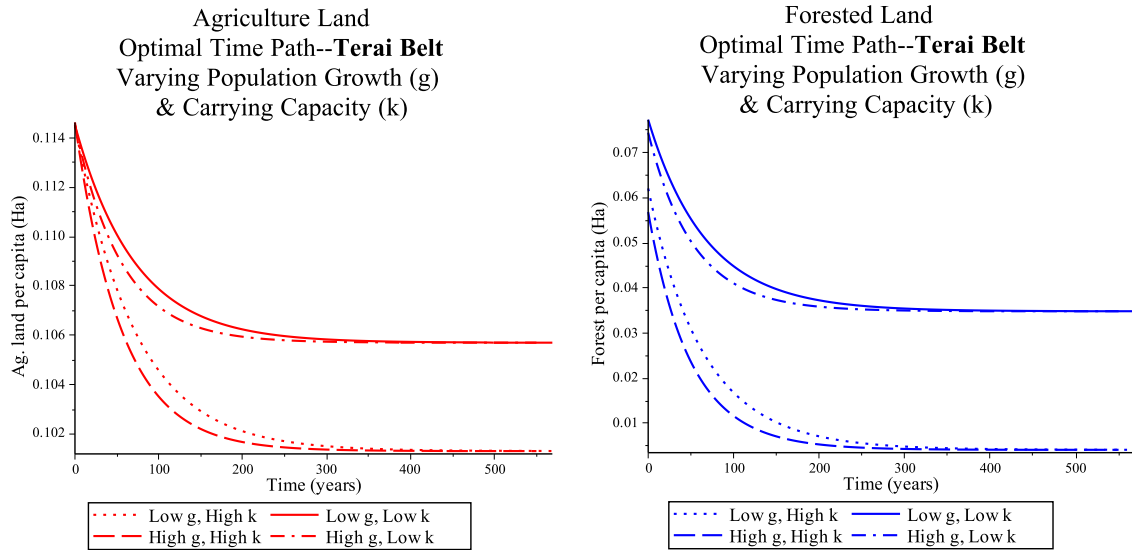


Figure 2-4 Optimal time paths, Mountain Belt, non-per capita.

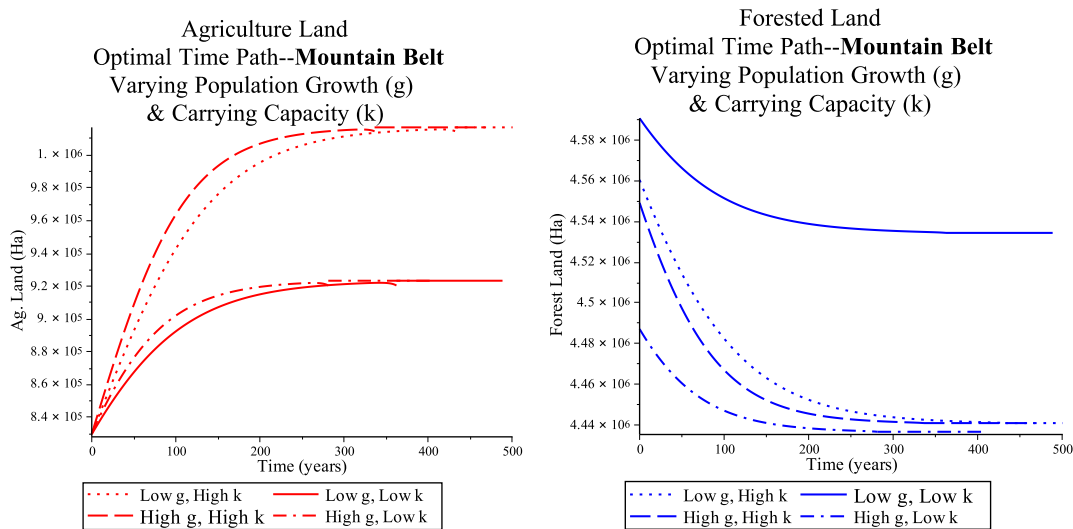


Figure 2-5 Optimal time paths, Hill Belt, non-per capita.

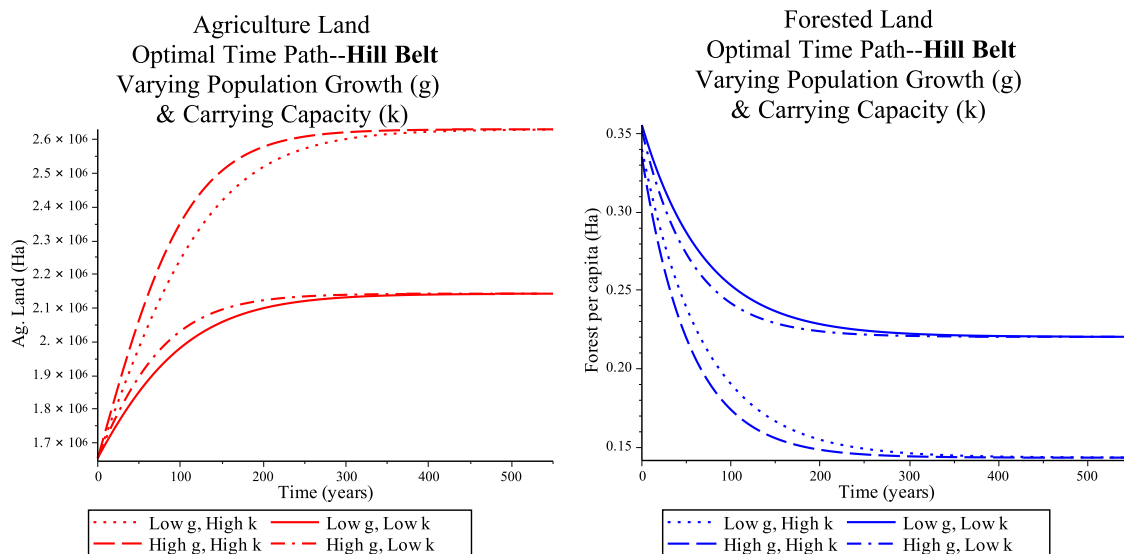
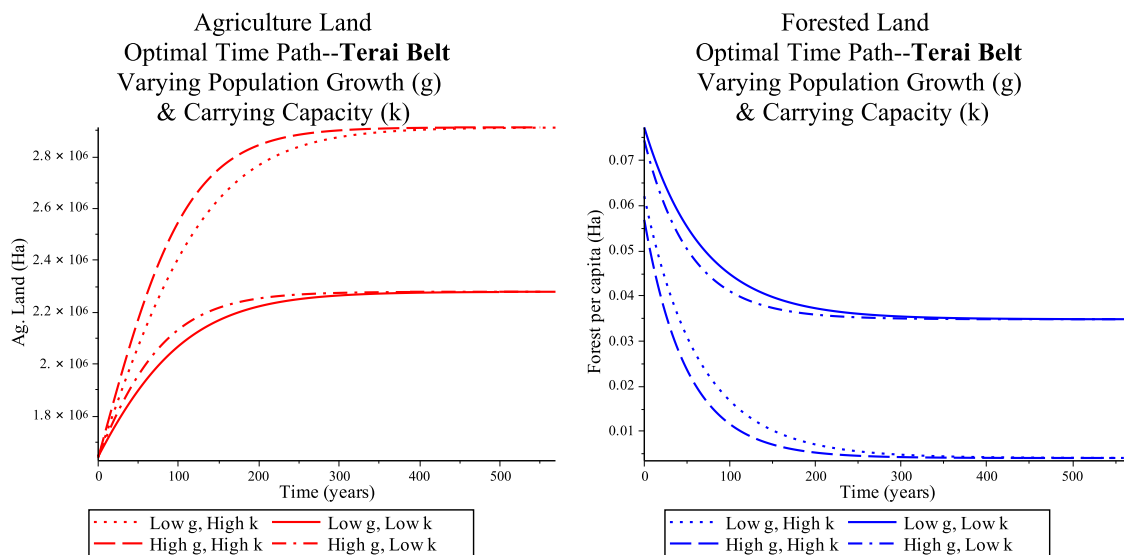


Figure 2-5 Optimal time paths, Terai Belt, non-per capita.



Chapter 3: Household Food Security in Nepal: Analyzing Natural Capital, Social Capital, and Coping Strategies

3.1 Introduction

Discussions of hunger may conjure up images of starving children in sub-Saharan Africa, where famine and food insecurity are rampant. However, food insecurity also exists in many other parts of the world. In Nepal, a survey by the World Food Programme (WFP) found that approximately 30% of the rural population does not have access to regular nutritious food, decreasing their levels of food security (WFP, 2006). Much of the food production in Nepal is seasonal, with lean periods lasting anywhere from two weeks to two months, at which time, citizens are forced to find alternative means to meet food needs. Food security also varies among the mountainous, hilly, and terai (plains) geographic bands across Nepal. The existence of environmental, conflict, and other shocks are also discussed by WFP to be contributors to Nepal's food security problems (WFP, 2006).

This quantitative analysis relies heavily on a household survey carried out by the WFP in 2005 (WFP, 2006). The surveys were carried out in nearly 1,700 households throughout all areas of Nepal. The survey collected a large number of data about the potential food security explanatory variables, providing a cross sectional look at the situation in Nepal. The study created an index of food security, based on the quality of food types and frequency of consumption by each household over the previous year. Spatial data on vegetation cover derived from the analysis of Thematic Mapper (TM) of 1990 and Enhanced Thematic Mapper (ETM+) of 2000 was used as a measure of Village Development Committee (VDC) level natural capital quality in which the households in the WFP survey reside, as well as the quality of natural capital in 10-30km bands around the VDCs. Spatial data was also used to measure

the density of roads in the VDCs, and the distance of VDCs to the capital Kathmandu. To further measure characteristics of household locations, including population density, food prices, and the extent of social networking groups, was taken from the 2003 Nepal Living Standard Survey. Additional data controlled for the level of violence that has occurred in each VDC, as it related to the Maoist conflict from 1996-2003.

The results of this study show that natural capital, measured as the quantity of primary and secondary vegetation in an area, strongly influences a household's food security in Nepal. There is a declining positive effect of natural capital stock the further the stock is from the household's VDC. Poorer access to clean drinking water sources, an additional form of natural capital, is seen to negatively impact household food security. Social networking indices for agriculture, forest, and water, individually and when aggregated with additional networking types, were seen to positively impact food security. Membership in a janjati caste group and other non-Brahmin and non-Chetarai castes is seen to negatively impact food security. Coping strategies that are seen to positively impact food security include access to financial credit, the receipt of remittances (from within Nepal or overseas), and being a beneficiary of food aid. The level of violence, measured in the number of civilian and military deaths in a VDC are seen to have a negative impact on food security.

The household survey data analyzed in this study was the data source for a WFP report that presented many of the food security issues and concerns existing in Nepal (WFP, 2006). The current study aims to further analyze some of the food security determinants that were discussed in the WFP report, as well as to expand the results through the addition of pertinent spatial environmental data and social cohesion data, representing the contributions that natural and social capital contribute to food security conditions. Such an analysis provides

insight useful for designing government and non-government policy interventions aimed at reducing food security in Nepal, and elsewhere.

The chapter proceeds as follows. First we present the development of the theoretical model used for analyzing food security in Nepal, including a discussion of the chosen econometric model and identified explanatory variables. The chapter continues with a presentation of the regression results using the OLS and instrumental variable analysis techniques. The results from the non-linear spatial treatment are then presented and discussed. The chapter concludes with a discussion of the results, and their relevance for food security policy making.

3.2 Theoretical Model

The theoretical model used in this study is based on the food security models developed previously by Feleke et al. (2005) and Singh et al. (1986), which expanded a household food consumption model. The model considers a utility function (U) for a household (i). In general form, this utility function may be written as follows.

$$U_i = U(C_i^H, C_i^M, D_{i,j}^H) \quad (3-1)$$

Consumption of home produced (H) goods is represented by vector C_i^H . Vector C_i^M represents consumption of market (M) purchased goods. Vector $D_{i,j}^H$ includes household health status and access to healthcare, access to education, environmental quality of the location, presence of violence, and other community and household characteristics that

influence welfare.¹⁰ Households maximize (3-1) subject to the constraints of household production (Y), income (I), and time (T).

Household production is represented by the following general equation

$$Y_{i,j} = Y(Q_i^{H,M}, L_i^{H,M}, A, K_{i,j}) \quad (3-2)$$

The term $Q_i^{H,M}$ represents a subset of C_i^H and C_i^M used by the household for production (including seeds, tools, animals, and other goods). The term $L_i^{H,M}$ represents household provided labor and hired labor. The quantity of land available is represented by A . The final term in (3-2), $K_{i,j}$, is a vector of capital stocks.¹¹ Feleke et al. (2005) consider capital as a single variable identified as a fixed stock of capital. This model considers $K_{i,j}$ as a primary collection of resources available for the production of food and other goods. These include manmade capital (K^m), human capital (K^h), financial capital (K^f), infrastructural capital (K^t), natural capital (K^n), and social capital (K^s). The capital vector can be restated as follows.

$$K_{i,j} = K(K_{i,j}^m, K_{i,j}^h, K_{i,j}^f, K_{i,j}^t, K_{i,j}^n, K_{i,j}^s) \quad (3-3)$$

Although households may be able to purchase K^m or send their children to school to improve K^h , many of these capital forms are exogenous to the household, strongly influenced by a given location. Households may, individually, have little or no control over the level and

¹⁰ It is assumed that the utility function is a twice differentiable, quasiconcave function.

¹¹ It is assumed that the production function is a twice differentiable, quasiconcave function.

quality of capital available for production. It is important to note that all households, whether consuming their production or selling their production in the market will be influenced by $Q_i^{H,M}$, $L_i^{H,M}$, A , and $K_{i,j}$. Therefore, any impact, whether positive or negative, on capital resources by a household or community may impact own production or the production of other households.

The income constraint is characterized by

$$I_{i,j} = p_j^H(Q_i^H - C_i^H) - p_j^M C_i^M + w_j(L_i^H - L_i^M) + N \quad (3-4)$$

where $(Q_i^H - C_i^H)$ represents goods in excess of consumption that the household sells in the market at prices, p_j^H . Prices of C_i^M are represented by p_j^M . Labor provided by the household (L_i^H) or hired by the household ($-L_i^M$) is compensated by the local wage rate (w). The variable N represents additional non-farm and non-labor income the household may receive, including financial assistance from government and non-government organizations. A simplifying assumption is made that capital does not directly appear in the income equation. However, it is understood that capital may indirectly impact components of the income equation. Social capital, for instance, may influence and individual's ability to secure wage labor.

The time constraint (T) is included as a matter of routine, whereas the earnings and welfare achieved from production, labor and leisure (E) are not without limits on an individuals' available time. The constraint is described as follows.

$$T_i = L^H + E \quad (3-5)$$

The utility function in (3-1) can be maximized to give the demand functions for the consumption of household and market purchased goods.

$$C_i^{H,M} = C(p_i^{H,M}, w, A, K_i, N, D_i^H) \quad (3-6)$$

For the purposes of this study, a subset of Eq. (3-6) is thought to represent the consumption of goods and services (namely food products) that contribute to a household's food security. It follows then, that Eq. (3-6) is suitable for describing a household's food security (FS_i).

3.3 Analytical Model and Data Components

Based on the theoretical model developed in the previous section, we develop an analytical approach to study how the following categorical vectors of explanatory variables influence household food security: natural capital ($NATCAP$), social capital ($SOCCAP$), coping mechanisms ($COPING$), violence ($VIOL$), household socioeconomic variables ($SOCEC$), and additional locational characteristics ($LOCAT$). The general econometric model is a linear ordinary least squares approach provided in equation 3-7.

$$FS_i = \beta_C + \beta_{NC} NATCAP + \beta_{SC} SOCCAP + \beta_{CO} COPING + \beta_{V} VIOL + \beta_L LOCAT + \beta_E SOCIOEC + \epsilon_i \quad (3-7)$$

The general model assumes the error term ϵ_i is normally distributed.

This section discusses the key data elements, and proposes hypotheses for the vector of beta coefficients for the econometric model. Additionally, we discuss issues related to endogeneity, and present a non-linear econometric model that incorporates the spatial impact of natural capital and conflict on household food security.

3.3.1 Food Security in Nepal

The WFP survey used in this study asked each head of household detailed questions about the frequency at which household members consumed various types of meat, dairy products, staple starches, beans, vegetables, fruits, oils and sugars. A principle component analysis (PCA) was used to group households with similar food consumption habits, giving food security categories of Very Poor, Poor, Fair, Good, and Very Good. Table 3-1 provides a description of each of the categories. The WFP used probability weighted data to account for the distribution of population across the Terai (plains), Hills, and Mountain ecological belts, and the Eastern, Central, Western, Mid West, and Far West Development regions of Nepal. Figure 3-1 shows the weighted distribution of households into food security groups. Malnutrition is prevalent in the poor and very poor food consumption groups, with approximately 60% of children in such households that are moderately to severely stunted (WFP, 2006).

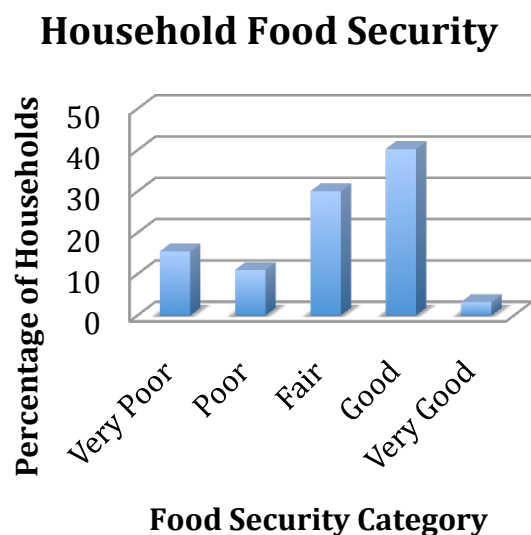


Figure 3-1 Weighted breakdown of household food security.

Additionally, the WFP calculated household food scores for each food category determined by the number of days in a week that a particular food type was consumed, with protein and dairy products weighted the highest. The aggregated score provides a food security index (*FOODINDEX*) for each household, with a higher value indicating greater food security, based on the following equation.¹²

$$\begin{aligned} \text{FOODINDEX} = & \text{staple starches}*.2 + \text{pulses}*.3 + \text{meat / fish / eggs}*.4 + \text{milk}*.4 \\ & + \text{fruit}*.1 + \text{vegetables}*.1 + \text{oil}*.05 + \text{sugar}*.05 \end{aligned} \quad (3-8)$$

3.3.2 Natural Capital

To capture the state of natural capital in Nepal we have measured the levels of vegetation quality (VEGQ). A study by Bhandari and Grant (2007) discussed the connection between deforestation, floods, soil erosion, and loss of arable land in Nepal, and the connection of such degradation to livelihood security, agriculture production, and food access. Although the Bhandari and Grant study was focused on a particular watershed in Nepal, the Kali-Khola watershed in a mountainous area, the results indicate the importance of forest natural capital throughout Nepal in keeping households out of poverty. This study uses satellite imagery from 2000 that measures the amount of mature forest growth, secondary growth, degraded vegetation, agriculture land, and bare land throughout the country.¹³ The map in Figure 3-2 shows the image of land cover in Nepal. The breakdown of each category of land cover throughout the entire country of Nepal is seen in Figure 3-3.

¹² The coefficients of the WFP index have been scaled down by a factor of 10 in order to make the scale of the index variable similar to the explanatory variables used in the model.

¹³ The imagery also captures a small percentage of cloud cover and unidentified areas, which give inconclusive information about the state of the forest cover. These are not included in the dataset.

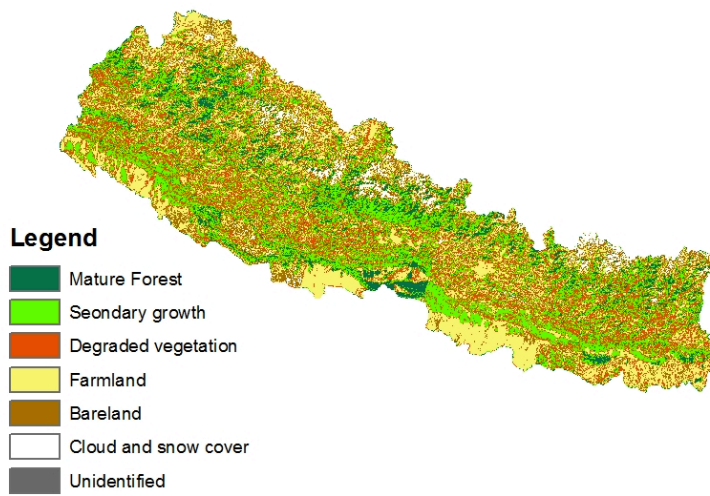


Figure 3-2 Land cover throughout Nepal [Based on the analysis of ETM+2000 imagery].

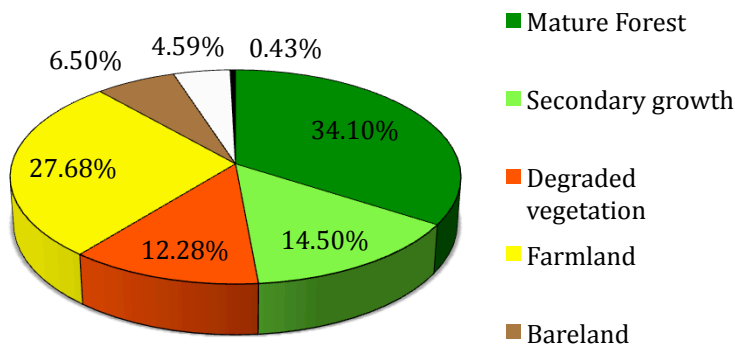


Figure 3-3 Breakdown of land cover by type.

To measure vegetation quality, we calculate the percentage of land covered with mature forest and secondary growth.

$$VEG = \frac{\text{Forest Area} + \text{Secondary Vegetation Area}}{\text{Total Land Area}} \quad (3-9)$$

Equation 3-9 was calculated at the VDC level (VEG^{VDC}), as well as for the areas 10 km (VEG^{10}), 20 km (VEG^{20}), and 30 km (VEG^{30}) away from the VDC. An example of these buffers is seen in Figure 3-4, where 10 km were created around each VDC. When conducting the analysis, only the rings around each VDC (and subsequent buffers) were considered so there would be no double counting of data within the VDC and within the buffer. Formally, the first alternative to the null hypothesis tested in the analysis is that vegetation quality available to households will strengthen the level of household food security.

HYPOTHESIS 1: $\beta_{VEG^{\Delta}} > 0$ for $\Delta = \{VDC, 10R, 20R, 30R\}$

This hypothesis states that forest quality at the VDC level, VDC plus a 10 km VDC buffer level, VDC plus a 20 km buffer level, and VDC plus a 30 level will have a positive effect on food security, ceteris paribus. Under this hypothesis we expect positive regression coefficients for VEG^{VDC} , VEG^{10R} , VEG^{20R} , and VEG^{30R} . Further, it was expected that higher vegetation quality will positively influence food security in each of these rings at a decreasing rate.

Formally, the second alternative to the null hypothesis is as follows.

HYPOTHESIS 2: $\beta_{VEG^{VDC}} > \beta_{VEG^{10R}} > \beta_{VEG^{20R}} > \beta_{VEG^{30R}}$

This hypothesis states that forest quality will have a positive but decreasing effect beginning with the household's VDC level quality, and extending out in rings of 10 km each. Under this hypothesis we expect positive and decreasing regression coefficients for VEG^{VDC} , VEG^{10R} , VEG^{20R} , and VEG^{30R} .

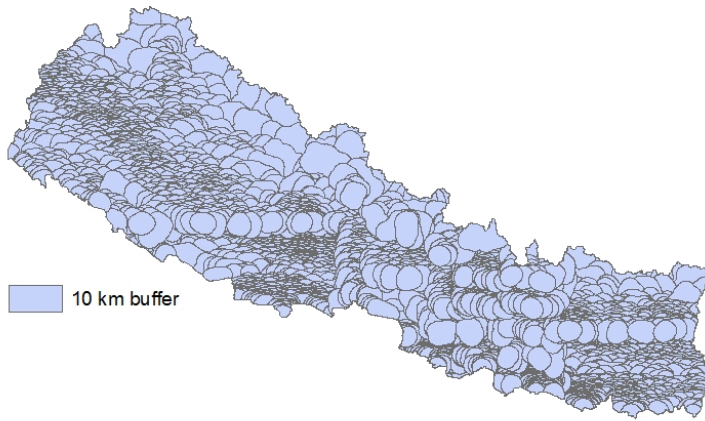


Figure 3-4. This map illustrates 10 km VDC buffers in which the percentage of primary and secondary forest growth was calculated.

An additional measure of natural capital used was the proximity, in hours, of a household to an improved water source (*WATDIS*). Respondents provided this information in the WFP survey. The WFP report (2006) discussed the direct impact of unsanitary water on malnutrition and health, saying frequent disease leads to further poor levels of food consumption. It was assumed that households would be more likely to substitute poor quality water for higher quality water if the distance traveled to reach the water is greater. Also, households spending more time reaching improved water will have less time available to partake in other activities that could improve their food security.

Formally, the third alternative to the null hypothesis is as follows.

$$\text{HYPOTHESIS 3: } \beta_{WATDIS} < 0$$

This hypothesis states that the measure of the distance members of a household must travel to find improved water will have a significant negative effect on household food security, *ceteris paribus*. Under this hypothesis we expect negative regression coefficients for *WATDIS* .

3.3.3 Social Capital

To analyze the effect of social capital on household food security, we measured the extent of community groups at the district level in Nepal. The Nepal Living Standards Survey (NLSS) measured the occurrence and intensity of community user groups throughout Nepal related to various themes, including agriculture (*AGRIC*), water management (*WATER*), forest conservation (*FOR*), and women's issues (*WOMEN*). The data included information about the length of time such groups have been in existence, the number of members in a group, and how often groups held meetings. Adhering to the method described by Nepal et al. (2007), we generated social capital indices that included the age of the group (*sage*), number of meetings held (*smtgs*), number of household members (*smemb*), and number of women members (*swom*).¹⁴ For each district (*d*), a social capital index (*SCI*) was calculated for each group theme (*m*) using the following equation.

$$SCI_{md} = \sum_{n=1}^4 \frac{X_{nd} - \min(X_n)}{\max(X_n) - \min(X_n)} \quad (3-10)$$

Measuring the extent of social capital quality for group themes individually was a way to isolate the themes that have stronger, or weaker, impacts on food security. An aggregate social capital index summing each individual themed index was also created and used in the analysis.

¹⁴ Unfortunately, VDCs from the NLSS user group data did not match the VDCs represented by households in the food security data. Therefore, we chose to use district level indexes to measure the social capital data.

Formally, the fourth alternative to the null hypothesis is that the extent of social capital available to households will impact the level of household food security.

HYPOTHESIS 4: $\beta_{SCI\Omega} > 0$ for $\Omega = \{AGRIC, WATER, FOR, WOMEN, ALL\}$

This hypothesis states that the extent of individual community user group types and the extent of community groups in aggregate will have a significant positive effect on household food security, ceteris paribus. Under this hypothesis, we expect positive regression coefficients for SCI^{AGRIC} , SCI^{WATER} , SCI^{FOR} , SCI^{WOMEN} and SCI^{ALL} .

The next form of social networking considered was the caste or ethnic group household respondents identified with. Das (2004) discusses the usefulness of caste membership, from lower castes to high castes, as beneficial for social networking. The informal social networking that takes place amongst members of a lower caste potentially may provide a necessary tool for survival in a society where upper castes are using social networks to navigate formal opportunities for success. The WFP (2006) study provides evidence that those households who are members of traditionally lower castes or ethnic groups tend to have lower levels of food security in Nepal. This insinuates those in lower castes are unable to use social networking as a means to improve their food security position. Dummy variables for membership in the Dalit caste (*DALIT*), Janjati ethnic minority groups (*JANJATI*) and other lower castes (*OTHERC*) were included as explanatory variables in the study. The control group for the dummy variable was membership in the higher or privileged castes of Brahmin and Chetarai.

Formally, the fifth alternative to the null hypothesis is as follows.

HYPOTHESIS 5: $\beta_{CASTEA} < 0$ for $\Lambda = \{DALIT, JANJATI, OTHERC\}$

This hypothesis states lower caste and ethnic minority groups have a significant negative relationship with food security, ceteris paribus. Under this hypothesis, we expect negative regression coefficients for $CASTE^{DALIT}$, $CASTE^{JANJAT}$, and $CASTE^{OTHER}$.

3.3.4 Coping Strategies

Households facing the probability of low food security may be able to implement mechanisms to improve their situation, particularly when conditions for traditional food production or other income-generating activities are less than favorable. Ex ante risk management strategies are those with high barriers to entry requiring some upfront investment and planning. Ex post approaches are those that may be turned to immediately when shocks occur (Lay et al, 2008). Several questions in the WFP survey allow for analysis of ex post and ex ante coping strategies. These are the ability of a household to access financial credit (*CREDIT*), remittances received by the household (*REMIT*) (from within and outside of Nepal), and the receipt of food aid from governmental and non-governmental sources (*FOODAID*). It is hypothesized that these coping strategies will positively impact food security due to their ability to overcome constraints, such as poor access to social capital, weaker stocks of natural capital, and communities disrupted by natural and manmade shocks.

Formally, the sixth alternative to the null hypothesis is as follows.

HYPOTHESIS 6: $\beta_{COP\Theta} > 0$ for $\Theta = \{REM, CREDIT, FOODAID\}$

This hypothesis states that all coping strategies implemented by households will significantly and positively impact the level of household food security, ceteris paribus. Under this

hypothesis, we expect positive regression coefficients for $COPE^{REM}$, $COPE^{CREDIT}$, and $COPE^{FOODAID}$.

3.3.5 Conflict

Until recently, Nepal had been experiencing political unrest and violence attributed to the decade long Maoist insurgency. The uprising began in the Midwest region of the country, but spread throughout Nepal (Bohara et al., 2006). This manmade shock disrupted the normalcy of many parts of Nepal, with numerous pro-Government and pro-Maoist killings. Such disruptions have been shown to cause disruption of access to water, access to education, access to healthcare, and access to food (Paudel and Kettle, 2006). Therefore, our analysis includes a measure of violence ($VIOL$) to account for conflict in Nepal.

Formally, the seventh alternative to the null hypothesis is as follows.

HYPOTHESIS 7: $\beta_{VIOL} < 0$

This hypothesis states that village level conflict will significantly and negatively impact the level of household food security, ceteris paribus. Under this hypothesis, we expect a positive regression coefficient for $VIOL$.

Additionally, we analyzed the combined effect of $VIOL$ with the violence in the district ($VIOL^{DIST}$) beyond (but not including) the VDC level violence. Formally, the eighth alternative to the null hypothesis is as follows.

HYPOTHESIS 8: $\beta_{VIOL^{VDC}} > \beta_{VIOL^{DIST}} > 0$

This hypothesis states that violence will have a positive but decreasing effect beginning with the household's VDC level violence, and extending out to the remaining district. Under this hypothesis we expect significant negative and increasing (decreasing in magnitude) regression coefficients for *VIOL* and *VIOL^{DIST}*.

Additional explanatory variables were included in the analysis to control for more characteristics of the location of the household (*LOCAT*). These include the local price of food measured by the price of rice, a main staple. Developed infrastructure capital is measured by road density (see Figure 3-4). The geographical belt where the household is located controls for additional geographical characteristics. Socioeconomic control variables (*SOCIOEC*) included measure household size, education of the head of household, percent of income obtained from agriculture, agricultural land size available, and household animal assets measured by the number of poultry owned by a household. Descriptive stats and descriptions of all variables are included in Table 3-2.

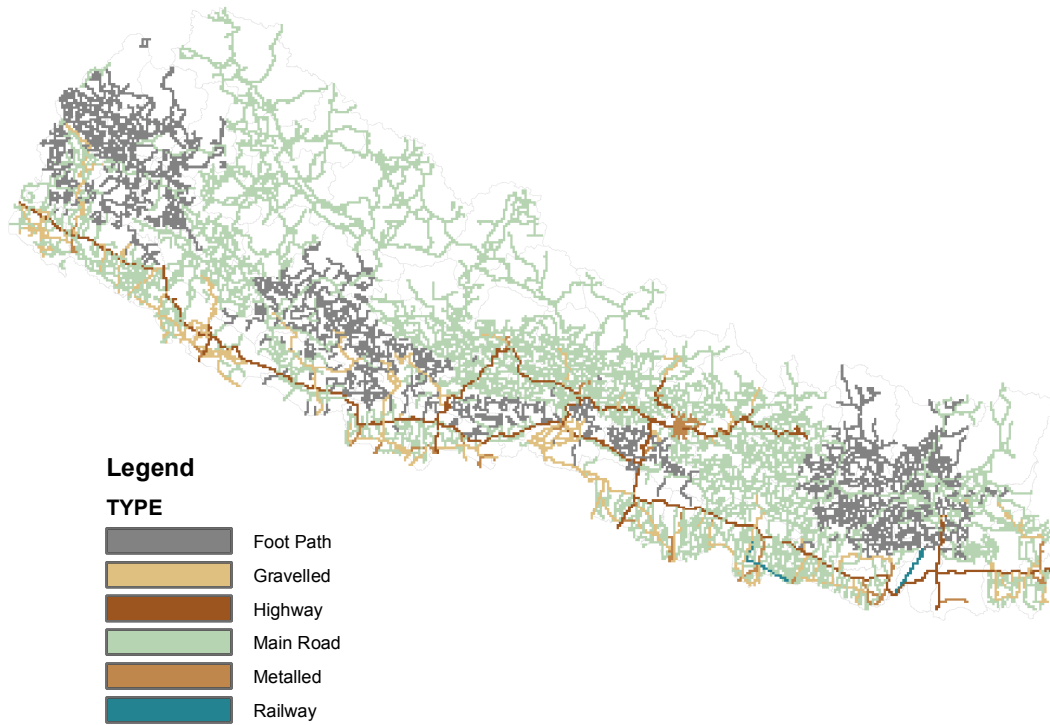


Figure 3-5. Road network in Nepal used to calculate road density by VDC and District.

3.3.6 Endogeneity

A potential difficulty with the analyses is that the food security measure may exhibit reverse causality with key explanatory variables. For instance, it is logical that in locations where there is poor food security, there may arise unrest or violence. Therefore, an analysis of conflict in Nepal may necessitate a food security measure as an explanatory variable. A similar argument could be made for recipients of food aid, as those eligible to receive food aid may have poor household food security. Our analyses included instrumental variable analyses and endogeneity tests to determine if explanatory variables were indeed correlated with the error term. It was necessary to choose appropriate instruments that have no relationship with the

dependent variable while being related to the explanatory variables whose independence is in question. Of primary concern were VEG^{VDC} , SCI^{Ω} , $FOODAID$, and $VIOL$. It was necessary to choose appropriate instruments that correlate with the potential endogenous variable, but not with the dependent variable. We included the density of foot paths in the VDC where the household is located ($FOOTDEN$). Another instrument was the monthly amount of firewood being purchased by respondents of the NLSS 2003 survey in the district where the households are located ($WOOD$). The VDC population density ($POPDEN$) was included as an instrument. A dummy variable for living in the Farwest ($FARWEST$) and Midwest ($MIDWEST$) districts of Nepal (impoverished regions, and where the Maoist conflict was started). The number of newspapers purchased in each district ($NEWS$) was used as an instrument. Finally, a variable for the number of migrants in the district ($MIGRANTS$), was included as an instrument.

3.3.7 Spatial Attributes

Several explanatory variables are available only at the district level, including the social capital index, the price of rice, and non-agriculture wages. The population density, road density, and conflict data is available at both the VDC level and the district level. Along with the vegetation quality data, variables with a spatial component were included in additional econometric models developed to account for the impacts of neighboring geographic area attributes on the food security index of households included in our study. This follows an approach by Artal-Tur et al. (2009), where neighboring effects of land availability and human capital measures influenced the location decisions of industrial firms. The spatial econometric model is as follows.

$$FS_i = \mathbf{X}_i \boldsymbol{\beta} + \mathbf{W} \mathbf{Y}_j^n \boldsymbol{\lambda} + z_i \quad i = 1, \dots, N; j = 1, \dots, J \quad (3-11)$$

The first two terms on the right hand side of the equation and the error term (z_i) represent the general econometric model, where \mathbf{X}_i is a vector of household characteristics and attributes of the household's own location, and \mathbf{Y}_j^n is a vector of location (j) characteristics whose corresponding neighboring location (n) attributes are also included in the model. These location characteristics are weighted by a vector of spatial decay functions (\mathbf{W}) representing the distance effect of attributes between locations n and j . The individual distance decay function is defined as follows:

$$W = \sum_{d=0}^D \left(\frac{\exp \boldsymbol{\kappa}}{1 + \exp \boldsymbol{\kappa}} \right)^d \quad (3-12)$$

Eq. (3-12) imposes $W > 0$. The decay effect is imposed by defining d such that it increases the further the distance from i . Two weighting functions are created for the different spatial relationships provided. The first weighting function is for the vegetation data effects, which are allowed to increase by 10km increments from the VDC. The second weighting function is for those variables that are included at the VDC level and at the district level. The term d is chosen to increase by a power with each increment from the VDC level data. In creating the vegetation quality rings, the VDC level data and additional ring data was not included. For the district level data, the VDC data was also subtracted out. This method ensures data is not double counted in each measure.

Now, we can expand equation 3-11 to account for both the VDC level vegetation and vegetation buffers. We also incorporate a weighted analysis of road density and violence, measuring the impact at the VDC level, and the district level.

$$\begin{aligned}
FS_i = & \mathbf{X}_i \boldsymbol{\beta} + \boldsymbol{\lambda}_1 \cdot \left(VEG_j^{VDC} + \left(\frac{\exp^{k_{vdc}}}{1 + \exp^{k_{vdc}}} \right)^1 VEG_j^{10R} + \left(\frac{\exp^{k_{vdc}}}{1 + \exp^{k_{vdc}}} \right)^2 VEG_j^{20R} + \left(\frac{\exp^{k_{vdc}}}{1 + \exp^{k_{vdc}}} \right)^3 VEG_j^{30R} \right) \\
& + \boldsymbol{\lambda}_2 \cdot \left(ROAD_j^{VDC} + \left(\frac{\exp^{k_{dist}}}{1 + \exp^{k_{dist}}} \right)^1 ROAD_j^{DIST} \right) \\
& + \boldsymbol{\lambda}_3 \cdot \left(VIOL_j^{VDC} + \left(\frac{\exp^{k_{dist}}}{1 + \exp^{k_{dist}}} \right)^1 VIOL_j^{DIST} \right) + \xi_i
\end{aligned} \tag{3-13}$$

The impact of each of each level of each spatial variable is expressed, generally, as follows.

$$\boldsymbol{\lambda} \cdot \left(\frac{\exp^{k_n}}{1 + \exp^{k_n}} \right)^d, \text{ where } n = vdc, dist \tag{3-14}$$

3.4 Econometric Results

3.4.1 General Results

The regression results for the general model are presented in Table 3-3. The general linear econometric analysis estimates eight different models with *FOODINDX* as the dependent variable in each case. In MODEL I, only the *LOCAT* and *SOCIOEC* explanatory variables were included. In MODEL IIa and IIb, the *NATCAP* explanatory variables were added, with MODEL IIb considering *VEG^{VDC}* endogenous. Models IIIa and IIIb introduce *SOCAP* explanatory variables using the aggregate *SCI^{ALL}* to analyze community user groups, with 3b including *SCI^{ALL}* as an endogenous variable. Model IVa and IVb add the *VIOL* explanatory variable. Model IVb includes *VIOL* as endogenous. The *COPING* explanatory variables were analyzed in Model Va and Vb, with IVb including *FOODAID* as an endogenous variable. All analyses reject the null that error terms are homoskedastic. Each analysis also accounts for the probability weights provided with the WFP (2006) data.

For those specifications analyzed with instrumental variables, a X^2 test for endogeneity is reported, along with the Hansen J overidentification test, Kleibergen-Paap rk Wald underidentification test, and Cragg-Donald Wald weak identification test of instruments are reported.¹⁵ The analyses show a consistent endogeneity problem for VEG^{VDC} . Therefore, we instrumentalize this variable in each of the models (IIb-Vb). The endogeneity tests for VEG^{VDC} consistently indicate specifications controlling for VEG^{VDC} endogeneity are preferred. The instruments *POPDEN*, *MIDWEST*, and *WOOD* are seen to be appropriate instruments. Additional instruments *NEWS* and *FOOTDEN* were added to control for VEG^{VDC} and *SCIALL* endogeneity in Model IIIb. The test statistics suggest the instruments are appropriate, yet *SCIALL* fails to reject the null of independence (meaning it is not endogenous). Model IVb uses *FOOTDEN*, *MIDWEST*, *WOOD*, and *MIGRANTS* to control for the potential endogeneity of VEG^{VDC} and *VIOL*. The test statistics suggest the instruments are appropriate, yet *VIOL* fails to reject the null of independence (meaning it is not endogenous). Model Vb uses *FOOTDEN*, *MIDWEST*, *FARWEST*, *WOOD*, *POPDEN*, and *MIGRANTS* to control for the potential endogeneity of VEG^{VDC} and *FOODAID*. The test statistics suggest the instruments are appropriate, and the null of *FOODAID* independence is rejected (meaning it is endogenous).

The models show fairly consistent AIC values, measuring the relative goodness of fit. The AIC for Model Vb, which appropriately corrects the endogeneity problems and includes all variables of interest, provides the best goodness of fit. Subsequent discussions of results will only include those that correctly control for endogeneity.

In each of the general linear models, the coefficients of VEG^{VDC} are significant, at a convincing 1%-5% level, with values ranging from 0.023-0.054. The values dip somewhat in Model V. The positive relationship between VEG^{VDC} and $FOODINDEX$ is the expected result, that level of vegetation cover in the VDC impacts household food security. The coefficients of the second $NATCAP$ variable, $WATDIST$, are significant at the 5-10% level in all models except Model IIb, where the coefficient is insignificant. Values of the $WATDIST$ coefficient ranged from -0.460 to -0.524, providing the expected inverse relationship between $WATDIST$ and $FOODINDEX$. When households spend time more time collecting water, their food security drops. The results for both of these variables provide strong evidence that the quality of natural capital, both represented by vegetation cover and access to clean drinking water, is important for increasing food security levels.

The coefficients of SCI^{ALL} are positive and highly significant at the 1%-5% level, ranging in value from 0.088 and 0.092. This positive relationship between SCI^{ALL} and $FOODINDEX$ is the expected result, suggesting more developed levels of social capital improves food security. Analyses using the individual user group type indices are discussed further in the results section. Of the caste explanatory variables, the coefficient of $JANJATI$ was highly significant at the 1% level in every model. The $JANJATI$ coefficient values ranged from of -0.955 to -1.119, providing evidence that being a member of a $JANJATI$ caste hinders the level of household food security. This suggests that if there are social networking benefits from identifying with a minority ethnic group, those benefits do not translate into increased $FOODINDEX$ levels. The coefficient of $DALIT$ was consistently negative, and significant at the 10% level in Models IV and V, with values of -0.0421 and -0.0527. The coefficient of $OTHERC$ was consistently negative, but only significant in Model IV at the

10% level. The analysis results of the *DALIT* and *OTHERC* variables provides evidence that being a member of the lowest castes, including the untouchable caste, will not necessarily decrease a household's food security. This provides some argument, but not definite evidence, of an informal social cohesion among members of lower castes that may offset some of the exclusions from the formal market faced by individuals in these castes (for example, access to land ownership or financial credit).

The coefficient of *VIOL* was negative and significant at the 5% level in Model IV with a value of -0.099. The variable is not significant in the preferred Model V (which is Vb, due to the endogeneity of food aid), with values of -0.091 and -0.099. This is an important variable to consider given the timeframe of the Maoist conflict, and the time horizon from which the data was collected. The result is consistent with the hypothesis that presence of conflict disrupts a community such that households located in VDC with higher levels of violence will be less able to meet basic needs, including accessing food.

The *COPING* variables showed significance when included in model V, with Vb being the preferred model (as discussed earlier due to the presence of endogeneity). The coefficient for *REMIT* was significant at the 10% level, with a value 0.023. The coefficient for *CREDIT* was significant at the 5% level, with a value of 0.339. The coefficient for *FOODAID* was significant at the 5% level with a value of 1.591. Prior to controlling for endogeneity, the *FOODAID* coefficient had a value of 0.669. These results provide the expected results that mechanisms for coping with potential manmade or natural shocks, or the consistent lack of economic opportunities, do improve a household's food security.

Several of the *SOCIOEC* variables produced coefficients consistently significant and will be discussed here. The coefficient of *HHSIZE* was positive and significant at the 1%-5%

level, with values ranging from 0.025 to 0.039. Initially, this positive relationship may seem to be a surprising result, as larger households require more food. Perhaps the result indicates larger households provide additional labor for producing food, or earning income to purchase food. The coefficient of *LANDSIZ* was positive and significant at the 5-10% level, with values ranging from 0.179 to 0.204, providing evidence that access to land capital provides better opportunities to grow food or earn income. Likewise, *POULT* was positive and significant at the 1% level for all preferred models except I, with coefficient values ranging from 0.306 to 0.650. This result quantifies the benefits of assets in improving food security. In the case of livestock assets, there is an obvious direct contribution to food consumption. The coefficients of *EDUC* are not consistently significant, but do show 1% significance in Model I, 10% significance in Model II, and 5% significance in and Model V. The values of the *EDUC* coefficients range from 0.095 to 0.159. Those households with higher education levels likely have access to better sources of income and technology, and may be better able to plan their food consumption so as to maintain the highest food security levels.

Results of the *LOCAT* coefficients will be discussed in this section. The coefficients of *MOUNT* and *HILL* show high levels of significance, at the 1% level for all preferred models. The values of the *MOUNT* coefficients ranged from -0.966 to -1.666. The values of the *HILL* coefficients ranged from -0.605 to -1.421. As expected, household food security is impacted negatively at a greater magnitude when existing in the *MOUNT* region than it is in the *HILL* region. Further, these results indicate the expected result of households in the Terai belt, with higher quality agricultural conditions than in the hills and mountains, have higher food security levels. The coefficients of *PRICES* are seen to be positive significant at the 1%-10% level, with values from 0.160-0.237. This result suggests higher rice prices improve food security. This is an opposite result than expected, as higher food prices of rice

would be assumed to negatively impact welfare. This variable may in fact be capturing the benefit achieved from rice suppliers, or potentially is capturing the effect of higher incomes demanding more rice, which would cause the price to increase.¹⁶ The coefficients of *ROAD* were insignificant in each of the models.

The standardized coefficients (beta coefficients) of the explanatory variables of food security are presented in Table 3-4 for the results of Model Vb in Table 3-3. These effects allow a comparison across all explanatory variables, to determine which influence *FOODINDEX* with the greatest magnitude. The rank of the top most influential variables are, *JANJATI*, *VEG^{VDC}*, *MOUNT*, *HILL*, and *FOODAID*.

3.4.2 Spatial Modeling Results

To analyze the spatial dimension of the data, a non-linear maximum likelihood technique was used.¹⁷ Non-Linear Model I incorporates only the VDC level vegetation data, while Non-Linear Model II adds 10km vegetation buffer data, Model III adds 20km vegetation buffer data, and Model IV and Model V add 30km vegetation buffer data. Non-Linear Model I –Model IV include the VDC level *ROAD* and *VIOL* data. Non-Linear Model V incorporates the district level data for *ROAD* and *VIOL*. Also important for the non-linear model is controlling for the endogeneity issues of the vegetation variables. To do this, a first stage regression of the vegetation variables was carried out, including those instruments used in the linear analysis in Table 3-3. The predicted values are then incorporated in the non-linear analysis.

¹⁶ Although not reported, endogeneity tests of *PRICE* do not indicate an endogeneity issue with this variable. These results are available upon request.

¹⁷ The STATA programming is included in the appendix.

To simplify the non-linear programming, and increase the chance of convergence of the numerical analysis, only those variables from Model IV in Table 3-3 were included in the analysis. The AIC results reported are lower in value than compared to the AIC values of Model IV in Table 3-3. The weighting coefficient for vegetation quality, κ^{veg} , is insignificant in each of the Non-Linear Models. Therefore, we estimate the decay weight function to be $\frac{1}{2}$, following equation (3-12), indicating a declining influence the further the buffer ring is from the VDC. Similarly, in Non-Linear Model V, κ^{dist} , is insignificant. We therefore estimate the decay weight function to be $\frac{1}{2}$ for district level data, indicating a declining influence of the data going from the VDC to the district level. Also presented are the values of η which are incorporated to ensure the sigma values of the maximum likelihood function are positive.¹⁸

The coefficients presented are for the entire impact of the variable type. For instance, the coefficient for $VEG^{VDC,10R,20R}$ incorporates the impact of vegetation at the VDC and at each of the buffer levels. The results indicate each of the vegetation measures is highly significant, at the 1% level, with magnitudes of 0.0520 to 0.0610. These results illustrate the importance of vegetation cover for food security, not only in the immediate VDC, but also in surrounding areas. The values are in a slightly higher range than in the linear model. The coefficient for $VIOL^{VDC}$ is significant in each Non-Linear Model, at the 5-10% levels. The variable $VIOL^{VDC,DIST}$ is significant at the 5% level in Non-Linear Model V. This result suggests the impact of conflict at the VDC and District level is an important factor in the determination of household food security. Much different than the linear analysis, $ROAD$ is highly significant, at the 1% level, in each of the Non-Linear Models. This result suggests built

¹⁸ It should be noted that the data in the non-linear analysis did not incorporate the probability weights, which were included in the linear model. This was to ensure a simpler max-likelihood function that would reach convergence when solved numerically.

infrastructure, for access to markets and job centers, is important for food security. To further analyze the impacts of each of the spatial areas an impact coefficient is calculated following equation 3-14, which incorporates the decaying weight factor. These results are presented in Table 3-6.

3.4.3 Social Capital Community Group Analysis

Model III from Table 3-3 was estimated again using each type of the social group indices created. The results of these analyses are in Table 3-7. As in the general model, the individual community group types were tested for the presence of endogeneity, using the same instruments as in Model III in Table 3-3. Only the SCI^{FOR} variable was observed to be endogenous. Levels of significance for the preferred models ranged from 5-10% for the specific community group types. The aggregate index results are also included, although these are the same results as seen in Table 3-3. The goodness of fit measures for these additional analyses verified that an inclusion of the broadest measure was most acceptable for the general analysis. The magnitudes of the beta coefficients, shown in Table 3-8 indicate the user group indices have the following rank order influence on $FOODINDEX$: $SCI^{FOR} > SCI^{ALL} > SCI^{AGRIC} > SCI^{WOMEN} > SCI^{WOMEN}$.

Table 3-9 summarizes the results of the eight primary hypotheses laid out in the Analytical Model and Data Components section.

3.6 Discussion and Conclusions

The results of this study provide quantitative evidence of increased food security with the existence of high quality natural capital stock, specifically primary forest and secondary vegetation cover. Further, this study illustrated that not only is nearby natural capital stock

important, but household food security is also impacted by the quality of natural capital at some distance from one's location. In addition to measuring forest natural capital, this study analyzed the impact of access to safe drinking water.

The analysis has illustrates the importance of social capital and food security. Our study primarily focused on an aggregate measure of the extent of community groups in the districts where our household's were located. Although we had no evidence of the community group participation of individual households in our study, the results indicate that there are, at a minimum, indirect benefits to household welfare through the involvement and empowerment of that community.

The availability of food aid, access to credit, and income in the source of remittances were all positively related to food security. There are wide ranges of activities that may be classified as coping strategies, or potential strategies to prevent food aid. Access to credit, sending a household member abroad, or receiving developmental food aid may all be considered as much prevention strategies as they are coping mechanisms.

Table 3-1. Description Of Food Security Rankings

Food Security Ranking (based on food consumption)	Description of Ranking	Average Index For Category
1. Very poor food consumption	Homogeneous diet, nutritionally inadequate, primarily consume carbohydrates, rarely eat animal products	4.3
2. Poor food consumption	Homogeneous diet, nutritionally inadequate, primarily consume carbohydrates, consumed milk products and pulses (more protein than group 1)	4.7
3. Fairly good food consumption	Diversified diet, daily consumption of rice and vegetables, some fruit, regular consumption of milk products or fish	5.8
4. Good food consumption pattern	Highly diversified diet, fruits and vegetables eaten frequently, milk and pulses eaten regularly, some meat	6.9
5. Very good food consumption	Highly diversified diet, very frequent consumption of fruits and vegetables, very regular consumption of milk and other animal products	8.6

Table 3-2. Variable Definitions and Descriptive Statistics

Variable	Description	Mean	SD	Min	Max
FOODINDX	Food Security Index (low value represents poor food security, high value represents strong food security). ^W	5.650	1.888	1.8	11.2
HHSIZE	Household size (total persons, adults and children). ^W	6.638	3.823	1	89
LANDSIZE	Land size (agricultural land available to the household, in hectares). ^W	0.821	0.921	0	7.5
AGINC	Income from agriculture (percentage of total income). ^W	22.218	30.794	0	100
EDUC	Dummy indicator variable of primary education completed (=1 if head of household completed primary school or above, else 0). ^W	2.004	1.587	0	8
POULT	Number of poultry owned by the household (in hundreds). ^W	0.045	0.288	0	10
MOUNT	Dummy indicator variable of Mountain ecological belt. ^W	0.159	0.366	0	1
HILLS	Dummy indicator variable of Hills ecological belt. ^W	0.667	0.471	0	1
ROAD	Road density in the VDC where the household is located (km of road per sq. km of land area). ^G	0.257	0.209	0	0.916
ROAD ^{DIST}	Road density of the District where the household is located beyond the VDC (km of road per sq. km of land area). ^G	0.243	0.150	0	0.826
PRICES	Average price of rice, a main staple food, in the district where the household was located (hundreds of rupees per kilo). ^N	0.406	0.779	0.136	5.586
WATDIS	Distance in terms of hours that a household has to travel to find improved, safe drinking water (hours). ^W	0.064	0.239	0	6
VEG ^{VDC}	Land covered by primary and secondary vegetation cover in the VDC where the household is located (% of land area). ^G	50.888	19.984	1.873	99.466
VEG ^{10R}	Land covered by primary and secondary vegetation cover in the 10 km buffer surrounding the VDC (% of land area). ^G	52.750	12.488	14.461	85.219
VEG ^{20R}	Land covered by primary and secondary vegetation cover in the 10- 20 km buffer ring surrounding the VDC (% of land area). ^G	54.004	9.834	23.949	75.989
VEG ^{30R}	Land covered by primary and secondary vegetation cover in the 20-30km buffer ring surrounding the VDC (% of land area). ^G	54.392	7.285	29.792	69.849
DALIT	Dummy indicator variable of household is recognized by the Dalit caste (1 if Dalit , else 0). ^W	0.187	0.390	0	1
JANJATI	Dummy indicator variable of household is recognized by the Janjati caste (1 if Janjati, else 0). ^W	0.374	0.484	0	1
OTHERC	Dummy indicator variable of household is identified by a caste other than Janjati, Dalit, and Brahmin or Chhetri (1 if Other, else 0). ^W	0.081	0.272	0	1
SCI ^{AGRIC}	Social capital index related for community groups focusing on issues pertaining to agriculture in the district where the household is located. ^N	0.583	0.607	0	2.556
SCI ^{WATER}	Social capital index related for community groups focusing on issues pertaining to water in the district where the household is located. ^N	0.717	0.863	0	3.036
SCI ^{FOR}	Social capital index related for community groups focusing on issues pertaining to forests in the district where the household is located. ^N	0.914	0.767	0	3.355
SCI ^{WOMEN}	Social capital index related for community groups focusing on issues pertaining to women in the district where the household is located. ^N	0.454	0.613	0	3.083
SCI ^{ALL}	Social capital index related to all community groups for the district where the household is located, including user groups related to agriculture, water, forests, women, and credit. ^N	3.393	2.023	0	10.182
REMIT	Annual amount of remittances received by the household (10,000 rupees per household member). ^W	2.429	6.678	0	114.286
CREDIT	Dummy variable representing the household's access to financial credit (1=has access to credit, else 0). ^W	0.731	0.444	0	1
FOODAID	Dummy variable indicating if members of the household received food aid in past six months (1=has access to credit, else 0). ^W	0.060	0.237	0	1
VIOL	Level of conflict that has occurred in the VDC where the household is located (Number of people killed between 1996 and 2003). ^C	0.454	1.131	0	7.4
VIOL ^{DIST}	Level of conflict that has occurred in the District where the household is located beyond the VDC (Number of people killed between 1996 and 2003) ^C	3.412	3.181	0	15.28

Data Sources: ^W—World Food Program survey (2005), ^N—Nepal Living Standard Survey (2003), ^C— Informal Sector Service Center (INSEC): Nepal Human Rights Year Book (2003), ^G—Spatial data collected by the University of Maryland, and processed at Central Missouri University.

Table 3-3 Estimates of household food security index in Nepal—Linear Model.

Dependent Variable: FOODINDX	MODEL 1	MODEL 2a	MODEL 2b	MODEL 3a	MODEL 3b	MODEL 4a	MODEL 4b	MODEL 5a	MODEL 5b
CONST	5.113*** (0.207)	4.789*** (0.233)	3.027*** (0.635)	3.222*** (0.702)	3.222*** (0.655)	3.640*** (0.595)	3.761*** (0.826)	3.621*** (0.561)	4.156*** (0.475)
LANDSIZE	0.179** (0.072)	0.177** (0.074)	0.186* (0.097)	0.187* (0.101)	0.186* (0.101)	0.187* (0.096)	0.187** (0.095)	0.190** (0.093)	0.204** (0.087)
HHSIZE	0.039*** (0.009)	0.037*** (0.009)	0.025** (0.012)	0.027** (0.012)	0.028** (0.012)	0.028** (0.012)	0.029** (0.011)	0.028*** (0.010)	0.029*** (0.009)
AGINC	0.008*** (0.002)	0.007*** (0.002)	0.005* (0.003)	0.004 (0.003)	0.004* (0.003)	0.005* (0.003)	0.005* (0.003)	0.005** (0.002)	0.005** (0.002)
EDUC	0.159*** (0.041)	0.148*** (0.041)	0.096* (0.050)	0.069 (0.049)	0.069 (0.049)	0.074 (0.047)	0.076 (0.047)	0.077* (0.045)	0.095** (0.042)
POULT	0.306** (0.139)	0.318** (0.126)	0.438*** (0.125)	0.590*** (0.165)	0.583*** (0.166)	0.598*** (0.158)	0.599*** (0.156)	0.625*** (0.160)	0.650*** (0.151)
MOUNT	-0.966*** (0.204)	-1.034*** (0.207)	-1.477*** (0.305)	-1.666*** (0.318)	-1.648*** (0.309)	-1.540*** (0.285)	-1.503*** (0.319)	-1.408*** (0.275)	-1.253*** (0.257)
HILLS	-0.605*** (0.162)	-0.692*** (0.179)	-1.421*** (0.362)	-1.362*** (0.418)	-1.306*** (0.403)	-1.140*** (0.364)	-1.079** (0.458)	-1.054*** (0.343)	-0.830*** (0.315)
ROAD	-0.185 (0.378)	-0.114 (0.374)	0.578 (0.440)	0.587 (0.507)	0.530 (0.520)	0.300 (0.480)	0.232 (0.660)	0.142 (0.452)	-0.126 (0.423)
PRICES	0.048 (0.081)	0.064 (0.078)	0.160* (0.093)	0.233** (0.096)	0.236*** (0.091)	0.237*** (0.091)	0.234*** (0.089)	0.227** (0.089)	0.212** (0.084)
WATDIS		-0.569** (0.246)	-0.473 (0.310)	-0.460* (0.276)	-0.460* (0.272)	-0.505* (0.263)	-0.513* (0.266)	-0.489** (0.241)	-0.524** (0.225)
VEG ^{VDC}		0.009** (0.004)	0.054*** (0.017)	0.054*** (0.016)	0.052*** (0.015)	0.045*** (0.014)	0.042** (0.018)	0.038*** (0.012)	0.023** (0.010)
CLASS ^{DALIT}				-0.352 (0.247)	-0.351 (0.250)	-0.421* (0.231)	-0.441* (0.240)	-0.431* (0.223)	-0.527** (0.210)
CLASS ^{LANJAT}				-0.955*** (0.186)	-0.966*** (0.183)	-1.011*** (0.170)	-1.026*** (0.187)	-1.022*** (0.164)	-1.119*** (0.153)
CLASS ^{OTHER}				-0.538* (0.306)	-0.496 (0.303)	-0.460 (0.291)	-0.435 (0.313)	-0.448 (0.281)	-0.340 (0.274)
SCI ^{ALL}				0.091** (0.036)	0.105** (0.048)	0.092*** (0.035)	0.091*** (0.035)	0.088*** (0.034)	0.088*** (0.033)
VIOL						-0.099** (0.050)	-0.112 (0.123)	-0.091* (0.050)	-0.081 (0.050)
COPE ^{REMIT}								0.021 (0.013)	0.023* (0.012)
COPE ^{CREDIT}								0.304** (0.139)	0.339** (0.135)
COPE ^{FOODAID}								0.669*** (0.252)	1.591** (0.717)
Obs.	1674	1674	1674	1674	1674	1674	1674	1674	1674
Log-Likelihood	-3345.117	-3334.259	-3512.304	-3474.479	-3463.887	-3408.157	-3390.199	-3354.767	-3302.468
AIC	6710.233	6692.517	7048.608	6980.958	6959.774	6850.314	6814.397	6749.534	6644.936
R-sq	0.115	0.126	-0.081	-0.033	-0.021	0.045	0.065	0.104	0.158
F-test	13.912	12.604	10.238	12.773	12.997	13.552	13.892	13.593	14.606
Kleibergen-Paap rk(LM)			49.568***	48.527***	48.495***	58.013***	29.951***	63.895***	72.782***
Cragg-Donald Wald			23.215 ^a	22.117 ^b	13.909 ^c	29.877 ^a	12.556 ^b	34.909 ^a	21.431 ^b
Hansen J			1.858	2.763	2.855	2.223	2.241	2.936	7.663
End. (X ²) VEG ^{VDC}			9.526***	13.284***	14.655***	12.628***	6.047**	10.373***	3.470*
End. (X ²) SCI ^{ALL}					0.001				
End. (X ²) VIOL							0.001		
End. (X ²) FOODAID									6.419**
Heter (X ²)	20.053**	23.663**	22.844**	42.148***	49.625***	44.205***	48.131***	49.618***	67.391***

Standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.01. ^a indicates exceeds Stock and Yogo (2005) critical values for bias reduction to no more than 5% of the OLS estimates and exceeds the critical value for 10% maximal IV size distortion; ^b indicates the same for bias reduction, and exceeding the critical value for 15% maximal IV size distortion; and ^c critical values for bias reduction to no more than 10% of the OLS estimates and exceeds the critical value for 10% maximal IV size distortion.

Table 3-4. Beta coefficients for Model 5b, the preferred full linear OLS IV model in Table 3-3.

Variable	BETA Coefficient	Rank of Magnitude
CASTE ^{ANJATI}	-0.273***	1
VEG ^{VDC}	0.258**	2
HILL	-0.218***	3
COPE ^{FOODAID}	0.203**	4
MOUNT	-0.195***	5
LANDSIZ	0.110**	6
CASTE ^{DALIT}	-0.109**	7
SCI ^{ALL}	0.103***	8
AGINC	0.091**	9
HHSIZE	0.090***	10
EDUC	0.079**	11
PRICES	0.077**	12
COPE ^{CREDIT}	0.076**	13
CASTE ^{OTHER}	-0.073	14
COPE ^{REM}	0.063*	15
POULT	0.061***	16
WATDIS	-0.053**	17
VIOL	-0.047	18
ROAD	-0.014	19

Table 3-5. Spatial Modeling Results

<i>Dependent Variable</i>	Non-Linear Model I	Non-Linear Model II	Non-Linear Model III	Non-Linear Model IV	Non-Linear Model V
FOODINDEX					
<i>ROAD^{VDC}</i>	1.0786*** (0.2528)	1.1277*** (0.2531)	1.1041*** (0.2529)	1.1092** (0.2528)	
<i>ROAD^{VDC, DIST}</i>					1.0027** (0.3870)
<i>VIOL^{VDC}</i>	-0.0918** (0.0403)	-0.0715* (0.0410)	-0.0777* (0.0406)	-0.0777* (0.0406)	
<i>VIOL^{VDC, DIST}</i>					-0.0845** (0.0364)
<i>VEG^{VDC}</i>	0.0610*** (0.0067)				
<i>VEG^{VDC, 10R}</i>		0.0520*** (0.0075)			
<i>VEG^{VDC, 10R, 20R}</i>			0.0553*** (0.0069)		
<i>VEG^{VDC, 10R, 20R, 30R}</i>				0.0557*** (0.0068)	0.0546*** (0.0173)
κ^{veg}		0.869 (1.608)	-0.549 (0.620)	-0.611 (-1.110)	-0.6359 (0.5756)
κ^{dist}					-2.3882 (3.2007)
<i>eta</i>	0.5815*** (0.0173)	0.5795*** (0.0173)	0.5800*** (0.0173)	0.5634*** (0.0228)	0.5800*** (0.0173)
<i>N</i>	1674	1674	1674	1674	1674
<i>Log-Likelihood</i>	-3348.69	-3345.43	-3346.24	-3346.20	-3346.15
<i>AIC</i>	6727.38	6720.86	6722.47	6722.40	6722.60

All of these models are estimated using a programmed nonlinear maximum likelihood method. The first model does not include a spatial component. Each additional model adds an additional spatial dimension. Model II includes the VDC vegetation measure and the 10km VDC vegetation radius. Model III adds the 20km radius. Model IV and V add the 30km radius. Model V also adds a weighted spatial dimension to the ROAD and VIOL measures, including VDC level and surrounding district level data. It should be noted that models I-IV include the weighting option for the survey data. This was removed for Model V to ensure model convergence. All models also included additional explanatory variables (following model IV from table 3-3). These results are suppressed for ease of presentation, but are available upon request.

Table 3-6. Spatial Modeling Variable Weighted Coefficient Values

<i>Dependent Variable</i> FOODINDX	Non-Linear Model I	Non-Linear Model II	Non-Linear Model III	Non-Linear Model IV	Non-Linear Model V
<i>ROAD^{VDC}</i>	1.0786***	1.0786***	1.1277***	1.1041***	1.0227**
<i>ROAD^{DIST}</i>	--	--	--	--	0.5014**
<i>VIOL^{VDC}</i>	-0.0918**	-0.0715*	-0.0777*	-0.0777*	-0.0845**
<i>VIOL^{DIST}</i>	--	--	--	--	-0.0423**
<i>VEG^{VDC}</i>	0.0610***	0.0520***	0.0553***	0.0557***	0.0546***
<i>VEG^{10R}</i>	--	0.0260***	0.0276***	0.0278***	0.0273***
<i>VEG^{20R}</i>	--	--	0.0138***	0.0139***	0.0137***
<i>VEG^{30R}</i>	--	--	--	0.0070***	0.0068***

These weighted coefficient values are calculated for each spatial level using the spatial results from table 3-5. The values are calculated following the general equation 3-14. For insignificant estimation results, a zero is provided. For those models that did not include a spatial level, -- is indicated. For the VDC level variable, the weighted coefficient value is equivalent to the estimated model parameter.

Table 3-7. Social capital's impact on food security (Using different community user group types for model 3 in Table 3-3).

Independent Variable: FOODINDEX	Model 3-1a	Model 3-1b	Model 3-2a	Model 3-2b	Model 3-3a	Model 3-3b	Model 3-4a	Model 3-4b	Model 3-5a	Model 3-5b
SCI^{AGRIC}	0.240* (0.128)	0.398 (0.278)								
SCI^{WATER}			0.174* (0.100)	0.268* (0.146)						
SCI^{FOR}					-0.032 (0.099)	0.575** (0.283)				
SCI^{WOMEN}							0.204* (0.119)	0.048 (0.418)		
SCI^{ALL}									0.091** (0.036)	0.105** (0.048)
Obs.	1674	1674	1674	1674	1674	1674	1674	1674	1674	1674
Log-Likelihood	-3515.832	-3555.776	-3474.086	-3470.435	-3468.510	-3628.534	-3464.620	-3491.330	-3474.479	-3463.887
AIC	7063.663	7143.553	6980.172	6972.869	6969.019	7289.069	6961.241	7014.661	6980.958	6959.774
R-sq	-0.086	-0.139	-0.033	-0.029	-0.026	-0.242	-0.021	-0.055	-0.033	-0.021
F-test	11.965	10.869	12.857	12.756	13.063	11.189	13.525	12.897	12.773	12.997
Kleibergen-Paap rk (LM)	50.513***	45.015***	49.238***	49.115***	49.680***	47.256***	47.648***	45.092***	48.527***	48.495***
Cragg-Donald Wald (F)	21.087 ^b	14.379 ^b	22.938 ^a	13.966 ^c	21.469 ^b	13.659 ^c	22.314 ^a	16.540 ^a	22.117 ^b	13.909 ^c
Hansen J	4.206	4.245	3.700	3.681	4.255	2.267	3.885	3.844	2.763	2.855
End. (X^2)	16.340***	20.020***	14.240***	14.988***	12.643***	22.254***	12.770***	14.853***	13.284***	14.655***
VEG^{VDC}										
End. (X^2) SCI		0.039		0.215		4.192**		0.150		0.001
Heter (X^2)	45.559***	47.163***	38.641***	47.740***	42.483***	35.967***	39.872***	35.063***	42.148***	49.625***

In the first column for each model (column "a"), the vegetation variable is instrumentalized, but the social capital measure is not. Both are endogenized in the second column (column "b") for each model. Standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. ^a indicates exceeds Stock and Yogo (2005) critical values for bias reduction to no more than 5% of the OLS estimates and exceeds the critical value for 10% maximal IV size distortion; ^b indicates the same for bias reduction, and exceeding the critical value for 15% maximal IV size distortion; and ^c critical values for bias reduction to no more than 10% of the OLS estimates and exceeds the critical value for 10% maximal IV size distortion.

Table 3-8. Beta coefficients for social capital model.

Independent Variable: FOODINDEX	VEG^{VDC} IV	SCI & VEG^{VDC} IV	Preferred Model	Rank Order of Impact (based on preferred model)
SCI^{FOR}	-0.012	0.223**	SCI &	1
SCI^{ALL}	0.107***	0.123**	VEG^{VDC} IV	2
SCI^{AGRIC}	0.088*	0.145	VEG^{VDC} IV	3
SCI^{WATER}	0.072*	0.110*	VEG^{VDC} IV	4
SCI^{WOMEN}	0.067*	0.016	VEG^{VDC} IV	5

Table 3-9. Hypothesis summary table of key explanatory variables. The initial hypotheses presented in the Analytical Model and Data Components section are listed. The resulting coefficient signs are listed in the result column.

	Hypothesis	Result
1	$\beta_{VEG^{\Delta}} > 0$ for $\Delta = \{VDC, 10R, 20R, 30R\}$	$\beta_{VEGVDC}, \beta_{VEG10R}, \beta_{VEG20R}, \beta_{VEG30R} > 0$
2	$\beta_{VEGVDC} > \beta_{VEG10R} > \beta_{VEG20R} > \beta_{VEG30R}$	$\beta_{VEGVDC} > \beta_{VEG10R} > \beta_{VEG20R} > \beta_{VEG30R}$
3	$\beta_{WATDIS} < 0$	$\beta_{WATDIS} < 0$
4	$\beta_{SCI^{\Omega}} > 0$ for $\Omega = \{AGRIC, WATER, FOR, WOMEN, ALL\}$	$\beta_{SCIAGRIC}, \beta_{SCIWATER}, \beta_{SCIFOR}, \beta_{SCIWOMEN}, \beta_{SCIALL} > 0$
5	$\beta_{CASTE^{\Lambda}} < 0$ for $\Lambda = \{DALIT, JANJATI, OTHERC\}$	$\beta_{CASTDALIT}, \beta_{CASTJANJATI} < 0$ $\beta_{CASTOTHER} = 0$
6	$\beta_{COP^{\Theta}} > 0$ for $\Theta = \{REM, CREDIT, FOODAID\}$	$\beta_{COPREM}, \beta_{COPCREDIT}, \beta_{COPFOODAID} > 0$
7	$\beta_{VIOL} < 0$	$\beta_{VIOL} < 0$
8	$\beta_{VIOLVDC} > \beta_{VIOLDIST} > 0$	$\beta_{VIOLVDC} > \beta_{VIOLDIST}$

Chapter 4: Provision of Global Aid for Natural Disasters

4.1 Introduction

Inadequate infrastructure and weak social safety nets make people in lower income countries particularly vulnerable to natural disasters. Emergency aid, typically donated by wealthier countries, is critical to ease immediate human suffering in the time of emergencies. Provision of the basic resources, including food, is also important in speeding up the recovery process following disasters. Without the maintenance of food security, communities are at risk of experiencing longer lasting effects from disasters, which may include longer-term poverty.

The research in this section carries out a dynamic analysis of the worldwide distribution of food aid as cataloged in the Food Aid Information System (FAIS), an international effort coordinated by the United Nations World Food Program (WFP) to provide reliable data on all food aid transactions by countries and NGOs, whether or not the food aid was distributed by the WFP. Approximately two thirds of food aid is coordinated through WFP, while remaining aid is distributed by source countries directly to recipient countries or non-government agencies in recipient countries (WFP, 2010). The data available in FAIS is from 1988-2010.

The study uses the FAIS data to measure the effect of emergency food aid flows to countries that have experienced a wide range of natural disasters, including climate related shocks, flooding, earthquakes, fires, and storms. This is important to understand the ability of the international community to respond effectively in times of disaster, to lessen human suffering and assist countries in long-term recovery efforts. We particularly analyze the effect of the magnitude of natural shocks, measured by the total number of people affected by a shock. Additional measures of violence and other country characteristic effects that may

impact food aid flows are also analyzed, including those characteristics that may make a country more resilient to the impacts of disaster in the first place (e.g. quality of institutions). The analysis considers for the lag effect of food aid and shocks, making a dynamic GMM econometric analysis an appropriate approach. Our results show a relationship between increased emergency food aid and increases in an aggregate measure of the number of individuals affected by all natural disasters, as well as for events directly related to the climate, geological events, and flooding. However, there is a lag between the time food aid reaches countries for several of the disaster types. There is also a positive relationship observed between increased conflicts and emergency food aid. Our contribution to the literature include providing a theoretical model of the use of emergency food aid, as well as using a dynamic approach to quantifying the distribution of emergency food aid based in the context of climate relevant shocks.

The chapter continues as follows. First, there is a literature review providing some background of determinants of emergency food aid. The next section is followed by a discussion of the theoretical model considered. Then, the data and econometric tools are presented. The final section presents a discussion of the results and conclusions.

4.2 Emergency Food Aid Background

Emergency food aid generally consists of that aid used to meet the acute food needs of individuals struck by natural disasters, epidemics, and war. WFP (2009) describes it as short-term food aid provided to targeted beneficiary groups on a grant basis, meaning it does not have to be paid for by those countries receiving it. Typically it is organized multilaterally, and distributed through NGOs. Less often it is distributed bilaterally. Emergency food aid is a subset of the aid labeled as food aid, which also includes project aid and program aid.

Project aid is the provision of food resources to beneficiary groups involved with longer

term nutritional, agricultural, or development projects. Program aid is food aid given bilaterally on a government-to-government basis, and may be used for multiple purposes, often given a loan basis. Unlike emergency aid, project and program aid may be sold on the open market (Barrett and Maxwell, 2005)

Prior to the 1980s, the majority of food aid was targeted for development assistance, with less available for emergency aid. By 2002 and 2003, emergency food aid was nearly triple that of development food aid (Barret and Maxwell, 2005). In recent years there has been movement of countries to pool resources in emergency assistance funds, such as the CERF, which gives UN agencies, including WFP, the ability to remain flexible with the way funds are used, and to respond quickly in times of emergencies (Harvey et al., 2010). Multilateral assistance has been considered a more effective approach for tackling emergency aid distribution than bilateral efforts (Barrett and Heisy, 2002). An aim of this study is to understand the aggregate international response, of multiple countries, to global emergency situations.

4.2.1 Historical Context

The Great Irish Famine is one of the most familiar instances of widespread hunger in Western history, killing an estimated one million people between 1845 and 1849. This famine was caused by potato blight and failed government policies. There are numerous examples of famines before and after Ireland, 7 million deaths in India from 1876-1879 due to drought and policy failure, 9 million deaths in the USSR from 1921-1922 due to drought and civil war, and 15 million deaths in China due to drought and floods (Ó Gráda, 2007). The early history of organized international intervention is less clear. There was the purchase of U.S. maize by the British government to assist the Irish in 1845 and 1846 (Gary, 1995). Modern food aid has its roots in Public Law 480 (PL480), the Agriculture Trade Assistance

Act, signed into law in 1954, and implemented by the U.S. Department of Agriculture (USDA) and the U.S. Agency for International Development (USAID). The U.S., along with Canada, provided over 90% of the global food aid through the 1970s. The aim of this bilateral aid approach was to promote the sale and distribution of surplus U.S. agricultural products for the mutual benefit of U.S. producers and poor people in developing countries. However, there is criticism that the focus has been slanted more towards the agricultural producers providing the aid (Barrett and Maxwell, 2005).

The question of proper targeting, effectiveness, and the potential for aid to cause more harm to an economic system were at the forefront of academic discussion in the initial years of PL480. An early paper published in the *American Economic Review* discussed observations of PL480, explaining the majority of aid targeted food deficit countries, and those with low level of foreign currency. PL480 replaced previous forms of aid, including famine relief aid (Davis, 1959). Sen (1960) discussed contrasting reactions among less developed countries in receiving food surpluses. Some countries thought of these new resources as important to improving the overall situation and nutritional status of poor populations, while others worried that international food surpluses would weaken local agriculture production. Sen mentions that food surpluses received by countries in times of emergency relief was always welcome. Sen argued for the merits of using food surpluses as a tool for positively affecting economic development. In contrast, Schultz (1960) discussed a less favorable view of the long-run potential of sending food surpluses to developing countries, fearing the adverse effects on local agriculture production would outweigh potential benefits. Fisher (1963) further analyzed the positive and negative impacts of foreign food surpluses on developing economies through the development of a theoretical framework focused on the impacts of surplus food on agriculture demand and supply.

Throughout much of the 1960s and 1970s, economists and political scientists continued to discuss the impact of food aid, particularly food aid geared towards development projects, on agricultural production and political stability of developing countries (see Kern, 1968; Dudley and Sandilands, 1975).

The World Food Program was established by the UN General Assembly and Food and Agricultural Organization, and began operations in 1963. By 1972, this multilateral food assistance approach had carried out nearly 516 development projects and 150 emergency operations were in process or had been completed in at least 88 countries (Costa, 1973). This was still a small amount in comparison to the bilateral aid of the U.S. The WFP became the primary coordinating body of food aid beginning with the UN Food Conference in Rome in 1974, where the international community agreed that a multilateral approach would be a more effective approach for targeting food aid (WFP, 2010). The U.S. has remained the primary supplier of food aid to WFP since that time. Although many organizations provide technical assistance to agriculture development projects, the majority of food aid distribution is coordinated by WFP. There were specific policy changes in the 1990s by the European Union and the U.S. to better address country food needs when making food aid decisions (Young and Abbott, 2008). Researchers have continued to be concerned with the ability of food aid to indeed target those beneficiaries most in need.

The study of the determinants of food aid is related to the broader literature of the determinants of international aid [see Neumayer, E., 2003]. Eggleston (1987) provided evidence that the flow of US food aid from 1955-1979 increased not only when the need for food increased, but also due to other factors including specific US political and military interests in recipient countries, the ability of countries to buy US agricultural products, and levels of foreign exchange holdings. Garst and Barry (1990) discuss the political and military

influences on U.S. food aid in Central America. Prinz (1991) studied food aid originating in Europe, noting that food aid in the 1960s and 1970s had less to do with the needs of countries, and more to do with the need to dispose of surplus food stocks. An econometric study of cross sectional and time series data by Ball and Johnson (1996) found evidence of political, economic and humanitarian interests driving PL480 food aid decisions, with an increasing trend towards food aid motivated by humanitarian needs in the 1980s. Zahariadis et al. (2000) use a two step model to show emergency aid is tied more to recipient need when compared to development aid, which is more motivated by political motives. A study by Diven (2001) looked particularly at the determinants of food aid shipments from the perspective of the producing countries, and provides evidence of a positive relationship between the quantity of rice and wheat shipments with U.S. economic and policy interests.

Much of the recent studies of the determinants of food aid have followed the approach of Barrett (2001) and Barret and Heisey (2002), who specifically analyze the ability of food aid to stabilize the food supply in beneficiary countries. The hypothesis is that food aid will flow towards those countries with low per capita food production, and to those countries deviating from long-term agriculture production. Barrett (2001) found minimal evidence that bilateral food aid stabilizes food production, while Barrett and Heisey (2002) found evidence that multilateral aid targets countries with food production shortfalls, and is better able to stabilize food availability, than bilateral food aid (Gupta et al., 2004).

There is often a sense that emergency food aid is less tied to politics than the development focused aid, as it is in direct response to civilian needs, but empirical evidence has been particularly lacking to fully support this argument. Typically, studies have used some measure of food availability, or food production (Barrett and Maxwell, 2005) to account for the needs of individuals. Neumayer (2005) argues that food supply should not be

the main consideration, as populations with ample food supply may not have access to this food when they do not have the ability to purchase it. This is similar to the argument by Amartya Sen (1981) of food insecurity being an issue of demand, not supply. The findings of Neumayer's two stage econometric approach shows particularly strong evidence for both development and emergency food aid in the 1990s to be strongly motivated by humanitarian needs, measured primarily by the number of refugees. Young and Abbott (2008) find higher quantities of food aid flow to those countries with the most severe deviations from their long-term food production trend for all forms of food aid, with levels of conflict increasing emergency and project food aid.

Of particular interest in this study is the effect of natural disaster shocks on food aid flows. Jayne et al. (2001) investigate food security determinants with controls for flooding and weather related shocks experienced by households in Ethiopia, with little evidence indicating those households experiencing shocks received greater amounts of aid. A recent paper by Kuhlitz et al. (2010) finds indications of food aid increases with rapid onset shocks such as floods, earthquakes, and conflict. More slow moving disasters such as drought and temperature changes do not show evidence of increased aid. A primary argument is that there is a greater response to more rapid onset disasters, as these rapid events have been seen to garner greater media attention (Eisensee and Strömberg, 2007). Our study considers the lag effect of gradual events, which show a significant increase in aid. It may be that the media response to gradual disasters occurs when the effects are seen, such as droughts and the resulting famines seen in the Horn of Africa. Lag effects of aid in emergency situations are potentially very devastating when considering the loss of human life. Such concerns point to the importance of understanding the humanitarian response to emergencies, and ensuring responses are managed to most efficiently achieve goals of

providing emergency humanitarian intervention.

4.3 Theoretical model

The starting point of our analysis considers the theoretical necessity of emergency food aid in the context of enabling communities and populations to maintain current and future food security. Food security implies consistent physical and economic access to sufficient, safe, and nutritious food to meet dietary requirements to lead a healthy and active life (World Food Summit, FAO, ROME, 1996), with freedom from the risk of going without food. An important aspect of food security is its dynamic nature, where an individual or household's consumption of resources in the present may impact the ability to consume in the future. Barret (2002) provides a theoretical model illustrating the linkages between improved current nutrition levels with increased ability to ensure future consumption through maintaining one's labor productivity by remaining healthy with the ability to maintain and increase asset holdings. Further, Barrett (2002) presents food security from the point of view of risk aversion, where individuals concerned about future consumption will minimize risk. This risk minimization may lead to cautious production, savings, investment and other decisions that may limit a poor household's future ability to accumulate assets allowing them to break the poverty cycle. The strategy of emergency food aid interventions is to maintain the safety net, and minimize the risk exposure of households faced with shocks (Barrett and Maxwell, 2005).

To further illustrate the impact of a natural disaster on a macro level, we first present a model based on the mathematical representation provided by Barrett (2002), which considers a household's dynamic expected utility maximizing problem as follows.¹⁹

¹⁹ The function U is assumed to be twice differentiable such that $U_c \geq 0$ and $U_{cc} \leq 0$.

$$\begin{aligned}
& \text{Max}_{C_{i,t}^{\eta}, Z_{i,t}^{\kappa}} E \left(\sum_{t=0}^T \beta_t U(C_{i,t}^{\eta}, Z_{i,t}^{\kappa}, A_{i,t}) \right) \\
& \text{s.t. } A_{i,t+1} = -C_{i,t}^{\eta} - \delta A_{i,t} + \theta Q_{i,t}^{\psi} - \phi \gamma S_{i,t}^f + \nu Z_{i,t}^{\kappa} + \tau W_{i,t} \\
& \quad + \sigma Y(L(C_{i,t}^{\eta}, Z_{i,t}^{\kappa}, S_{i,t}^f), K(R_{i,t}^{\rho}, S_{i,t}^f, Z_{i,t}^{\kappa})) \\
& \quad A_{i,t}, C_{i,t}^{\eta}, Z_{i,t}^{\kappa} \geq 0
\end{aligned} \tag{4-1}$$

Where household, i , has a level of food security expected utility dependent on the level of current consumption of food (f) and non-food (nf) items ($C_{i,t}^{\eta}$, where $\eta =$ food or non-food), humanitarian aid ($Z_{i,t}^{\kappa}$ where $\kappa =$ food or non-food aid), and the asset stocks, for future consumption ($A_{i,t}$), and. The functional form of $U(C_{i,t}^{\eta}, A_{i,t}, Z_{i,t}^{\kappa})$ is assumed to be monotonic and twice differentiable with respect to $C_{i,t}^{\eta}$, $A_{i,t}$, and $Z_{i,t}^{\kappa}$.²⁰ Further, it is assumed U_C , U_A , and U_Z are ≥ 0 , while U_{CC} , U_{AA} , and U_{ZZ} are ≤ 0 . The discount factor is represented by β_t .

Utility is directly influenced by the asset stock, so consumption decisions are subject to future asset stocks ($A_{i,t+1}$). The model indicates $A_{i,t+1}$ is negatively impacted by $C_{i,t}^{\eta}$ and the depreciation of $A_{i,t}$ occurring at rate δ , where $0 \leq \delta \leq 1$. A vector of shocks ($S_{i,t}^f$) occurring with probability ϕ , where $0 \leq \phi \leq 1$, decrease $A_{i,t+1}$ by a magnitude γ , where $0 \leq \gamma \leq 1$. Types of shocks, which include natural and manmade shocks, are represented by f . When shocks do occur, ϕ goes to 1. Aid, particularly aid that is not directly consumed,

²⁰ The first and second partial derivatives of functions $U(C_{i,t}^{\eta}, Z_{i,t}^{\kappa}, A_{i,t})$ and $Y(C_{i,t}^{\eta}, Z_{i,t}^{\kappa}, S_{i,t}^f, R_{i,t}^{\rho})$ with respect to $C_{i,t}^{\eta}$ are denoted as U_C , U_{CC} , Y_C and Y_{CC} . This notation is used for all arguments of $U_{i,t}$, $Y_{i,t}$.

will impact the stock of assets by a rate of \mathbf{v} of $Z_{i,t}^{\mathbf{K}}$, where $\mathbf{v} \geq 0$, and therefore enters positively into $A_{i,t+1}$. Asset stocks may also be directly influenced by the neighborhood characteristics ($Q_{i,t}^{\Psi}$), at magnitude θ , with $0 \leq \theta \leq 1$. The term ψ represents amenities such as access to markets and hospitals. These are important, as improved infrastructure will improve the quality of assets, potentially off-setting the need for food aid in times of emergencies. The value of asset stocks will also be impacted by a vector of income sources, $W_{i,t}^r$, where r represents income sources such as remittances or wage income.

Additionally, household production $Y_{i,t}$ is added to $A_{i,t+1}$ at a rate σ where $0 \leq \sigma \leq 1$. Household production includes the production of food and other resources, which can be consumed directly, or sold on the market place. The function $Y_{i,t}$ is assumed to be monotonic and twice differentiable with respect to L and K . It is expected that L will be impacted by $C_{i,t}^{\eta}$, $Z_{i,t}^{\mathbf{K}}$, and $S_{i,t}^f$. It is expected that K will be impacted by $R_{i,t}^{\eta}$, $Z_{i,t}^{\mathbf{K}}$, and $S_{i,t}^f$. The term $R_{i,t}^{\rho}$ is a vector of productive capital available to a household ($R_{i,t}^{\rho}$), where ρ represents institution quality, infrastructure, and other community or neighborhood characteristics. There may be some overlap between the items included in $R_{i,t}^{\rho}$ and $Q_{i,t}^{\Psi}$. For instance, access to markets may influence assets directly, but it may also indirectly influence the asset stock through the production function. It is expected that aid will have a positive impact on the labor supply, as a labor force able to meet basic needs will be more productive. We can combine terms and rewrite the production function as $Y_{i,t} = Y(C_{i,t}^{\eta}, Z_{i,t}^{\mathbf{K}}, S_{i,t}^f, R_{i,t}^{\rho})$. It is expected that partial derivatives $Y_C, Y_Z, Y_R \geq 0$, while $Y_S \leq 0$. The second derivatives are less clear. The signs of Y_{CC} and Y_{ZZ} are assumed

negative, as consumption today will leave less available to put towards productive use. Also, assuming a declining benefit of $Z_{i,t}^K$ on $Y_{i,t}$ aligns with the consideration of individuals or communities being aid dependent. In other words, too much aid will decrease production over the longer term. Where these turning points for $C_{i,t}$ and $Z_{i,t}^K$ are on $Y_{i,t}$ is not investigated in this study. The sign of Y_{RR} and Y_{SS} may be positive or negative, and fall out of the scope of this study.

Solving Eq. 1 gives optimal time paths for various consumption types, level of aid, and asset stocks, which maximize expected household utility.

$$C_{i,t}^{\eta*} = C^{\eta}(Q_{i,t}, S_{i,t}, R_{i,t}, W_{i,t}) \quad (4-2)$$

$$Z_{i,t}^{K*} = Z^K(Q_{i,t}, S_{i,t}, R_{i,t}, W_{i,t}) \quad (4-3)$$

$$A_{i,t}^* = A(Q_{i,t}, S_{i,t}, R_{i,t}, W_{i,t}) \quad (4-4)$$

Assuming (4-3) represents the optimal aid received by a household, the country level aid function is the summation of (4-3), allowing the household subscript (i) to be dropped, giving a starting point for developing an econometric analysis.

$$\sum_{i=0}^N Z_{i,t}^{K*} = Z^K(Q_t, S_t, R_t, W_t) \quad (4-5)$$

4.4 Econometric Modeling

Our dynamic cross-country analysis is based on the developed theoretical model given in equation (4-5). As discussed earlier in the chapter, it is important to keep in mind that actual aid decisions by the international community may also include other factors not

directly related to the level of welfare of the recipient country. Our econometric analysis must also control for the dynamic nature of the data. Our basic econometric model can be represented as

$$AIDP_{i,t} = \tau AIDP_{i,t-k} + \theta S_{i,t} + \beta X_{i,t} + u_i + v_{i,t} \quad (4-6)$$

Where $AIDP_{i,t}$ is emergency aid received by country i in time period t , scaled by the population of the receiving country. Following previous models (including Kuhlitz et al., 2010) lags of the dependent variable, $AIDP_{i,t-k}$, account for omission bias due to previous emergency aid impacting current food aid levels. The number of lags included, denoted by k , may go beyond the first lag, depending on the presence of autocorrelation in the data. It was hypothesized that $AIDP_{i,t-k}$ would be positively related to $AIDP_{i,t}$. The term $S_{i,t}$ is a vector of natural disasters and conflict shocks, while $X_{i,t}$ is a vector representing the remaining explanatory variables. The term u_i measures unobserved country level effects, while $v_{i,t}$ is the disturbance term.²¹

4.4.1 Data

Emergency aid data is taken from the WFP's Food Aid Information System (FAIS) database²², measured in tons. FAIS records all food aid distributed world wide, from WFP and directly from donor countries. The development of FAIS was to specifically address the need for a centralized database to monitor country specific food aid allocations and shipments in order to improve food aid management, reporting, and data analysis. The

²¹ For simplicity we avoid using the i and t subscripts, although $t-1$ and $t-2$ continue to denote lags 1 and 2, respectively.

²² United Nations World Food Program, Food Aid Information System, <http://www.wfp.org/faais/> (January 12, 2012)

database is cross-checked against several sources to ensure data quality, and is updated when new information arrives. Although data of food aid to specific locations within a country would provide more precise measure of analysis, it is difficult to collect data on that scale. Following Kuhlitz et al. (2010), we argue that macro level data is an acceptable level of analysis to determine donor targeting approaches for analyzing food aid flows. We scale the aid data by population, such that $AIDP$ is measured in tons per 10,000 people.

Natural disaster data comes from the International Disaster Database, EM-DAT.²³ Disaster types included are categorized as climatological (extreme temperatures, drought, and wildfires), hydrological (floods, avalanches, subsidence, and rock slides), meteorological (tropical storms, sand storms, and snowstorms), geophysical (earthquakes and volcanoes), and biological (including disease outbreaks and insect infestations). Following Kuhlitz et al. (2010) we consider the response of emergency aid to disasters with sudden impact ($SUDISP$) and gradual impact ($GRADISP$). Disasters labeled $SUDISP$ include all hydrological disasters, all geophysical disasters, wildfires, and insect infestations. Disasters labeled $GRADISP$ include extreme temperatures, drought, and disease outbreaks. Additionally, we use an aggregate measure of all natural disasters ($TOTDISP$). The natural disasters are measured as the total number of people injured, affected, and left homeless after a disaster, per 10,000 people in the population.²⁴ We also included the lagged versions of each of the disaster variables ($SUDISP_{t-1}$, $GRADISP_{t-1}$, and $TOTDISP_{t-1}$) to account for potential delays in the emergency aid that may be sent to a country following a natural disaster. It was hypothesized that all disaster measures would be positively related to $AIDP$.

²³ Center for Research on the Epidemiology of Disasters (2009). Available <http://www.emdat.be/> (January 12, 2012)

²⁴ Data was not available for each disaster measure for each country and year, leading to different numbers of observations for each type. As advised in the guidelines accompanying the EM-DAT data we did not include missing data as zeros.

It was expected that the magnitude of the lagged disaster coefficients would be highest for *GRADISP*, as a disaster with a gradual effect may elicit a gradual response.

Conflict data was taken from the Integrated Network for Societal Conflict Research at the Center for Systemic Peace, which provides the number of internally displaced people (IDPs) within a country from war, as well as the number of war refugees from abroad being hosted in a country.²⁵ The total number of IDPs and refugees people per 10,000 people in the population (*DISPP*) was included as an explanatory variable in this analysis. Similar to sudden onset natural disasters, in areas where people are displaced due to manmade shocks, it is hypothesized that emergency food aid would be increased to meet acute food needs.

We include an index of democracy (*DEMOC*) as an explanatory variable, which was also created by the Center for Systemic Peace Polity IV project.²⁶ It is expected that countries with a higher level of democracy will have better-developed institutions, which give them the tools to respond to natural disasters, and hence requiring less foreign assistance. Therefore, an inverse relationship between *AIDP* and *DEMOC* is expected.

To control for agriculture production, we include the tons of cereal grains produced per 10,000 people (*FOODP*), with gross domestic product per capita (*GDPP*) included to measure country level productivity and potential consumption of goods and services. As discussed there is a likelihood that *AIDP* will positively impact production. But, we expect countries with a higher level of economic output, and agriculture production, will have increased consumption. Therefore, it is expected that wealthier countries will be less reliant

²⁵ Center for Systemic Peace, Integrated Network for Societal Conflict Research, <http://www.systemicpeace.org/inscr/inscr.htm> (January 12, 2012)

²⁶ Center for Systemic Peace, Polity IV Project, <http://www.systemicpeace.org/polity/polity4.htm> (January 2012)

on emergency food aid in times of disaster. It follows that the relationship of *GDPP* and *FOODP* with *AIDP* will be negative.

The natural expectation is that economic growth is derailed immediately following a disaster. However, several previous studies discuss the potential of higher economic growth after a disaster due to enhanced production ability, due to such things as capital investments in roads and the upgrading of communication technology. A high frequency and high intensity of such disasters may impede this benefit though (Hallegatte and Dumas, 2009). These issues may contribute to an endogeneity problem for both *GDPP* and *FOODP*, which we control for in our analysis.

The value of imports and exports as a percentage of *GDPP* (*TRADE*) was used to control for the country's openness to trade, with the expectation that a country more open to international trade will be more likely to receive international assistance in times of need. Population (*POP*) was included to control for the size of the recipient country. There is a potential multicollinearity problem between an aggregate welfare measure and *POP*. Keeping terms in per capita form lessen this risk. The data for *GDPP*, *FOODP*, *TRADE*, and *POP* was taken from the World Development Indicators (WDI) database.²⁷

Our analysis considered a log-log model. Table 4-1 summarizes the log-transformed data for all variables from low and middle income countries, and for all countries.²⁸ Additionally, correlation matrices are presented in Table 4-2 for low and middle-income countries and all countries. These tables show minimal correlation between *POP* and *GDPP*, further alleviating fears of multicollinearity. There are only thirteen high-income

²⁷ The World Bank, World Development Indicators (WDI), <http://data.worldbank.org/indicator> (January 12, 2012)

²⁸ Income groups are based on the classification of the WDI (2012), which labels upper income countries as those with a GNI per person greater than \$12, 275 (in 2010 US dollars).

countries with non-zero values of $AIDP$, and the primary sources of $AIDP$ come from upper income countries. For these reasons, the dynamic GMM analysis was carried out for only low and middle income countries, and for all countries.

In addition to $AIDP_{t-1}$, it was expected the disaster variables, $SUDISP_t$, $GRADISP_t$, $TOTDISP_t$, $SUDISP_{t-1}$, $GRADISP_{t-1}$, and $TOTDISP_{t-1}$ are predetermined, but not strictly exogenous. Although natural disasters are exogenous shocks, they affect future country characteristics such as $FOODP$, $GDPP$, and $TRADE$.

4.5 GMM Analysis Approach

This section is included to provide a step-by-step understanding of the GMM model. The GMM, formalized in the literature by Hansen (1982), is a broad categorization of econometric modeling techniques often applied to semi and non-parametric data where the full shape of the distribution function is unknown. In contrast, the more efficient Maximum Likelihood Estimation (MLE) approach is restricted by the assumptions of the data's distribution. There are circumstances where the level of computational difficulty is such that the simpler GMM approach is preferred over MLE, particularly if the probability distribution function is unknown, which is required for calculating the log-likelihood function.²⁹

The GMM approach is an extension of the method of moments (MM) estimation approach of Pearson (1895), where MM estimated parameters solve the moment conditions, such as the mean, variance and median of a sample. The Ordinary Least Squares (OLS) estimator may be found using the MM approach, where y_i is a $n \times 1$ vector of observations

²⁹ Much of this section can be found in Greene's (2011) *Econometric Analysis 7th Edition* (Chapter 13).

dependent on a $n \times k$ matrix of explanatory variables, \mathbf{x}_i , such that $y_i = \mathbf{x}_i\beta + e_i$, where β is a $k \times 1$ vector of parameters and e_i is a $n \times 1$ vector of disturbance terms. The OLS moment conditions for the population are (i)

$$E[\mathbf{x}'_i(y_i - \mathbf{x}_i\beta - e_i)] = 0 \rightarrow E[\mathbf{x}'_i(y_i - \mathbf{x}_i\beta)] = 0, \text{ assuming } E[\mathbf{x}'_ie_i] = 0; \text{ (ii) } \text{Var}(e_i) = \sigma_i^2;$$

and (iii) $E(e_ie_j) = 0$, for $i \neq j$. Using (i) the sample moment condition from which the

parameters are estimated is written as $\frac{1}{N} \sum_{i=1}^N \mathbf{x}'_i(y_i - \mathbf{x}_i\hat{\beta}) = 0$. As long as $N \geq k$, the

$$\text{moment conditions will be met such that, } \hat{\beta}_{MMOLS} = \sum_{i=1}^n \mathbf{x}'_iy_i (\sum_{i=1}^n \mathbf{x}'_i\mathbf{x}_i)^{-1}.$$

If we drop the assumption of $E[\mathbf{x}'_ie_i] = 0$, then a $n \times m$ matrix of instrumental variables \mathbf{z}_i , is included, such that $\mathbf{z}'_iy_i = \mathbf{z}'_i\mathbf{x}_i\beta + \mathbf{z}'_ie_i$. To ensure the estimator is consistent and unbiased, \mathbf{z}_i is correlated with \mathbf{x}_i , with $E[\mathbf{z}'_ie_i] = 0$. The sample moment conditions

$$\text{become } \frac{1}{N} \sum_{i=1}^N \mathbf{z}'_i(y_i - \mathbf{x}_i\hat{\beta}) = 0, \text{ with } \hat{\beta}_{MMIV} = \sum_{i=1}^n \mathbf{z}'_iy_i (\sum_{i=1}^n \mathbf{z}'_i\mathbf{x}_i)^{-1}, \text{ as long as } m = k.$$

Typically, there are more instruments than explanatory variables, $m \neq k$ causing the system to be over-identified, with more moment conditions than parameters. This requires using predicted values of \mathbf{x}_i . We get the result directly by transforming \mathbf{x}_i using a symmetric and

idempotent projection matrix, $\mathbf{P}_z = \mathbf{z}_i(\mathbf{z}'_i\mathbf{z}_i)^{-1}\mathbf{z}'_i$ such that the sample moment conditions

$$\text{for OLS become } \frac{1}{N} \sum_{i=1}^N \mathbf{x}'_i\mathbf{P}_z(y_i - \mathbf{P}_z\mathbf{x}_i\hat{\beta}) = 0, \text{ with } \hat{\beta}_{MM2SLS} = \sum_{i=1}^n \mathbf{x}'_i\mathbf{P}_zy_i (\sum_{i=1}^n \mathbf{P}_z\mathbf{x}_i)^{-1}, \text{ or}$$

$$\hat{\beta}_{MM2SLS} = \sum_{i=1}^n \mathbf{x}'_i\mathbf{z}_i(\mathbf{z}'_i\mathbf{z}_i)^{-1}\mathbf{z}'_iy_i (\sum_{i=1}^n \mathbf{z}_i(\mathbf{z}'_i\mathbf{z}_i)^{-1}\mathbf{z}'_i\mathbf{x}_i)^{-1}.$$

The GMM approach defines a general statement of the moment conditions as

$E[\mathbf{m}(y_i, \mathbf{x}_i, \boldsymbol{\beta})] = 0$, where $\mathbf{m}(y_i, \mathbf{x}_i, \boldsymbol{\beta})$ is a set of moment equations defining a relationship known to exist in the population. The sample corresponding general sample moments are

$$\bar{\mathbf{m}}(y_i, \mathbf{x}_i, \mathbf{z}_i, \hat{\boldsymbol{\beta}}) = \frac{1}{N} \sum_{i=1}^N \mathbf{m}(y_i, \mathbf{x}_i, \mathbf{z}_i, \hat{\boldsymbol{\beta}}),$$

including a vector of instruments, \mathbf{z}_i . The OLS and Instrumental Variable (IV) estimators presented above use specific forms of the GMM sample moment conditions, providing the true parameter value, $\boldsymbol{\beta}_0$, that allows the moment conditions to hold. With model over-identification, it is not possible to find the actual $\boldsymbol{\beta}_0$ amongst the sample data. The goal is to find a $\hat{\boldsymbol{\beta}}_{GMM}$ that most closely resembles $\boldsymbol{\beta}_0$ and minimizes the value of $\bar{\mathbf{m}}(y_i, \mathbf{x}_i, \mathbf{z}_i, \hat{\boldsymbol{\beta}})$. The solution proposed by Hansen (1982) is to minimize a norm function (measuring the distance between $\bar{\mathbf{m}}(y_i, \mathbf{x}_i, \mathbf{z}_i, \hat{\boldsymbol{\beta}})$ and zero) using a positive semi-definite quadratic form.³⁰ The problem is

$$\min_{\hat{\boldsymbol{\beta}}} \left[\frac{1}{N} \sum_{i=1}^N \mathbf{m}(y_i, \mathbf{x}_i, \mathbf{z}_i, \hat{\boldsymbol{\beta}}) \right]' \cdot \mathbf{W} \cdot \left[\frac{1}{N} \sum_{i=1}^N \mathbf{m}(y_i, \mathbf{x}_i, \mathbf{z}_i, \hat{\boldsymbol{\beta}}) \right] \quad (4-7)$$

The parameter is expected to be consistent, where $\hat{\boldsymbol{\beta}}_{GMM} \rightarrow \boldsymbol{\beta}_0$ as $n \rightarrow \infty$. The weighting matrix, \mathbf{W} , determines the weight of each moment in the model estimation. Assuming the moment conditions are continuously differentiable, we get the first order conditions.

³⁰ Referred to lecture notes by Sorensen (2007), available www.uh.edu/~bsorensen/GMM1.pdf (accessed June 19, 2012) and Roodman (2009).

$$\left[\frac{1}{N} \sum_{i=1}^N \nabla_{\hat{\beta}} \mathbf{m}(y_i, \mathbf{x}_i, \mathbf{z}_i, \hat{\beta}) \right]' \cdot W \cdot \left[\frac{1}{N} \sum_{i=1}^N \mathbf{m}(y_i, \mathbf{x}_i, \mathbf{z}_i, \hat{\beta}) \right] = 0 \quad (4-8)$$

$$\text{where } \nabla_{\hat{\beta}} \mathbf{m}(y_i, \mathbf{x}_i, \mathbf{z}_i, \hat{\beta}) = \begin{bmatrix} \frac{\partial}{\partial \beta_1} \mathbf{m}(y_i; \mathbf{x}_i; \mathbf{z}_i; \hat{\beta}_1, \hat{\beta}_2, \dots, \hat{\beta}_n)' \\ \frac{\partial}{\partial \beta_2} \mathbf{m}(y_i; \mathbf{x}_i; \mathbf{z}_i; \hat{\beta}_1, \hat{\beta}_2, \dots, \hat{\beta}_n)' \\ \dots \\ \frac{\partial}{\partial \beta_n} \mathbf{m}(y_i; \mathbf{x}_i; \mathbf{z}_i; \hat{\beta}_1, \hat{\beta}_2, \dots, \hat{\beta}_n)' \end{bmatrix}$$

Returning to the sample moment conditions $\frac{1}{N} \sum_{i=1}^N \mathbf{z}'_i (y_i - \mathbf{x}_i \hat{\beta}) = 0$ where $m \neq k$, first order

conditions for GMM are

$$\begin{aligned} \left[\frac{1}{N} \sum_{i=1}^N \mathbf{z}'_i \mathbf{x}_i \right]' \cdot W \cdot \left[\frac{1}{N} \sum_{i=1}^N \mathbf{z}'_i (y_i - \mathbf{x}_i \hat{\beta}) \right] &= 0 \rightarrow \\ \left[\frac{1}{N} \sum_{i=1}^N \mathbf{z}_i \mathbf{x}'_i \right] \cdot W \cdot \left[\frac{1}{N} \sum_{i=1}^N \mathbf{z}'_i (y_i - \mathbf{x}_i \hat{\beta}) \right] &= 0 \end{aligned} \quad (4-9)$$

With

$$\hat{\beta}_{GMM} = \left[\left(\frac{1}{N} \sum_{i=1}^N \mathbf{z}_i \mathbf{x}'_i \right) \cdot W \cdot \frac{1}{N} \sum_{i=1}^N \mathbf{z}'_i \mathbf{x}_i \right]^{-1} \cdot \left(\frac{1}{N} \sum_{i=1}^N \mathbf{z}_i \mathbf{x}'_i \right) \cdot W \cdot \left(\frac{1}{N} \sum_{i=1}^N \mathbf{z}'_i y_i \right) \quad (4-10)$$

If $W = \mathbf{z}'_i \mathbf{z}_i$, then $\hat{\beta}_{GMM} \rightarrow \hat{\beta}_{2SLS}$. Setting $W = \mathbf{z}'_i \mathbf{z}_i$ does not necessarily provide the most efficient estimators, though. The idea is to weight the moment conditions with less variance than the moment conditions, as measured by the covariance-matrix of the population moments, as the smaller variance moments will provide more information on the true values of the estimator, β_0 . Setting W equal to the inverse of the variance covariance-matrix

provides the most efficient $\hat{\beta}_{GMM}$. This population variance is unknown though, unless the number of observations approach N , so it must be estimated. One way is through a two-step process, where the first step estimates $\hat{\beta}_{GMM}$ using $W = \mathbf{z}'_i \mathbf{z}_i$. In step 2 the model is re-estimated setting W equal to the inverse of the covariance matrix estimated in step 1.

The GMM estimator is particularly superior over Two-Stage Least Squares (2SLS) when there are multiple endogenous variables, and when the model is dynamic. GMM can produce model estimators using only a few assumptions about the moments. The tradeoff is a decrease in efficiency when compared to other approaches, like MLE, but GMM is easier to implement if the known data distribution is highly complex.

4.5.1 GMM System Analysis

The GMM System method was developed by Holtz-Eakin, et al. (1988), Arellano and Bond (1991), Arellano and Bover (1995), and Blundell and Bond (1998).³¹ This GMM approach is designed for panel data models with fixed effects that may be arbitrarily distributed, dynamic processes with the dependent variable influenced by the lag of the dependent variable, panel data may be small, with a large number of observations and multiple endogenous and non-strictly exogenous predetermined explanatory variables. Also accounted for, are idiosyncratic error not correlated across individuals, and that have individual patterns of heteroskedasticity. This approach relies on lags and lagged difference values of the explanatory variables to be instruments.

The general model considered is

$$y_{i,t} = y_{i,t-1}\alpha + \mathbf{x}_{i,t}\beta + u_i + v_{i,t} \quad (4-11)$$

³¹ Roodman (2009) explains the methodology and provides guidance on its implementation through a program developed for the STATA econometric package, XTABOND2.

The term $y_{i,t}$ is a $n \times 1$ vector of panel dependent variables that change over time, t . The term $y_{i,t-1}$ is the lag of $y_{i,t}$. The term $x_{i,t}$ is a $n \times k$ matrix of explanatory variables. The term u_i ($n \times 1$) represents fixed individual level effects, while $v_{i,t}$ ($n \times 1$) is an idiosyncratic error term. There is dynamic panel bias since $y_{i,t-1}$ is correlated with u_i . Two approaches are typically used to purge this bias.

First, the dynamic bias can be removed by differencing all of the data (following Holtz-Eakin, et al., 1988), as $\Delta u_j = 0$. This modified equation is as follows.

$$\Delta y_{i,t} = \Delta y_{i,t-1} \alpha + \Delta x_{i,t} \beta + \Delta u_i + \Delta v_{i,t} \quad (4-12)$$

Although we have eliminated fixed effects with (4-1), there still remains correlation between $y_{i,t-1}$ in $\Delta y_{i,t-1} = y_{i,t-1} - y_{i,t-2}$ and $v_{i,t-1}$ in $\Delta v_{i,t} = v_{i,t} - v_{i,t-1}$. Any differenced predetermined explanatory variable not strictly exogenous will have a similar problem. The difficulty of finding instruments correlated with the endogenous variables, but which maintain orthogonal moments with the error terms has been well documented (including Bound et al., 1995 and Arellano, 1995). Following Arellano and Bond (1991), internal variables can be chosen to serve as appropriate instruments, particularly further lags of the dependent variable. Lags of the level terms³² beyond $t-1$ for predetermined variables, will be orthogonal to the transformed error term, and can serve as instruments to further transform the differenced data, as $E(y_{i,t-2} v_{i,t}) = 0$ and $E(y_{i,t-2} v_{i,t-1}) = 0$. This same approach can be used for additional differenced non-strictly exogenous variables, however for endogenous differenced variables ($\Delta x_{i,t}^{ed}$), the second lag must be used, as $x_{i,t-1}^{ed}$ in $\Delta x_{i,t}^{ed}$ is correlated

³² Where level term refers to non-differenced data.

with both $v_{i,t}$ and $v_{i,t-1}$ in $\Delta v_{i,t} = v_{i,t} - v_{i,t-1}$. The instrumentalized transformed equation, (where \mathbf{z}_i is a matrix of appropriately lagged internal variables) now takes the following form, with $E(\Delta u_i) = 0$ and $E(\mathbf{z}_i' \Delta v_{i,t}) = 0$.

$$\mathbf{z}_i' \Delta y_{i,t} = \mathbf{z}_i' \Delta y_{i,t-1} \alpha + \mathbf{z}_i' \Delta \mathbf{x}_{i,t} \beta + \mathbf{z}_i' \Delta u_i + \mathbf{z}_i' \Delta v_{i,t} \quad (4-13)$$

The second commonly used approach is to directly use instruments to purge the correlation between $y_{i,t-1}$ and u_i , as well as $v_{i,t}$. Much like the difference approach, we consider internal variables that make appropriate instruments. However, with a level equation, lagged level instruments may be weak and cause the difference GMM to perform badly if the dependent variable is close to behaving as a random walk (Blundell and Bond, 1998). The Blundell-Bond alternative is to use differences of the lagged level non-strictly exogenous variables as instruments for the non-strictly exogenous regressors. The differenced instruments are valid as long as $E(\Delta y_{i,t-2} u_i) = 0$, $E(y_{i,t-1} v_{i,t}) = 0$, and $E(y_{i,t-2} v_{i,t}) = 0$. Additional non-strictly exogenous variables can be instrumentalized this way as well. The instrumentalized equation, (where $\Delta \mathbf{z}_i$ is a matrix of differenced lagged internal variables) is as follows, with $E(\Delta \mathbf{z}_i' u_i) = 0$ and $E(\Delta \mathbf{z}_i' v_{i,t}) = 0$.

$$\Delta \mathbf{z}_i' y_{i,t} = \Delta \mathbf{z}_i' y_{i,t-1} \alpha + \Delta \mathbf{z}_i' \mathbf{x}_{i,t} \beta + \Delta \mathbf{z}_i' u_i + \Delta \mathbf{z}_i' v_{i,t} \quad (4-14)$$

A problem with the approach of using differenced values as instruments arises when there are missing data observations. If the previous observation is missing, no difference term can be created, and we are left with missing variables for the transformed data.

Alternatively, we can use another transformation called orthogonal deviations (Arellano and Bover, 1995). In this case, instead of previous observations being subtracted from current

observations, this approach subtracts the average of all future observations from the current observation. Therefore, the issue of gaps in the data are not a hindrance to creating a set of instruments.

In summary, data can be differenced to purge correlation with u_i , and then further instrumentalized with appropriate lagged level variables to purge correlation with $v_{i,t}$. Secondly, the level equation can be directly instrumentalized using internal lagged variables to purge correlation with both u_i and $v_{i,t}$. The GMM system approach takes advantage of both of these methods, estimating a system of equations consisting of (4-12) and (4-13). This increases the number of observations used to run the regression analysis. It is assumed that the same linear function holds for both transformed and untransformed equations.

4.5.2 Diagnostic testing

It is necessary to test for autocorrelation of the idiosyncratic error term, which would invalidate the use of some internal lags as instruments. The Arellano-Bond tests for autocorrelation between differenced idiosyncratic error terms. We expect first order autocorrelation in differences, where $E(\Delta v_{i,t} \Delta v_{i,t-1}) \neq 0$ because $\Delta v_{i,t}$ and $\Delta v_{i,t-1}$ share the term $v_{i,t-1}$. However, if we find second order autocorrelation in differences, where

$E(\Delta v_{i,t} \Delta v_{i,t-2}) \neq 0$, there is first degree autocorrelation in levels, where $E(v_{i,t-1} v_{i,t-2}) \neq 0$.

If $E(v_{i,t-1} v_{i,t-2}) \neq 0$, then $E(y_{i,t-2} v_{i,t-1}) \neq 0$, making $y_{i,t-2}$ an invalid instrument for

$\Delta y_{i,t-1}$. In this case, deeper lags, $y_{i,t-3}$ or greater, may be appropriate, unless autocorrelation is found in these higher orders.

To test the exogeneity of instruments, as a group, we use the Sargan or Hansen overidentification tests.³³ Due to the overidentified nature of the GMM analysis, where the instruments outnumber the regressors, it is not possible to find a vector of parameters β_0 that exactly ensures a matrix of instruments, Z , is exactly uncorrelated with estimated error, \hat{E} . The overidentification test is a Wald test of whether or not the sample moments are randomly distributed around 0. If it holds, the expression $(\frac{1}{N} Z' \hat{E})' Var[ze]^{-1} (\frac{1}{N} Z' \hat{E})$ has a chi-sq distribution with degrees of freedom equal to the degree of overidentification. If it holds, then the vector of parameters $\hat{\beta}_{GMM}$ is considered efficient and feasible. Additional difference-in-Sargan and difference-in-Hansen tests are implemented to test the exogeneity of the model's instruments. These tests report the difference in the full model Sargan or Hansen chi-sq. values with the chi. sq. of the model excluding instruments or subsets of instruments. For example, in the system model, the difference-in-Sargan/Hansen can be used to test the validity of the level instruments as a group. The J value with and without the instruments is calculated. Stronger instruments will not increase the J value much when added to the analysis. The Hansen tests, as opposed to the Sargan tests, are more appropriate when the two-step GMM process is used, are robust to autocorrelation and heteroskedasticity.

This GMM system approach avails a large number of valid instruments, which is beneficial for increasing the efficiency of the analysis. However, it has been documented that including instruments that far outnumber the number of regressors, even though valid, can become collectively invalid for finite samples. Too many instruments may overfit

³³ The Sargan overidentification test applies to one-step GMM function, while the Hansen applies to the two-step function.

endogenous variables, provide imprecise estimates of the GMM weight matrix, bias standard errors downward, and invalidate overidentification tests. Roodman (2009) discusses these problems, as well as several guidelines to avoid the problem of too many instruments. One approach is to limit the number of lags for the lagged level and difference instruments included in the model. Another alternative is to collapse instruments into smaller sets by creating instruments for each variable and lag distance, rather than one for each variable, lag distance, and time period. As an example, consider the use of $y_{i,t-2}$ as an instrument of $\Delta y_{i,t-1}$. The corresponding instrument uncollapsed matrix (\mathbf{Z}) takes the form

$$\mathbf{Z} = \begin{pmatrix} 0 & 0 & 0 & 0 & 0 & 0 & \dots \\ y_{i,1} & 0 & 0 & 0 & 0 & 0 & \dots \\ 0 & y_{i,2} & y_{i,1} & 0 & 0 & 0 & \dots \\ 0 & 0 & 0 & y_{i,3} & y_{i,2} & y_{i,1} & \dots \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \ddots \end{pmatrix}. \text{ Once } \mathbf{Z} \text{ is collapsed, we have a new}$$

$$\text{matrix, } \mathbf{Z}^{collapse} = \begin{pmatrix} 0 & 0 & 0 & \dots \\ y_{i,1} & 0 & 0 & \dots \\ y_{i,2} & z_{i,1} & 0 & \dots \\ y_{i,3} & y_{i,2} & y_{i,1} & \dots \\ \vdots & \vdots & \vdots & \ddots \end{pmatrix}. \text{ The first row of } \mathbf{Z} \text{ and } \mathbf{Z}^{collapse} \text{ represent}$$

$t = 2$, as there are no observed difference variables in $t = 1$. The first available lagged instrument for $\Delta y_{i,2}$ appears in $t = 3$, hence zeros in the first row of both \mathbf{Z} and $\mathbf{Z}^{collapse}$.

The uncollapsed instrument matrix of differenced lagged variables ($\Delta \mathbf{Z}$) takes the form

$$\Delta \mathbf{Z} = \begin{pmatrix} 0 & 0 & 0 & 0 & \dots \\ 0 & \Delta z_{i,1} & 0 & 0 & \dots \\ 0 & 0 & \Delta z_{i,2} & 0 & \dots \\ 0 & 0 & 0 & \Delta z_{i,3} & \dots \\ \vdots & \vdots & \vdots & \vdots & \ddots \end{pmatrix}, \text{ while the collapsed matrix } \Delta \mathbf{Z}^{\text{collapse}} = \begin{pmatrix} 0 \\ \Delta z_{i1} \\ \Delta z_{i2} \\ \Delta z_{i3} \\ \vdots \end{pmatrix}.$$

The first row of $\Delta \mathbf{Z}$ and $\Delta \mathbf{Z}^{\text{collapse}}$ represent $t = 1$. The first available lagged differenced instrument for $y_{i,1}$ appears in $t = 2$, hence zeros in the first row of both \mathbf{Z} and $\mathbf{Z}^{\text{collapse}}$.

This approach may sacrifice some statistical efficiency, but it reduces the risk of bias that may occur as the number of instruments grows large.

4.6 Empirical Analysis Results

4.6.1 General Results

The regression estimates for low and middle income countries are presented in Table 4-4. Five different models are included. Each model includes $AIDP_{t-1}$, POP , $DEMOC$, $GDPP$, $TRADE$, $FOODP$, $GRADISP$ and $SUDISP$ explanatory variables. In Model II-Model V, we include $AIDP_{t-2}$ to deal with potential serial correlation. Model III-Model IV add the lags of the natural disaster variables, $SUDISP_{t-1}$ and $GRADISP_{t-1}$. Model IV and Model V include the $DISPP$ term. The aggregate natural disaster terms $TOTDISP$ and $TOTDISP_{t-1}$ are included in model V. All models include year dummies to control time effects, and regional dummies to control for other unobserved regional characteristics (regions include Africa, Asia, Oceania, Europe, North America, with Latin America the excluded dummy variable). The year dummies show minimal to no significance and are not reported in the data tables. All non-dummy variables, including the dependent variable were in natural log form, so the corresponding coefficients can be considered as percentage

change values. As discussed above, the issue of too many instruments may invalidate the results. Therefore, a sensitivity analysis was carried out for the full models IV and V, adjusting the number of lags. These results, labeled models VI-XI are presented in Table 4-5. The analysis is repeated using all countries (low, middle, and upper income), including a sensitivity analysis with all countries. These results are included in Table 4-6 and Table 4-7.

Our analysis used the robust two-step model GMM estimator, with instruments calculated using the orthogonal deviations approach, with instruments collapsed to minimize instrument counts, as discussed earlier.³⁴ Each model includes the number of observations and number of countries included in each analysis. Following the advice of Roodman (2009), each model presents the instrument count, the Arellano-Bond test statistic for the second-degree autocorrelation test, the p-value for the Hansen overidentification test of joint validity of instruments, the difference-in-Hansen p-values for All System instruments and those of the lags of the dependent variable. In these models, the number of lags included for instruments was 10. In Model I, the Arellano-Bond test weakly rejected the hypothesis of second-degree autocorrelation. When including $AIDP_{t-2}$ to deal with potential serial autocorrelation as a predetermined and strictly exogenous explanatory variable, Models II-V all showed no second-degree autocorrelation.

4.6.2 Instrument Sensitivity Testing

The p-values of the difference-in-Hansen test suggest instruments are valid jointly, as a group, in all models. Because the difference-in-Hansen test can be negatively affected by large number of instruments, Roodman (2009) suggests that p-values above 0.25 may be less reliable than smaller values. This was a concern in our models. The sensitivity analysis of the

³⁴ We use the XTABOND2 canned analysis approach in STATA 11.

full models show that a reduction in the number of lags, and hence a decrease in the instrument count, lowers the p-values, while preserving the majority of the coefficient values and significance levels. The Hansen p-values of the overidentification test were lower for the restricted instrument models to values closer to and below the 0.25 threshold indicated by Roodman (2009). However, for the full country analysis, the Hansen p-values for model XI of the sensitivity analysis go below the level for which the instruments may be considered exogenous. For all other models, this was not an issue. The Arellano-Bond (AR2) tests results and the Difference-in-Hansen tests are also in acceptable ranges for all models, except XI of the full country analysis, which indicated Difference-in-Hansen p-values below the acceptable range to consider instruments exogenous. The occasions where there are differences in coefficient values are highlighted in the results section below. This check of robustness provides an important level of confidence in our GMM econometric methodology.

In each model (I-XI), for both the low and middle income country and full country analyses, the coefficients of $AIDP_{t-1}$ are positive and highly significant at the 1% level. Values range from 0.484 to 0.570 for low and middle income countries, and range from 0.493 to 0.532 for the full country analysis. Likewise, the coefficients of $AIDP_{t-2}$ are positive and highly significant in each model except model II in the low and middle income country analysis, where it is insignificant. Values are smaller for $AIDP_{t-2}$ than $AIDP_{t-1}$, ranging from 0.103 to 0.135 for low and middle income countries, and range from 0.121 to 0.157 for the full country analysis. These values indicate emergency aid is likely to show up in those locations where it had been in a previous time period, but at a declining rate. This may be explained as a response to a disaster occurring over multiple years. In other words, a

country may receive *AIDP* over several years following a single natural disaster or other shock. It may also indicate that existing channels for *AIDP* make it easier for countries to receive emergency aid when a shock occurs.

The coefficients for *POP* indicate a positive and significant relationship at the 1% levels for only models II-IV of the low and middle income country analysis, with values ranging from 0.123 to 0.134. The *POP* coefficients for the full country analysis are only significant at the 5% level in models II-III and the 10% level in models IV-V, with values ranging from 0.117-0.142. This gives the result that larger countries are more likely to receive larger quantities of food aid, per capita.

The coefficients for *DEMOC* and *TRADE* are seen to be insignificant in each model, both for the low and middle income country analysis, and the full country analysis.

The coefficients for *GDPP* in the low and middle income analysis are negative and significant at the 1% level in model I-VI, at the 5% level for model IX, and at the 10% level in models VII and X. The coefficient values range from -.715 to -.377, with values slightly lower in the sensitivity analysis. For the full country analysis, the coefficients for *GDPP* are negative and significant at the 1% level only for models III. For models I-II, IV, and VI, the coefficients for *GDPP* are negative and significant at the 5% level. For models V and IX, the coefficients for *GDPP* are negative and significant at the 1% level. Coefficient values in the full country analysis ranged from -.581 to -.350. Generally, the coefficients for *GDPP* have lower values of significance, and value in the reduced instrument models. These results suggests more productive and developed countries, are less likely to require large quantities of emergency food aid.

The coefficient values and significance for *FOODP* are somewhat inconsistent, in both the low and middle income analysis and full country analysis, showing less significance

in the instrument sensitivity test. The *FOODP* coefficient is negative and significant at the 1% level for models II and III, negative and significant at the 10% level in models I, IV, V, VII and VIII, and not significant in any of the remaining models. Coefficient values of *FOODP* ranged from -.337 to -.467 in the low and middle income analysis. Similarly in the full country analysis, the *FOODP* coefficient is negative and significant at the 1% level for models II and III, negative and significant at the 5% level in models I and V, and significant at the 10% level in models VII. Much like the results of the *GDPP* term, it may be suggested that these countries are able to take care of their own food needs in times of emergencies, while countries with lower food production rely more heavily on outside assistance.³⁵

The coefficients for *SUDISP* are positive and significant in each model of the low and middle income country analysis in which the variable was included. The *SUDISP* coefficient is significant at the 1% level in model III and IV; significant at the 5% level in models II, VI and VIII; and significant at the 10% level in models I and VII. The *SUDISP* coefficient values for the low and middle income countries range from 0.030 to 0.037. For the full country analysis, the coefficients for *SUDISP* is significant at the 5% level for each model in which the variable was included, except model III, where it is significant at the 1% level. The coefficients values of *SUDISP* range from 0.028-0.033. Coefficients for *SUDISP_{t-1}* are not significant in any of the models that included the variable, for both the low and middle country analysis and the full country analysis. These results indicate sudden natural disasters such as floods, storms, and earthquakes will result in increases in food aid during the year in which they occur. In other words, the international community reacts more immediately to a sudden natural disaster.

³⁵ In several regression analyses we included food shocks, measured as deviations from food production trends. These variables were not seen to be significant, nor did they change the overall regression results.

The coefficients for $GRADISP$ were not significant in any of the models that included the variable, for both the low and middle income country analysis and the full country analysis. In contrast, the coefficients for $GRADISP_{t-1}$ are positive and significant at the 1% level in each model of the low and middle income country analysis in which the variable was included. The value of $GRADISP_{t-1}$ coefficients in the low and middle income country analysis range from 0.057 to 0.061. The coefficients for $GRADISP_{t-1}$ are positive and significant at the 1% level in each model of the full country analysis in which the variable was included, except model VII, where the coefficient is significant at the 5% level. The value of $GRADISP_{t-1}$ coefficients in the full country analysis range from 0.060 to 0.065. These results indicate a delay in the international food aid response to slow onset natural disasters such as droughts and extreme temperature events.

The coefficients for the aggregate natural disaster term, $TOTDISP$, are positive and significant at the 5% level in all models of the low and middle income country analysis and full country analysis that included the variable. Values of $TOTDISP$ range from .030 to .035 in the lower and middle income country analysis, and from .029 to .036 in the full country analysis. The coefficients for $TOTDISP_{t-1}$ are also significant in each model in which it is included. In the lower and middle income country analysis, $TOTDISP_{t-1}$ is significant at the 1% level in models IX and X, and significant at the 5% level in models V and XI, with values between 0.034 and 0.038. In the full country analysis, $TOTDISP_{t-1}$ is significant at the 1% level in models IX and X, and significant at the 5% level in models V and XI, with values between 0.032 and 0.040. The positive coefficients of both $TOTDISP$ and

$TOTDISP_{t-1}$ appear to correspond with the results of sudden natural disasters and lagged gradual disasters appearing separately in the analysis as $SUDISP$ and $GRADISP_{t-1}$.

The coefficients for $DISPP$ are positive and significant at the 1% level for all models of the lower and middle income country analysis except model V, where it is significant at the 5% level. Coefficient values ranged from 0.709 to 0.984. For the full country analysis, the coefficients for $DISPP$ are positive and significant at the 1% level for models IV and VI, positive and significant at the 5% level in models V and IX, and positive and significant at the 10% level in models VII and VIII. The coefficients are not significant in models X and XI. The values ranged from 0.474 to 0.703. These results, particularly with the low and middle country analysis, are the expected results of increased emergency aid being provided to those countries with increased numbers of displaced peoples due to conflict. In the full country analysis, these results are less consistent. This may be explained by the large number of refugees that go to developed countries, such as the United States, but receive assistance in other forms than emergency international food aid.

Two geographic regions with somewhat consistent results in the low and middle income country analysis are $AFRICA$ and $ASIA$, which have negative coefficients with low levels of significance in approximately half of the models. The values of the coefficients for $AFRICA$ range from -0.891 to -0.604, while the coefficient values for $ASIA$ range from -0.595 to -0.509. These results are not present in the full country analysis, however the full country analysis shows very consistent positive and significant coefficients for both $EUROPE$ and $NORTHAM$. The coefficients of $NORTHAM$ are significant at the 1% level in Models I-IV; significant at the 5% level in models V-IX and X; and significant at the 10% level in model XI. Values of $NORTHAM$ coefficients range from 1.314-1.911. The coefficients of $EUROPE$ are significant at the 1% level in Models I-IV and IX; and

significant at the 5% level in models V, VI-VIII, and X-XII. Values of *EUROPE* coefficients range from 0.852-1.179. Although these results lack in consistency across the models, there may be some indication that the countries in *NORTHAM* and *EUROPE*, the source of much of the emergency food aid, are likely to respond to emergency needs in their own regions prior to addressing emergency needs in other parts of the world.

4.6.3 Non-Per Capita Analysis

For an additional robustness check, we repeated these four analyses using non per capita data, while continuing to control for the size of the countries with the population included as an explanatory variable. These results are in Table 4-8 through 4-11. Each of the explanatory variable names drops the *P* at the end of name, to indicate the variable is not in per capita terms. The primary differences between the per capita results and the non-per capita results are presented in this section.

The *POP* variable is significant at the 1% level in each model of the low and middle country analysis and the full country analysis, as expected when variables are not scaled by the population size. The coefficients of the *GDP* term are more consistently significant in the non-per capita analyses than they are in the per capita analysis. In the non-per capita model the variable *FOOD* shows less significance than in the per capita model. The significance of the disaster terms, namely *SUDIS* and *GRADIS_{t-1}*, show very similar results in both the per capita and non-per capita models. However, coefficients of the aggregate terms, *TOTDIS* and *TOTDIS_{t-1}*, are not significant in models X and XI of the sensitivity analysis. The term *DIS* is significant in each of the models of the non-per capita analysis.

A summary of the results of our empirical hypotheses is found in table 4-12.

4.7 Discussion and Conclusions

Our dynamic analysis provides several key results regarding the flow of international aid in times of emergencies. Several of the key findings from the data analysis will be discussed here.

First, we show strong evidence of the dynamic nature of emergency aid, with its levels strongly influenced by the flow of aid in previous periods. This result is consistent with previous studies, and reiterates the importance of choosing a data analysis approach, such as the GMM system method, that can properly account for the dynamic nature of the data. It should be noted that the coefficient values we have presented for the rapid onset and gradual onset natural disaster variables are similar in range to those presented

Our most important results come from the natural disaster variables included. Through the inclusion of lagged natural disaster variables, we are able to illustrate the differences in aid flow due to responses to sudden natural disasters and natural disasters with a gradual onset. Rapid natural disasters such as the 2004 tsunami in eastern and southern Asia, or the 2010 earthquake in Haiti, generate a prompt international food aid response. In contrast, climate related disasters such as the 2011 drought in the Horn of Africa are less likely to receive aid promptly enough to stave off malnutrition and death. There are early warning systems in place to monitor food production and drought situations, but the international response to these early warnings do not appear to be heeded with the same urgency as more rapid onset disasters are. Also, our results show a very strong effect of the presence of refugees resulting in conflict.. This is not an unaccepted result, however the inclusion of this term is clearly important when gaining a fully understanding of why emergency food aid reaches a country.

Finally, we conclude with several thoughts about the dynamic GMM system analysis approach used. It is fairly easy to generate statistically significant model test results that on the surface validate the GMM system approach, particularly for the Hansen overidentification and difference-in tests. We found it very useful to carry out the robustness checks discussed in our results section. With these, we were given more confidence in our approach.

Table 4-1. Summary Statistics

Variable	Definition	Source	Low and Middle Income Countries		All Countries	
			Mean	S.d.	Mean	S.d.
<i>(ln)AIDP</i>	Emergency food aide (log of grain equivalent metric tons per 10,000 people)	United Nations World Food Program, Food Aid Information System, http://www.wfp.org/fais/ (January 12, 2012)	1.3237	1.6641	1.0190	1.5635
<i>(ln)POP</i>	Population (log of people in tens of thousands)	The World Bank, World Development Indicators http://data.worldbank.org/indicator (January 12, 2012)	16.2102	1.5006	16.2195	1.4707
<i>(ln)TRADE</i>	GDP originating from trade (log of % of GDP)	Ibid.	4.2247	0.5070	4.2398	0.4981
<i>(ln)DEMOC</i>	POLITY Democracy Index (log of transformed democracy index, 0 to 3.04, where 3.04 is most democratic)	Center for Systemic Peace, Polity IV Project, http://www.systemicpeace.org/polity/polity4.htm (January 12, 2012)	2.3596	0.6779	2.4681	0.7060
<i>(ln)GDPP</i>	GDP (log of 2000 USD per 10,000 people)	Ibid.	6.7087	1.0815	7.3958	1.5874
<i>(ln)FOODP</i>	Dry grain production levels (log of metric tons per 10,000 people)	Ibid.	7.0812	1.3877	7.3005	1.4492
<i>(ln)SUDISP</i>	Rapid onset natural disasters (floods, storms, earthquakes, volcanoes, etc.) (log of people affected)	Centre for Research on the Epidemiology of Disasters, The International Disaster Database, http://www.emdat.be/ (January 12, 2012)	1.7542	2.2138	1.4681	2.0726
<i>ln)GRADISP</i>	Natural disasters with a slower onset (droughts, (log of people affected)	Ibid.	0.8059	1.8761	0.6344	1.6978
<i>(ln)DISPP</i>	Number of displaced people, internally and from abroad (log of displaced people, in tens of thousands)	Center for Systemic Peace, Integrated Network for Societal Conflict Research, http://www.systemicpeace.org/inscr/inscr.htm (January 12, 2012)	0.1192	0.2391	0.1089	0.2454
Region Dummy Variables (=1 if the country is in the region, otherwise=0)						
<i>LATCARB</i>	Latin American or Caribbean Countries		0.2031	0.4024	0.1549	0.3619
<i>AFRICA</i>	Countries in Africa		0.4309	0.4953	0.3286	0.4698
<i>ASIA</i>	Countries in Asia		0.2831	0.4506	0.2719	0.4450
<i>OCEANLA</i>	Countries in Oceania		0.0096	0.0973	0.0146	0.1198
<i>EUROPE</i>	Countries in Europe		0.0830	0.2759	0.2301	0.4210
<i>NORTHAM</i>	Countries in North America		0.0000	0.0000	0.0146	0.1198

Table 4-2. Correlation of Explanatory Variables—Low and Middle Income Countries.

	$(ln)AIDP_{t-1}$	$(ln)AIDP_{t-1}$	$(ln)POP$	$(ln)TRADE$	$(ln)DEMOC$	$(ln)GDPP$	$(ln)FOODP$	$(ln)SUDISP$	$(ln)SUDISP_{t-1}$	$(ln)GRADISP$	$(ln)GRADISP_{t-1}$
$(ln)AIDP_{t-2}$	0.815										
$(ln)POP$	-0.1058	-0.0981									
$(ln)TRADE$	-0.0133	-0.0219	-0.4696								
$(ln)DEMOC$	-0.1183	-0.1186	0.0455	0.0041							
$(ln)GDPP$	-0.4549	-0.4375	0.0034	0.1654	0.2379						
$(ln)FOODP$	-0.1961	-0.188	0.4113	-0.1757	0.0129	0.0333					
$(ln)SUDISP$	-0.0378	-0.0038	0.3035	-0.1019	0.145	-0.0037	0.084				
$(ln)SUDISP_{t-1}$	-0.0011	-0.0245	0.3052	-0.0902	0.1255	-0.0044	0.0678	0.3537			
$(ln)GRADISP$	0.11	0.1521	0.0589	-0.0747	-0.0303	-0.1722	-0.0506	0.0613	0.0609		
$(ln)GRADISP_{t-1}$	0.1602	0.1047	0.056	-0.0728	-0.0225	-0.1634	-0.0367	0.03	0.0661	0.0666	
$(ln)DISPP$	0.3785	0.3454	-0.0601	-0.0648	-0.1786	-0.1458	-0.2285	-0.094	-0.1001	0.0391	0.0397

Table 4-3. Correlation of Explanatory Variables—All Countries.

	$(ln)AIDEC_{AP,t-1}$	$(ln)AIDEC_{AP,t-2}$	$(ln)POP$	$(ln)TRADE$	$(ln)DEMOC$	$(ln)GDPP_{CA}$	$(ln)SUPPLY_{CA}$	$(ln)SUDDIS_{CA}$	$(ln)SUDDIS_{CA,t-1}$	$(ln)GRADIS_{CA}$	$(ln)GRADIS_{CA,t-1}$
$(ln)AIDP_{t-2}$	0.8271	1									
$(ln)POP$	-0.0973	-0.0897	1								
$(ln)TRADE$	-0.0263	-0.0343	-0.5156	1							
$(ln)DEMOC$	-0.1905	-0.1876	0.067	0.0009	1						
$(ln)GDPP$	-0.5223	-0.508	0.0444	0.0974	0.3552	1					
$(ln)FOODP$	-0.2451	-0.2364	0.3753	-0.1425	0.206	0.2294	1				
$(ln)SUDISP$	0.0504	0.0786	0.2923	-0.1404	0.0591	-0.1869	0.0134	1			
$(ln)SUDISP_{t-1}$	0.0792	0.056	0.293	-0.1252	0.047	-0.1785	0.0028	0.3898	1		
$(ln)GRADISP$	0.1607	0.1975	0.0524	-0.0856	-0.071	-0.2388	-0.0828	0.1089	0.1036	1	
$(ln)GRADISP_{t-1}$	0.2042	0.1531	0.0501	-0.0836	-0.0633	-0.2297	-0.0698	0.0856	0.1105	0.1131	1
$(ln)DISPP$	0.3311	0.3009	-0.1348	-0.0158	-0.1553	-0.1399	-0.2266	-0.0677	-0.0742	0.0483	0.0484

Table 4-4. Dynamic Panel Analysis (GMM System): Low and Middle Income Countries-Per Capita Analysis.

Dep. (ln)AIDCAP	I	II	III	IV	V
CONSTANT	6.378*** (2.110)	6.029*** (1.886)	4.633*** (1.563)	3.681** (1.717)	4.349** (1.702)
(ln)AIDP _{t-1}	0.570*** (0.056)	0.533*** (0.112)	0.518*** (0.049)	0.484*** (0.048)	0.486*** (0.050)
(ln)AIDP _{t-2}		0.090 (0.076)	0.125*** (0.037)	0.112*** (0.032)	0.103*** (0.037)
(ln)POP	0.102 (0.096)	0.134* (0.078)	0.123* (0.067)	0.123* (0.073)	0.115 (0.075)
(ln)DEMOC	-0.073 (0.116)	-0.089 (0.103)	-0.136 (0.093)	-0.044 (0.094)	-0.057 (0.087)
(ln)TRADE	0.176 (0.191)	0.136 (0.156)	0.109 (0.133)	0.210 (0.143)	0.197 (0.157)
(ln)GDPP	-0.715*** (0.238)	-0.677*** (0.193)	-0.506*** (0.168)	-0.517*** (0.154)	-0.552*** (0.207)
(ln)FOODP	-0.378* (0.207)	-0.418*** (0.151)	-0.363*** (0.119)	-0.303* (0.160)	-0.337* (0.181)
(ln)SUDISP	0.030* (0.016)	0.033** (0.015)	0.037*** (0.012)	0.035*** (0.013)	
(ln)SUDISP _{t-1}			0.004 (0.013)	0.008 (0.013)	
(ln)GRADISP	0.008 (0.017)	0.014 (0.020)	0.024 (0.015)	0.013 (0.015)	
(ln)GRADISP _{t-1}			0.061*** (0.011)	0.059*** (0.011)	
(ln)TOTDISP					0.030** (0.013)
(ln)TOTDISP _{t-1}					0.038*** (0.012)
(ln)DISPP				0.984*** (0.175)	0.957*** (0.198)
AFRICA	-0.855* (0.442)	-0.891** (0.367)	-0.670* (0.340)	-0.604* (0.330)	-0.622* (0.363)
ASIA	-0.560 (0.401)	-0.590* (0.333)	-0.509* (0.290)	-0.528* (0.301)	-0.565* (0.308)
N	2196	2110	2110	1989	1989
Countries	114	114	114	113	113
Instruments	81	80	85	85	75
Arellano–Bond AR(2)	0.058	0.795	0.951	0.736	0.617
Hansen Overid. test (p-value)	0.193	0.292	0.546	0.689	0.424
Difference-In-Hansen (p-values)					
All System Instruments	0.863	0.959	0.243	0.374	0.191
Dep. Variable Instruments	0.580	0.949	0.801	0.869	0.846
Number of Instrument Lags	10	10	10	10	10

GMM estimation with the two-step estimator, using forward orthogonal deviations to account for missing data. Twice-lagged up to the 10th lagged levels of endogenous variables are included as instruments (for (ln)AIDCAP_{t-1} in Models II-V, (ln)GDPCAP, and (ln)SUPPLYCAP). Once-lagged up to the 10th lagged levels of predetermined, non-strictly exogenous variables as are included as instruments (for (ln)FASTDISCAP in Model I, (ln)FASTDISCAP_{t-1}, (ln)GRADDISCAP, (ln)GRADISCAP_{t-1}, (ln)TOTDISCAP, and (ln)TOTDISCAP_{t-1}). All regressions include year dummies and continent dummies. Robust standard errors are in parentheses. * significant at 10%, ** significant at 5%, *** significant at 1%.

Table 4-5. Dynamic Panel Analysis (GMM System): Instrument Sensitivity Testing--Per capita analysis--Lower and Middle Income Countries.

Dep. (ln)AIDCAP	VI	VII	VIII	IX	X	XI
CONSTANT	3.538* (1.813)	3.822* (2.022)	4.084** (2.032)	4.443** (1.896)	4.093* (2.139)	4.266* (2.471)
(ln)AIDP _{t-1}	0.493*** (0.052)	0.507*** (0.056)	0.514*** (0.058)	0.477*** (0.053)	0.490*** (0.062)	0.515*** (0.063)
(ln)AIDP _{t-2}	0.109*** (0.034)	0.124*** (0.039)	0.131*** (0.039)	0.114*** (0.037)	0.133*** (0.040)	0.135*** (0.041)
(ln)POP	0.104 (0.073)	0.102 (0.073)	0.111 (0.080)	0.082 (0.079)	0.093 (0.077)	0.111 (0.093)
(ln)DEMOC	-0.040 (0.093)	-0.089 (0.095)	-0.092 (0.089)	-0.047 (0.090)	-0.091 (0.092)	-0.089 (0.098)
(ln)TRADE	0.200 (0.134)	0.155 (0.138)	0.114 (0.134)	0.206 (0.148)	0.167 (0.135)	0.118 (0.136)
(ln)GDPP	-0.496*** (0.183)	-0.377* (0.216)	-0.331 (0.204)	-0.580** (0.229)	-0.422* (0.240)	-0.348 (0.225)
(ln)FOODP	-0.260 (0.157)	-0.383* (0.203)	-0.467* (0.268)	-0.253 (0.189)	-0.369 (0.236)	-0.487 (0.358)
(ln)SUDISP	0.032** (0.014)	0.032* (0.016)	0.036** (0.017)			
(ln)SUDISP _{t-1}	0.006 (0.013)	0.012 (0.015)	0.003 (0.016)			
(ln)GRADISP	0.019 (0.017)	0.023 (0.015)	0.022 (0.018)			
(ln)GRADISP _{t-1}	0.058*** (0.012)	0.057*** (0.014)	0.060*** (0.015)			
(ln)TOTDISP				0.031** (0.014)	0.035** (0.014)	0.033** (0.015)
(ln)TOTDISP _{t-1}				0.036*** (0.012)	0.038*** (0.013)	0.034** (0.015)
(ln)DISPP	0.940*** (0.171)	0.852*** (0.214)	0.725*** (0.229)	0.979*** (0.202)	0.863*** (0.236)	0.709*** (0.269)
AFRICA	-0.552 (0.350)	-0.475 (0.368)	-0.435 (0.353)	-0.642* (0.386)	-0.492 (0.387)	-0.443 (0.404)
ASIA	-0.516* (0.310)	-0.417 (0.295)	-0.309 (0.268)	-0.595* (0.309)	-0.433 (0.293)	-0.311 (0.285)
N	1989	1989	1989	1989	1989	1989
Countries	113	113	113	113	113	113
Instruments	75	55	45	64	48	40
Arellano–Bond AR(2)	0.700	0.768	0.842	0.783	0.941	0.871
Hansen Overid. test (p-value)	0.446	0.226	0.132	0.257	0.084	0.024
Difference-In-Hansen (p-values)						
All System Instruments	0.126	0.420	0.069	0.110	0.151	0.014
Dep. Variable Instruments	0.142	0.357	0.698	0.376	0.475	0.515
Number of Instrument Lags	8	4	2	8	4	2

GMM estimation with the two-step estimator, using forward orthogonal deviations to account for missing data. Twice-lagged up to the 10th lagged levels of endogenous variables are included as instruments (for (ln)AIDCAP_{t-1} in Models II-V, (ln)GDPCAP, and (ln)SUPPLYCAP). Once-lagged up to the 10th lagged levels of predetermined, non-strictly exogenous variables as are included as instruments (for (ln)FASTDISCAP in Model I, (ln)FASTDISCAP_{t-1}, (ln)GRADDISCAP, (ln)GRADISCAP_{t-1}, (ln)TOTDISCAP, and (ln)TOTDISCAP_{t-1}). All regressions include year dummies and continent dummies. Robust standard errors are in parentheses. * significant at 10%, ** significant at 5%, *** significant at 1%. Those regions which show no significance are left off the table for ease of presentation.

Table 4-6. Dynamic Panel Analysis (GMM System): All Countries-Per Capita Analysis.

Dep. (ln)AIDCAP	I	II	III	IV	V
CONSTANT	5.717*** (1.885)	4.499*** (1.573)	3.534*** (1.322)	3.502** (1.704)	3.901** (1.775)
(ln)AIDP _{t-1}	0.532*** (0.065)	0.496*** (0.051)	0.501*** (0.046)	0.485*** (0.049)	0.493*** (0.054)
(ln)AIDP _{t-2}		0.121*** (0.038)	0.147*** (0.036)	0.132*** (0.033)	0.127*** (0.038)
(ln)POP	0.116 (0.087)	0.142** (0.066)	0.117** (0.057)	0.134* (0.075)	0.138* (0.079)
(ln)DEMOC	0.093 (0.130)	0.082 (0.109)	-0.000 (0.093)	0.055 (0.112)	0.050 (0.106)
(ln)TRADE	-0.004 (0.152)	-0.044 (0.121)	0.001 (0.103)	0.057 (0.133)	-0.007 (0.136)
(ln)GDPP	-0.581** (0.229)	-0.430** (0.174)	-0.350*** (0.130)	-0.443** (0.175)	-0.395* (0.209)
(ln)FOODP	-0.427** (0.176)	-0.459*** (0.149)	-0.361*** (0.123)	-0.344* (0.203)	-0.430** (0.212)
(ln)SUDISP	0.030** (0.014)	0.033** (0.013)	0.033*** (0.012)	0.033** (0.013)	
(ln)SUDISP _{t-1}			0.004 (0.011)	0.006 (0.011)	
(ln)GRADISP	0.002 (0.017)	0.014 (0.018)	0.026* (0.016)	0.014 (0.016)	
(ln)GRADISP _{t-1}			0.065*** (0.012)	0.065*** (0.013)	
(ln)TOTDISP					0.030** (0.012)
(ln)TOTDISP _{t-1}					0.040*** (0.013)
(ln)DISPP				0.703*** (0.217)	0.582** (0.251)
EUROPE	1.179*** (0.404)	1.032*** (0.333)	0.867*** (0.273)	0.916*** (0.333)	1.006*** (0.294)
NORTHAM	1.911*** (0.637)	1.586*** (0.509)	1.314*** (0.411)	1.502*** (0.502)	1.541*** (0.486)
N Countries	2872 147	2761 147	2761 147	2608 146	2608 146
Instruments	82	82	86	86	73
Arellano-Bond AR(2)	0.044	0.933	0.821	0.873	0.780
Hansen Overid. test (p-value)	0.116	0.247	0.596	0.826	0.595
Difference-In-Hansen (p-values)					
All System Instruments	0.658	0.990	0.704	0.877	0.442
Dep. Variable Instruments	0.162	0.907	0.971	0.822	0.661
Number of Instrument Lags	10	10	10	10	10

GMM estimation with the two-step estimator, using forward orthogonal deviations to account for missing data. Twice-lagged levels of endogenous variables as are included as instruments (for GDP and SUPPLY). Once-lagged levels of predetermined, non-strictly exogenous variables as are included as instruments (for AID_{t-1}, FASTDIS, FASTDIS_{t-1}, GRADDIS, GRADIS_{t-1}, TOTDIS, and TOTDIS_{t-1}). All regressions include year dummies and continent dummies. Robust standard errors are in parentheses. * significant at 10%, ** significant at 5%, *** significant at 1%. Those regions which show no significance are left off the table for ease of presentation.

Table 4-7. Dynamic Panel Analysis (GMM System): Instrument Sensitivity Testing--Per capita analysis—All Countries.

Dep. (ln)AIDCAP	VI	VII	VIII	IX	X	XI
CONSTANT	3.522** (1.772)	3.062 (2.339)	4.096* (2.321)	3.982** (2.006)	2.784 (2.737)	4.288 (3.143)
(ln)AIDP _{t-1}	0.493*** (0.051)	0.510*** (0.061)	0.511** (0.061)	0.493*** (0.058)	0.520*** (0.070)	0.521*** (0.083)
(ln)AIDP _{t-2}	0.125*** (0.037)	0.150*** (0.043)	0.140** (0.043)	0.124*** (0.041)	0.157*** (0.044)	0.147*** (0.048)
(ln)POP	0.120 (0.079)	0.151 (0.100)	0.123 (0.093)	0.113 (0.095)	0.172 (0.115)	0.138 (0.138)
(ln)DEMOC	0.040 (0.108)	0.028 (0.105)	0.004 (0.097)	0.050 (0.105)	0.011 (0.105)	0.003 (0.105)
(ln)TRADE	0.058 (0.125)	0.042 (0.128)	0.011 (0.125)	-0.011 (0.127)	0.051 (0.128)	0.002 (0.135)
(ln)GDPP	-0.430** (0.192)	-0.213 (0.266)	-0.289 (0.254)	-0.407* (0.232)	-0.166 (0.310)	-0.262 (0.374)
(ln)FOODP	-0.321 (0.205)	-0.551* (0.314)	-0.517* (0.302)	-0.366 (0.249)	-0.623* (0.367)	-0.611 (0.477)
(ln)SUDISP	0.028** (0.014)	0.031** (0.016)	0.033** (0.016)			
(ln)SUDISP _{t-1}	0.003 (0.012)	0.007 (0.014)	0.001 (0.015)			
(ln)GRADISP	0.018 (0.017)	0.021 (0.016)	0.021 (0.018)			
(ln)GRADISP _{t-1}	0.065*** (0.014)	0.060*** (0.016)	0.060** (0.016)			
(ln)TOTDISP				0.029** (0.013)	0.036** (0.014)	0.033** (0.016)
(ln)TOTDISP _{t-1}				0.036*** (0.013)	0.037*** (0.013)	0.032** (0.015)
(ln)DISPP	0.693*** (0.224)	0.516* (0.280)	0.474* (0.248)	0.624** (0.273)	0.404 (0.314)	0.399 (0.349)
EUROPE	0.852** (0.364)	0.874** (0.406)	0.895** (0.395)	0.927*** (0.351)	0.937** (0.433)	1.011** (0.479)
NORTHAM	1.438** (0.566)	1.372** (0.670)	1.496** (0.652)	1.470** (0.566)	1.391* (0.747)	1.628** (0.807)
N	2608	2608	2608	2608	2608	2608
Countries	146	146	146	146	146	146
Instruments	76	56	46	65	49	41
Arellano–Bond AR(2)	0.773	0.970	0.898	0.779	0.901	0.962
Hansen Overid. test (p-	0.584	0.396	0.176	0.343	0.250	0.051
Difference-In-Hansen (p-values)						
All System Instruments	0.616	0.160	0.071	0.336	0.082	0.016
Dep. Variable	0.227	0.314	0.311	0.359	0.365	0.126
Number of Instrument Lags	8	4	2	8	4	2

GMM estimation with the two-step estimator, using forward orthogonal deviations to account for missing data. Twice-lagged levels of endogenous variables as are included as instruments (for GDP and SUPPLY). ce-lagged levels of predetermined, non-strictly exogenous variables as are included as instruments (for AID_{t-1}, FASTDIS, FASTDIS_{t-1}, GRADDIS, GRADIS_{t-1}, TOTDIS, and TOTDIS_{t-1}). All regressions include year dummies and continent dummies. Robust standard errors are in parentheses. * significant at 10%, ** significant at 5%, *** significant at 1%. Those regions with insignificant coefficients have been removed for clarity of presentation.

Table 4-8. Dynamic Panel Analysis (GMM System): Low and Middle Income Countries.

Dep. (ln)AID	I	II	III	IV	V
CONSTANT	8.935 (7.757)	6.882 (6.667)	8.394 (6.482)	7.927 (8.159)	8.967 (8.756)
(ln)AID _{t-1}	0.371*** (0.058)	0.508*** (0.136)	0.424*** (0.039)	0.386*** (0.049)	0.368*** (0.052)
(ln)AID _{t-2}		0.063 (0.073)	0.122*** (0.028)	0.108*** (0.031)	0.112*** (0.030)
(ln)POP	3.343*** (0.927)	3.693*** (1.002)	3.792*** (0.913)	3.911*** (1.222)	3.723*** (1.215)
(ln)DEMOC	0.079 (0.472)	-0.161 (0.404)	-0.250 (0.391)	-0.296 (0.392)	-0.152 (0.429)
(ln)TRADE	0.514 (0.560)	0.538 (0.495)	0.662 (0.494)	0.365 (0.496)	0.381 (0.499)
(ln)GDP	-2.497*** (0.640)	-2.434*** (0.692)	-2.568*** (0.584)	-2.235*** (0.725)	-2.324*** (0.719)
(ln)FOOD	-0.258 (0.322)	-0.606 (0.383)	-0.619 (0.379)	-1.197* (0.624)	-0.931 (0.693)
(ln)SUDIS	0.039** (0.020)	0.043* (0.022)	0.041** (0.019)	0.054*** (0.017)	
(ln)SUDIS _{t-1}			-0.003 (0.016)	0.009 (0.019)	
(ln)GRADIS	-0.004 (0.019)	0.002 (0.022)	-0.004 (0.017)	-0.013 (0.017)	
(ln)GRADIS _{t-1}			0.053*** (0.016)	0.048*** (0.017)	
(ln)TOTDIS					0.037** (0.018)
(ln)TOTDIS _{t-1}					0.032* (0.016)
(ln)DISP				0.274*** (0.090)	0.283*** (0.088)
AFRICA	-1.619 (1.275)	-2.725** (1.147)	-2.946** (1.220)	-3.442** (1.510)	-3.369** (1.458)
ASIA	-1.244 (1.349)	-2.077* (1.149)	-2.124* (1.176)	-2.218* (1.269)	-2.318* (1.325)
N	2196	2110	2110	1989	1989
COUNTRIES	114	114	114	113	113
INSTRUMENTS	81	80	85	85	75
Arellano–Bond AR(2)	0.132	0.702	0.493	0.823	0.636
Hansen test validity of instruments (p-value)	0.067	0.198	0.629	0.647	0.466
Difference-Hansen Instrument test (p-values)					
ALL SYSTEM	0.271	0.360	0.898	0.718	0.129
AID _{t-1}	0.033	0.332	0.627	0.556	0.514
Number of GMM Instrument	10	10	10	10	10

GMM estimation with the two-step estimator, using forward orthogonal deviations to account for missing data. Twice-lagged levels of endogenous variables as are included as instruments (for (ln)GDP and (ln)SUPPLY). Once-lagged levels of predetermined, non-strictly exogenous variables as are included as instruments (for (ln)AID_{t-1}, (ln)FASTDIS, (ln)FASTDIS_{t-1}, (ln)GRADDIS, (ln)GRADIS_{t-1}, (ln)TOTDIS, and (ln)TOTDIS_{t-1}). All regressions include year dummies and continent dummies. Robust standard errors are in parentheses. * significant at 10%, ** significant at 5%, *** significant at 1%. Those regions with insignificant coefficients have been removed for clarity of presentation.

Table 4-9. Dynamic Panel Analysis (GMM System): Instrument Sensitivity Testing—Low and Middle Income Countries.

Dep. (ln)AID	VI	VII	VIII	IX	X	XI
CONSTANT	9.370 (8.236)	2.595 (8.787)	2.396 (9.200)	12.034 (9.430)	4.908 (8.494)	1.520 (8.821)
(ln)AID _{t-1}	0.387*** (0.048)	0.393*** (0.041)	0.386*** (0.041)	0.363*** (0.055)	0.383*** (0.046)	0.390*** (0.044)
(ln)AID _{t-2}	0.104*** (0.030)	0.108*** (0.033)	0.111*** (0.034)	0.098*** (0.032)	0.111*** (0.034)	0.119*** (0.035)
(ln)POP	3.327*** (1.241)	4.330*** (1.274)	4.321*** (1.263)	3.327*** (1.248)	3.959*** (1.284)	3.982*** (1.256)
(ln)DEMOC	-0.090 (0.416)	-0.321 (0.370)	-0.179 (0.381)	0.048 (0.417)	-0.113 (0.382)	-0.080 (0.372)
(ln)TRADE	0.435 (0.483)	0.178 (0.440)	0.187 (0.470)	0.470 (0.495)	0.358 (0.462)	0.336 (0.461)
(ln)GDP	-2.160*** (0.769)	-1.956*** (0.709)	-1.973*** (0.706)	-2.421*** (0.800)	-2.090*** (0.724)	-1.884*** (0.719)
(ln)FOOD	-0.820 (0.638)	-1.710** (0.807)	-1.687* (0.868)	-0.604 (0.656)	-1.324* (0.754)	-1.465* (0.769)
(ln)SUDIS	0.054*** (0.017)	0.052*** (0.019)	0.046** (0.021)			
(ln)SUDIS _{t-1}	0.011 (0.018)	-0.004 (0.020)	-0.008 (0.022)			
(ln)GRADIS	-0.006 (0.017)	-0.013 (0.016)	-0.013 (0.017)			
(ln)GRADIS _{t-1}	0.044** (0.019)	0.045** (0.019)	0.045** (0.022)			
(ln)TOTDIS				0.041** (0.018)	0.035* (0.018)	0.032 (0.020)
(ln)TOTDIS _{t-1}				0.034** (0.016)	0.024 (0.018)	0.021 (0.022)
(ln)DISP	0.291*** (0.093)	0.236** (0.092)	0.232** (0.097)	0.334*** (0.101)	0.263*** (0.094)	0.233** (0.096)
AFRICA	-2.990** (1.402)	-2.994** (1.184)	-2.858** (1.106)	-3.195** (1.395)	-2.932** (1.286)	-2.563** (1.219)
ASIA	-2.202* (1.206)	-1.837* (1.080)	-1.744 (1.067)	-2.424* (1.253)	-1.831 (1.128)	-1.624 (1.102)
N	1989	1989	1989	1989	1989	1989
Countries	113	113	113	113	113	113
Instruments	75	55	45	64	48	40
Arellano–Bond AR(2)	0.821	0.819	0.714	0.846	0.696	0.588
Hansen Overid. test (p-value)	0.640	0.821	0.288	0.444	0.437	0.066
Difference-In-Hansen (p-values)						
All System Instruments	0.138	0.387	0.254	0.022	0.101	0.046
Dep. Variable Instruments	0.705	0.693	0.178	0.497	0.442	
Number of Instrument Lags	8	4	2	8	4	2

GMM estimation with the two-step estimator, using forward orthogonal deviations to account for missing data. Twice-lagged levels of endogenous variables as are included as instruments (for (ln)GDP and (ln)SUPPLY). Once-lagged levels of predetermined, non-strictly exogenous variables as are included as instruments (for (ln)AID_{t-1}, (ln)FASTDIS, (ln)FASTDIS_{t-1}, (ln)GRADDIS, (ln)GRADIS_{t-1}, (ln)TOTDIS, and (ln)TOTDIS_{t-1}). All regressions include year dummies and continent dummies. Robust standard errors are in parentheses. * significant at 10%, ** significant at 5%, *** significant at 1%. Those regions with insignificant coefficients have been removed for clarity of presentation.

Table 4-10. Dynamic Panel Analysis (GMM System): All Countries.

Dep. (ln)AID	I	II	III	IV	V
CONSTANT	8.321 (7.050)	4.420 (6.445)	5.013 (5.468)	6.886 (7.204)	8.962 (8.544)
(ln)AID _{t-1}	0.360*** (0.058)	0.391*** (0.043)	0.410*** (0.040)	0.372*** (0.046)	0.350*** (0.054)
(ln)AID _{t-2}		0.107*** (0.031)	0.112*** (0.028)	0.099*** (0.028)	0.097*** (0.032)
(ln)POP	2.892*** (0.734)	3.368*** (0.697)	3.086*** (0.720)	3.025*** (0.982)	2.838*** (0.893)
(ln)DEMOC	0.403 (0.383)	0.244 (0.354)	0.177 (0.302)	0.313 (0.307)	0.371 (0.316)
(ln)TRADE	-0.112 (0.452)	-0.206 (0.401)	-0.045 (0.381)	-0.148 (0.394)	-0.126 (0.373)
(ln)GDP	-2.021*** (0.560)	-1.891*** (0.412)	-1.838*** (0.367)	-1.761*** (0.410)	-1.889*** (0.453)
(ln)FOOD	-0.403 (0.347)	-0.835* (0.446)	-0.696 (0.421)	-0.899 (0.656)	-0.623 (0.641)
(ln)SUDIS	0.040** (0.017)	0.038** (0.017)	0.035** (0.016)	0.043*** (0.015)	
(ln)SUDIS _{t-1}			-0.003 (0.015)	0.003 (0.015)	
(ln)GRADIS	-0.007 (0.019)	-0.011 (0.018)	-0.008 (0.017)	-0.017 (0.017)	
(ln)GRADIS _{t-1}			0.051*** (0.014)	0.046*** (0.016)	
(ln)TOTDIS					0.032** (0.015)
(ln)TOTDIS _{t-1}					0.024* (0.014)
(ln)DISP				0.276*** (0.073)	0.290*** (0.075)
AFRICA	-0.684 (0.975)	-1.535* (0.802)	-1.457* (0.757)	-1.853** (0.895)	-1.863** (0.825)
EUROPE	2.230*** (0.816)	2.492*** (0.750)	2.426*** (0.747)	2.257** (0.958)	1.977** (0.816)
NORTHAM	2.917** (1.263)	3.316*** (1.092)	3.358*** (1.093)	2.868* (1.503)	2.475* (1.256)
N	2872	2761	2761	2608	2608
Countries	147	147	147	146	146
Instruments	82	82	86	86	73
Arellano–Bond AR(2)	0.094	0.555	0.689	0.952	0.838
Hansen Overid. test (p-value)	0.040	0.269	0.679	0.705	0.616
Difference-In-Hansen (p-values)					
All System Instruments	0.304	0.896	0.943	0.794	0.228
Dep. Variable Instruments	0.010	0.517	0.788	0.879	0.930
Number of Instrument Lags	10	10	10	10	10

GMM estimation with the two-step estimator, using forward orthogonal deviations to account for missing data. Twice-lagged levels of endogenous variables as are included as instruments (for (ln)GDP and (ln)SUPPLY). Once-lagged levels of predetermined, non-strictly exogenous variables as are included as instruments (for (ln)AID_{t-1}, (ln)FASTDIS, (ln)FASTDIS_{t-1}, (ln)GRADDIS, (ln)GRADIS_{t-1}, (ln)TOTDIS, and (ln)TOTDIS_{t-1}). All regressions include year dummies and continent dummies. Robust standard errors are in parentheses. * significant at 10%, ** significant at 5%, *** significant at 1%. Those regions with insignificant coefficients have been removed for clarity of presentation.

Table 4-11. Dynamic Panel Analysis (GMM System): Instrument Sensitivity Testing—All Countries.

Dep. (ln)AID	VI	VII	VIII	IX	X	XI
CONSTANT	7.211 (7.534)	2.299 (9.432)	2.894 (9.627)	11.523 (9.575)	4.704 (9.641)	3.746 (10.193)
(ln)AID _{t-1}	0.378*** (0.046)	0.380*** (0.045)	0.378*** (0.043)	0.354*** (0.057)	0.371*** (0.049)	0.380*** (0.049)
(ln)AID _{t-2}	0.101*** (0.028)	0.101*** (0.032)	0.108*** (0.034)	0.086** (0.033)	0.102*** (0.035)	0.113*** (0.036)
(ln)POP	2.846*** (0.961)	3.671*** (1.075)	3.707*** (1.121)	2.540*** (0.945)	3.194*** (0.983)	3.318*** (1.022)
(ln)DEMOC	0.378 (0.324)	0.252 (0.298)	0.229 (0.314)	0.437 (0.337)	0.323 (0.309)	0.243 (0.311)
(ln)TRADE	-0.082 (0.376)	-0.087 (0.360)	-0.144 (0.360)	-0.032 (0.402)	0.007 (0.401)	-0.062 (0.397)
(ln)GDP	-1.747*** (0.427)	-1.700*** (0.454)	-1.724*** (0.462)	-1.968*** (0.515)	-1.730*** (0.500)	-1.673*** (0.535)
(ln)FOOD	-0.776 (0.640)	-1.410* (0.825)	-1.430 (0.878)	-0.379 (0.640)	-1.036 (0.731)	-1.172 (0.795)
(ln)SUDIS	0.043*** (0.015)	0.041** (0.016)	0.038** (0.017)			
(ln)SUDIS _{t-1}	0.006 (0.015)	-0.006 (0.017)	-0.008 (0.018)			
(ln)GRADIS	-0.013 (0.016)	-0.018 (0.015)	-0.017 (0.016)			
(ln)GRADIS _{t-1}	0.049*** (0.017)	0.044** (0.017)	0.046** (0.020)			
(ln)TOTDIS				0.034** (0.015)	0.028* (0.015)	0.027 (0.016)
(ln)TOTDIS _{t-1}				0.028* (0.014)	0.021 (0.015)	0.021 (0.017)
(ln)DISP	0.264*** (0.080)	0.242*** (0.083)	0.240*** (0.085)	0.309*** (0.087)	0.265*** (0.085)	0.251*** (0.091)
AFRICA	-1.704** (0.803)	-1.950*** (0.679)	-2.036*** (0.706)	-1.812** (0.813)	-1.750** (0.721)	-1.855** (0.766)
EUROPE	2.187** (0.973)	2.566** (1.023)	2.699** (1.046)	1.822* (0.935)	2.146** (0.933)	2.359** (0.968)
NORTHAM	2.738* (1.515)	3.693** (1.536)	3.843** (1.559)	2.335 (1.429)	3.118** (1.427)	3.252** (1.497)
N	2608	2608	2608	2608	2608	2608
Countries	146	146	146	146	146	146
Instruments	76	56	46	65	49	41
Arellano–Bond AR(2)	0.945	0.956	0.805	0.918	0.845	0.698
Hansen Overid. test (p-value)	0.772	0.880	0.433	0.553	0.491	0.115
Difference-In-Hansen (p-						
All System Instruments	0.336	0.508	0.413	0.064	0.175	0.087
Dep. Variable Instruments	0.946	0.720	0.196	0.937	0.423	0.046
Number of Instrument Lags	8	4	2	8	4	2

GMM estimation with the two-step estimator, using forward orthogonal deviations to account for missing data. Twice-lagged levels of endogenous variables as are included as instruments (for (ln)GDP and (ln)SUPPLY). Once-lagged levels of predetermined, non-strictly exogenous variables as are included as instruments (for (ln)AID_{t-1}, (ln)FASTDIS, (ln)FASTDIS_{t-1}, (ln)GRADDIS, (ln)GRADDIS_{t-1}, (ln)TOTDIS, and (ln)TOTDIS_{t-1}). All regressions include year dummies and continent dummies. Robust standard errors are in parentheses. * significant at 10%, ** significant at 5%, *** significant at 1%. Those regions with insignificant coefficients have been removed for clarity of presentation.

Table 4-12. Hypothesis summary table of explanatory variables.

	Hypothesis	Result
1	$\beta_{AID_{t-1}} > 0$	$\beta_{AID_{t-1}} > 0$
2	$\beta_{POP} > 0$	$\beta_{POP} = 0$
3	$\beta_{DEMOC} < 0$	$\beta_{DEMOC} = 0$
4	$\beta_{TRADE} > 0$	$\beta_{TRADE} = 0$
5	$\beta_{GDPCAP} < 0$	$\beta_{GDPCAP} < 0$
6		
7	$\beta_{SUDDIS, SUDDIS_{t-1}} > 0$	$\beta_{SUDDIS} > 0$ and $\beta_{SUDDIS_{t-1}} = 0$
8	$\beta_{GRADDIS, GRADDIS_{t-1}} > 0$	$\beta_{GRADDIS} = 0$ and $\beta_{GRADDIS_{t-1}} > 0$
9	$\beta_{TOTDIS, TOTDIS_{t-1}} > 0$	$\beta_{TOTDIS, TOTDIS_{t-1}} > 0$

Chapter 5: Conclusions and Discussion

5.1 Summary of the Dissertation

This dissertation has analyzed various decisions made by households, governments, and the international community that impact household food security in the presence of changing social and environmental conditions. The starting point for the dissertation is framing the problem of food security as one of an economic trade-off between consumption in the present with investments in assets and capital that ensure future availability of food. The first analysis developed this relationship with an optimal control model, simulating the relationship between consumption and asset investment. Then an applied econometric analysis of household food security focusing on the role of natural and social capital, and coping strategies, was presented. The final analysis considered the international food aid response to natural and manmade disasters, which is important in maintaining food security when exogenous shocks occur. This section provides a discussion of the key conclusions for each chapter, and potential extensions of the research.

5.2 Optimal Control Model

This model illustrates the trade-offs that occur between consumption in the current period and long-term protection of capital stocks. The study specifically highlighted the contribution of forest ecosystem services in agricultural production. The data analysis illustrates a direct relationship between declining agriculture production costs and increased forest stocks. The optimal control results of the case study in Nepal indicate a steady state value for both per capita forest cover and agricultural land in the three primary geographic belts, the Terai, Hills, and Mountain regions. An important component of control model is the incorporation of the user cost of depleting the forest stock.

The model has included investment in improving the stock of forests as a constant variable. Regional investments would likely be required, over individual village investments, as there may be

minimal incentive for individual residents and villages to invest in natural capital when the benefits are gained from a larger region or watershed that is forested. A further study could incorporate investments as a choice variable in the model, indicating the optimal long-term investment strategies for forest protection or reforestation.

Also, a further study could analyze the substitutability between forest stock and agricultural inputs. We may also expect that labor is more productive in locations with higher forest stocks, as firewood, freshwater, and other products and services relying on forests are more easily accessible to the local population. Less time has to be spent collecting forest related products. A further study may also more directly analyze the trade-off between labor availability and forest stock.

5.4 Household Food Security

The results of the study in Chapter 3 provide quantitative evidence of increased food security with the existence of high quality natural capital stock, specifically primary forest and secondary vegetation cover. The positive results of the spatial dimension of the analysis are important, particularly when developing policy from a regional perspective. Tree planting and conservation practiced in one VDC may prove effective, but will have a larger impact on food security if all communities coordinate their conservation efforts. The result points to a potential free rider problem, as the optimal management of natural capital stocks relies on the management of this natural capital over a very large area. A further study may be one that analyzes not only the natural capital stock, but also the collective conservation efforts in the same spatial areas as the natural capital measure.

This analysis also illustrates a positive relationship between improved access to drinking water and food security. This result highlights the poverty trap associated with food security. Those who have minimal access to clean water are more at risk of waterborne illnesses. These individuals

are likely incapacitated from achieving higher food security levels, further damaging their health. Further investing in water infrastructure should be of high priority, as well as further protection of current natural capital protecting water resources.

The analysis also provides evidence that social capital is an important indicator of food security. A further study should capture the individual involvement in such community groups, in order to analyze the direct impact on welfare. Individual involvement, as well as measures of social capital at the village level (as opposed to district measures used in this study), may capture stronger effects of social capital on welfare measures.

The use of food aid, access to credit, and receipt of remittances were all seen to be positively related to food security. One's lower caste identity or status as an ethnic minority may indicate what type of coping strategy will be undertaken. For example, the results indicated that remittances add to a household's ability to improve their food security levels. It may be that those individuals burdened by their caste or ethnic status in Nepal may find it easier to work in a location where they are unimpeded by the caste system. A further study may investigate this potential link between social status and coping strategies.

5.4 Emergency Food Aid

The dynamic analysis undertaken in Chapter 4 provides several key results regarding the flow of international aid in times of emergencies. Primarily, this analysis provides strong evidence of the dynamic nature of emergency aid, with its levels strongly influenced by the flow of aid in previous periods. This result is consistent with previous studies, and reiterates the importance of choosing a data analysis approach, such as the GMM system method, that can properly account for the dynamic nature of the data.

The most important results come from the natural disaster variables included. Through the inclusion of lagged natural disaster variables, we are able to illustrate the differences in aid flow due to responses to sudden natural disasters and natural disasters with a gradual onset. Rapid natural disasters such as the 2004 tsunami in eastern and southern Asia, or the 2010 earthquake in Haiti, generate a prompt international food aid response. In contrast, climate related disasters such as the 2011 drought in the Horn of Africa are less likely to receive aid promptly enough to stave off malnutrition and death. There are early warning systems in place to monitor food production and drought situations, but the international response to these early warnings do not appear to be heeded with the same urgency as more rapid onset disasters are. The results also show a very strong effect of the presence of refugees resulting in conflict, with a nearly 9 to 16% increase in food aid with a percent change in the quantity of refugees per 1,000 of a country's citizens. This is not an unaccepted result, however the inclusion of this term is clearly important when gaining a fully understanding of why emergency food aid reaches a country.

The analysis provides some evidence of the importance of the food supply for predicting the quantity of aid that is delivered. The lack of consistent evidence may further illustrate the wisdom of Amartya Sen, who explained food security is less dependent on food supply than it is on the demand for food. For example, the presence of the violent Lord's Resistance Army in northern Uganda in the late 20th and early 21st century forced many residents into displaced person camps, where they relied on emergency food aid for survival. Meanwhile, many other secure locations in Uganda were experiencing abundant food crops. Much of the food aid delivered to those northern camps was purchased locally. In this case, it was not a matter of a lack of food supply in Uganda, rather it was a lack of market power of people in the camps. The role of the international community was to ensure the supply moved to where it was needed most. This is not to understate the role of a country's food supply. Future analyses may concentrate on the inclusion of a food supply shock variable that

measures deviation of the long-run trends of food production. In such a model, we may expect food aid to increase when the food supply deviates negatively from the trend.

5.5 Policy Implications

5.5.1 General Policies

Each of the analyses undertaken in this body of research has important policy implications. In the optimal control analysis, the growth in agriculture land is discussed in light of the trade-offs that accompany this growth. Most policy makers, development professionals, researchers, and community members would likely welcome increased agriculture production. However, it is important to consider the vital role ecosystem services play in improving and maintaining agriculture production. Policy should ensure strategies to protect important ecosystems, particularly those areas in fragile frontier zones. This research should lend support to investing in these vital resources, not only in Nepal but also throughout the developing and developed world. Also, those less productive agriculture lands may be important areas for rehabilitating back to a natural state.

The spatial analysis of household food security in Nepal particularly highlights those factors that make people vulnerable to food insecurity. Government policy should be aimed at investments in those measures that give households improved safety nets against food security. Individuals have a role in maintaining vegetation in a local area, but this research indicates regional strategies to protect vegetation are also vital to strengthening food security. Also, ensuring better access to clean water, and other survival dependent resources, policy makers can ensure communities have more time to invest in longer-term poverty reduction activities that lead to increased food security.

Policies to promote social networking are also indicated in this research. Investments should be made to strengthen these networks to provide the social capital communities need for sharing information and resources. Government and other development policy should particularly invest in

protecting those members of lower social status who have less access to the formal safety nets and resources to improve food security.

The dynamic analysis highlights the effectiveness of international food aid responses in times of emergencies, suggesting policies in place to respond to needs should be continued. This analysis does point to the need for international policy and multilateral coordination, which aggressively provides food aid during emergencies, as soon as they occur. This is particularly the case for those slow moving disasters such as droughts. The use of media and social networking, such as Facebook, should be used to bring the gradual disasters into the consciousness of the public as early as possible. Such public interest may encourage more rapid response.

5.5.2 Climate Change

The research presented here is ever more important in light of global climate change. While the ecosystem services provided by forests have always been important, climate change only magnifies the need for protection. For instance, as glaciers in Nepal melt, the chance for flooding, erosion, and the loss of soil fertility increase. A greater stock of mature forest would be better able to absorb floodwaters, and ensure soil stability. Changing climate conditions also drive the migration of individuals to those locations with the most favorable conditions. This has the potential to put rapid pressure on the social systems in those communities undergoing change. Finally, there is an expectation that climate change will contribute to more frequent natural disasters, including storms, flooding, droughts, epidemics, and extreme temperature events. This will require redoubling efforts to ensure rapid response to meet food needs in times of emergencies.

5.6 Final Remarks

The world has made much progress in towards development and improving standards of living across the globe. Yet, the reality of extreme poverty, particularly in the form of hunger remains. The empathetic nature of humanity causes people not to be satisfied with such a large

number of men, women, and children remaining in extreme poverty and facing hunger. With continued population growth and the growing reality of climate change, careful monitoring, protection, and investment in the critical natural and social systems relied on for global food security must be undertaken. The research presented here has merged economic theory and analytical tools to be part of this effort. Many policy makers, non-governmental organizations and their staff, and academicians engaged in research are addressing these pressing issues. It is hoped that these research results will provide useful insight to those designing and implementing development policies and activities and emergency programs throughout the world.

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Appendix A Optimal Control Stata Code

```
/*bring in dist pop*/  
clear all  
clear matrix  
drop _all  
set memory 500m  
set matsize 800  
mata: mata set matafavor speed, perm  
global DIR "D:\Data\users\sarchambault\dissertation_data\"
```

```
insheet using ${DIR}dist_pop2.csv, names  
merge 1:1 dist_name using ${DIR}dist_name_code.dta  
drop _merge  
save ${DIR}dist_pop.dta, replace
```

```
clear all  
clear matrix  
drop _all  
set memory 500m  
set matsize 800  
mata: mata set matafavor speed, perm  
use ${DIR}nlss2003/c2_nlss_public.dta  
keep c2_pi_nepal03 WWW  
duplicates drop  
rename c2_pi_nepal03 pindex  
save ${DIR}pindex2003.dta, replace
```

```
clear all  
clear matrix  
drop _all  
set memory 500m  
set matsize 800  
mata: mata set matafavor speed, perm  
use ${DIR}nlss1996/Aggregate/prices.dta  
keep pindex WWW  
duplicates drop  
save ${DIR}pindex1996.dta, replace  
append using ${DIR}pindex2003.dta  
save ${DIR}pindex9603.dta, replace
```

```
clear all  
clear matrix  
drop _all
```

```
set memory 500m
```

```

set matsize 800
mata: mata set matafavor speed, perm
use ${DIR}nlss1996/Aggregate/prices.dta
rename district dist
keep WWW belt region dist urbrural group
rename group stratum
merge 1:1 WWW using ${DIR}DistrictN_vdc_match.dta
rename dist2 dist_name
drop _merge
replace vdc=upper(vdc)
drop vdc_dist
save ${DIR}www_distcode_distname1996.dta, replace
merge 1:m WWW using ${DIR}rural_wardinfo96.dta
drop _merge
save ${DIR}rural_vdcdist_1996.dta, replace

```

```

clear all
clear matrix
drop _all
set memory 500m
set matsize 800
mata: mata set matafavor speed, perm
use ${DIR}nlss2003/R1A1.dta
rename S1A1_VDC vdc
replace vdc=upper(vdc)
rename S1A1_01 hhsinward03
rename S1A1_WNO wardno
rename S1A1_02 wardpop03
save ${DIR}rural_vdc_names_2003.dta, replace

```

```

clear all
clear matrix
drop _all
set memory 500m
set matsize 800
mata: mata set matafavor speed, perm
insheet using ${DIR}www_distcode_distname2003.csv
rename psu WWW
rename districtcode dist
rename districtname dist_name
replace stratum="4" if stratum=="C"
replace stratum="3" if stratum=="B"
replace stratum="2" if stratum=="A"
replace stratum="6" if stratum=="D"
destring stratum, replace
replace belt="1" if belt=="M"
replace belt="2" if belt=="H"
replace belt="3" if belt=="I"

```

```

destring belt, replace
rename devreg region
rename urbrur urbrural
replace dist_name=upper(dist_name)
save ${DIR}www_distcode_distname2003.dta, replace
merge 1:1 WWW using ${DIR}rural_vdc_names_2003.dta
drop _merge
save ${DIR}rural_vdcdist_2003.dta, replace
merge m:1 WWW using ${DIR}rural_vdcdist_1996.dta
rename dist dist_codea
keep dist_codea WWW wardpop96 hhsinward96 wardno hhsinward03 wardpop03 vdc
dist_name
save ${DIR}wardpop0396.dta, replace

/*merge all districts with WWW info and price indexes*/
clear all
clear matrix
drop _all
set memory 500m
set matsize 800
mata: mata set matafavor speed, perm
use ${DIR}dist_pop.dta

use ${DIR}www_distcode_distname2003.dta
merge 1:1 WWW using ${DIR}www_distcode_distname1996.dta
drop _merge panel team phase hhweightnominal noofhhsinthedatasets noofhhsintheStraum
noofpsusintheStratum
merge m:1 WWW using ${DIR}pindex9603.dta
drop _merge
merge m:1 dist using ${DIR}cv_w_cv.dta
drop if WWW==.
drop _merge
replace dist_name="DAILEKH" if dist_name=="DAILEKHA"
replace dist_name="DADEL DHURA" if dist_name=="DANDEL DHURA"
replace dist_name="DADEL DHURA" if dist_name=="DADHEL DHURA"
replace dist_name="DHANUSA" if dist_name=="DHANUSHA"
replace dist_name="DOLKHA" if dist_name=="DOLAKHA"
replace dist_name="KAVRE" if dist_name=="KAVREPALANCHOC"
replace dist_name="KAVRE" if dist_name=="KAVREPALANCHOK"
replace dist_name="MAKAWANPUR" if dist_name=="MAKWANPUR"
merge m:1 dist_name using ${DIR}dist_pop.dta
replace vdc=upper(vdc)
replace dist_name=upper(dist_name)
egen vdc_dist=concat(vdc dist_name), punct(_)
replace vdc_dist=upper(vdc_dist)
save ${DIR}www_all_distname0396a.dta, replace

replace dist_name=upper(dist_name)

```

```

keep dist dist_name cv_w cv_d
rename dist dist_codea
duplicates drop

replace dist_codea=42 if dist_name=="MUSTANG" & dist_codea==.
replace dist_codea=29 if dist_name=="RASUWA" & dist_codea==.
drop if dist_codea==.
save ${DIR}cv2.dta, replace

/*merge rural district info only with WWW info, and price indexes*/
clear all
clear matrix
drop _all
set memory 500m
set matsize 800
mata: mata set matafavor speed, perm
use ${DIR}rural_vdcdist_2003.dta
merge 1:1 WWW using ${DIR}rural_vdcdist_1996.dta
drop _merge panel team phase hhweightnominal noofhhsinthedatasets noofhhsintheStraum
noofpsusintheStratum
merge m:1 WWW using ${DIR}pindex9603.dta
drop _merge

save ${DIR}distname_WWW9603.dta,replace
merge m:1 dist using ${DIR}cv_w_cv.dta
drop _merge
replace dist_name="DADEL DHURA" if dist_name=="DANDEL DHURA"
replace dist_name="DAILEKH" if dist_name=="DAILEKHA"
replace dist_name="DADEL DHURA" if dist_name=="DADHELDHURA"
replace dist_name="DHANUSA" if dist_name=="DHANUSHA"
replace dist_name="DOLKHA" if dist_name=="DOLAKHA"
replace dist_name="KAVRE" if dist_name=="KAVREPALANCHOC"
replace dist_name="KAVRE" if dist_name=="KAVREPALANCHOK"
replace dist_name="MAKAWANPUR" if dist_name=="MAKWANPUR"
merge m:1 dist_name using ${DIR}dist_pop.dta
replace vdc=upper(vdc)
replace dist_name=upper(dist_name)
drop _merge
egen vdc_dist=concat(vdc dist_name), punct(_)

save ${DIR}www_rural_distname0396a.dta, replace

keep dist dist_name region belt distpop*
duplicates drop
replace belt=1 if dist_name=="MUSTANG"
replace belt=1 if dist_name=="RASUWA"
save ${DIR}dist_pop_data.dta, replace

```



```

clear all
clear matrix
drop _all
set memory 500m
set matsize 800
mata: mata set matafavor speed, perm
use ${DIR}forest_buff_20001990.dta
drop vdc_dist
rename vdc_dist2 vdc_dist
duplicates tag vdc_dist, gen(dup_vdc)
replace vdc_dist="GOPALPUR_DHANUSHA" if vdc_dist=="GOPALPUR 1_DHANUSA"
replace vdc_dist="TRIBENI_SUSTA_NAWALPARASI" if vdc_dist=="TRIBENI_SUSTA
1_NAWALPARASI"
replace vdc_dist="LAKSMIPUR_SARLAHI" if vdc_dist=="LAKSMIPUR 1_SARLAHI"

egen sumt090=sum(t090), by(vdc_dist)
egen sumt190=sum(t190), by(vdc_dist)
egen sumt290=sum(t290), by(vdc_dist)
egen sumt390=sum(t390), by(vdc_dist)
egen sumt490=sum(t490), by(vdc_dist)
egen sumt590=sum(t590), by(vdc_dist)
egen sumt690=sum(t690), by(vdc_dist)
egen sumt790=sum(t790), by(vdc_dist)

egen sumt000=sum(t2000_0), by(vdc_dist)
egen sumt100=sum(t2000_1), by(vdc_dist)
egen sumt200=sum(t2000_2), by(vdc_dist)
egen sumt300=sum(t2000_3), by(vdc_dist)
egen sumt400=sum(t2000_4), by(vdc_dist)
egen sumt500=sum(t2000_5), by(vdc_dist)
egen sumt600=sum(t2000_6), by(vdc_dist)
egen sumt700=sum(t2000_7), by(vdc_dist)

replace t090=sumt090
replace t190=sumt190
replace t290=sumt290
replace t390=sumt390
replace t490=sumt490
replace t590=sumt590
replace t690=sumt690
replace t790=sumt790

replace t2000_0=sumt000
replace t2000_1=sumt100
replace t2000_2=sumt200
replace t2000_3=sumt300
replace t2000_4=sumt400
replace t2000_5=sumt500

```

```

replace t2000_6=sumt600
replace t2000_7=sumt700

egen sumroadsum=sum(roadsum), by(vdc_dist)
replace roadsum=sumroadsum

egen sumarean1911=sum(arean1911), by(vdc_dist)
replace arean1911=sumarean1911

gen tsum00=t2000_1 + t2000_2 + t2000_3 + t2000_4 + t2000_5
gen tsum90=t190 + t290 + t390 + t490 + t590

keep t2000_1 t2000_4 t190 t490 arean1911 districtc50 vdc_dist tsum90 tsum00 roadsum
duplicates drop
save ${DIR}forest_reduced.dta, replace
gen per_ag90=t490/tsum90
gen per_ag00=t2000_4/tsum00
gen per_ma90=t190/tsum90
gen per_ma00=t2000_1/tsum00

/*1=mature, 2=second, 3=degraded, 4=farm, 5=bareland, 6=cloud and snow, 7=unidentified*/
/*convert to kmsq*/
replace arean1911=arean1911/1000000
rename arean1911 areakmsq
egen allarea=sum(areakmsq)

/*vdc level ag & ma in km---total land area multiplied by % of ag & ma
ma is mature forest, ag is ag land*/

gen ag90vdc=per_ag90*areakmsq*100
gen ag00vdc=per_ag00*areakmsq*100
gen ma90vdc=per_ma90*areakmsq*100
gen ma00vdc=per_ma00*areakmsq*100
rename districtc50 dist_name
merge m:1 dist_name using ${DIR}www_rural_distname0396b.dta
drop _merge

gen districtc50=dist_name
egen distareakmsq=sum(areakmsq), by(dist)
egen dist90=sum(tsum90), by(dist)
egen dist00=sum(tsum00), by(dist)
sum dist90 dist00
gen areahect=areakmsq*100

/*hectares--district level*/

```

```

egen ag90dist=sum(ag90vdc), by(districtc50)
egen ag00dist=sum(ag00vdc), by(districtc50)
egen ma90dist=sum(ma90vdc), by(districtc50)
egen ma00dist=sum(ma00vdc), by(districtc50)
gen disthct=distareakmsq*100
gen per_ag90dis=ag90dist/(disthct)
gen per_ag00dis=ag00dist/(disthct)
gen per_ma90dis=ma90dist/(disthct)
gen per_ma00dis=ma00dist/(disthct)

/*change in cover---percent*/
gen chmad=per_ma00dis-per_ma90dis
gen chagd=per_ag00dis-per_ag90dis
gen madotd=chmad*disthct
gen agdotd=chagd*disthct

egen roadsum_dist=sum(roadsum), by(districtc50)
gen roadden_dist=roadsum_dist/distareakmsq

egen distsum90=sum(tsum90), by(districtc50)
egen distsum00=sum(tsum00), by(districtc50)

keep agdotd madotd ag90dist ag00dist per_ma00dis per_ag00dis per_ag90dis per_ma90dis
chmad chagd ma90dist ma00dist distareakmsq disthct districtc50 dist_name roadden_dist ///
distsum90 distsum00 belt*
duplicates drop
/*merge with population data*/

merge 1:m dist_name using ${DIR}dist_pop.dta
drop _merge

rename dist dist_codea
drop if dist_codea==.

/*regional belt dummies*/
gen belt1=0
replace belt1=1 if belt==1
gen belt2=0
replace belt2=1 if belt==2
gen belt3=0
replace belt3=1 if belt==3
gen belt4=0
replace belt4=1 if dist_name=="KATHMANDU" | dist_name=="LALITPUR" |
dist_name=="BHAKTAPUR"
replace belt1=1 if dist_name=="MUSTANG"
replace belt1=1 if dist_name=="RASUWA"
gen mnt=0
gen ter=0

```

```

gen hil=0
gen kat=0
gen nokat=0
replace mnt=1 if belt1==1
replace hil=1 if belt2==1
replace ter=1 if belt3==1
replace kat=1 if belt4==1
replace nokat=1 if belt4==0 & hil==1

save ${DIR}forest_dist2.dta, replace

clear all
clear matrix
drop _all
set memory 500m
set matsize 800
mata: mata set matafavor speed, perm
use ${DIR}forest_dist2.dta

/*population growth 1990-2000*/
gen popg=(distpop2000-distpop1990)

/*ag land per hh in 1990*/
gen agpp90=ag90dist/(distpop1990)
gen agpp00=ag90dist/(distpop2000)

/*growth in agric land needed*/
gen growag90=(agpp90)*(distpop1990)
gen growag00=(agpp00)*(distpop2000)
gen growag2=(distpop2000)*(agpp90+agpp00)/2
gen second=disthct-ma90dist-ag90dist
gen secondpp=second/distpop1990
gen secondper=second/disthct
gen madotd10=madotd/10
gen growag210=distpop2000*agpp00
gen ma90distper=ma90dist/disthct
gen agdotd10=agdotd/10
gen agdotdistpop=agdotd10*distpop1990

ivreg2 madotd10 ma90distper growag210 second , robust
egen mnt_area2=sum(disthct) if mnt==1 & dist_name~="RASUWA" &
dist_name~="MUSTANG"
egen nokat_area=sum(disthct) if nokat==1

ivreg2 madotd10 ma90distper growag210 second ter mnt nokat, robust
/*testing for endogeneity*/
ivreg2 madotd10 second (ma90distper=roadden distpop1990) growag210 ter mnt nokat ///
, robust endog(ma90distper)

```

```

ivreg2 madotd10 ma90distper (second =roadden distpop1990) growag210 ter mnt nokat ///
, robust endog(second )
ivreg2 madotd10 ma90distper second (growag210 =roadden distpop1990) ter mnt nokat ///
, robust endog(growag210)

```

```

save ${DIR}madot_analysis2.dta, replace
/*land owned 1996*/
clear matrix
drop _all
set memory 500m
set matsize 800
mata: mata set matafavor speed, perm
use ${DIR}nlss1996/Z12A1B.dta
merge 1:1 WWWHH S12A1PNO using ${DIR}nlss1996/Z12A1C.dta
drop _merge
merge 1:1 WWWHH S12A1PNO using ${DIR}nlss1996/Z12A1D.dta
drop _merge

```

```

/*revenue from rent and uses of land*/
rename S12A118C rent_wet
rename S12A118K inkind_wet
rename S12A115C rent_dry
rename S12A115K inkind_dry
rename S12A1_14 use_dry
rename S12A1_17 use_wet
destring WWW, replace
destring HH, replace
egen WWW_HH=concat(WWW HH), punct(_)
rename S12A1PNO PNO
rename S12A1_04 dist_codea
rename S12A103D land_unit
rename S12A103A ones_place
rename S12A103B seconds_place
rename S12A103C threes_place
rename S12A1_13 est_value
rename S12A1_06 irrigation
rename S12A1_07 seasonal_irrigation
rename S12A1_05 upland

```

```

drop if PNO==.
gen year=1996
destring WWWHH, replace
destring WWW, replace
save ${DIR}land_owned96.dta, replace

```

```

/*owned land 2003*/
clear matrix
drop _all

```

```

set memory 500m
set matsize 800
mata: mata set matafavor speed, perm
use ${DIR}nlss2003/Z11A1C.dta
append using ${DIR}nlss2003/NLSS2_PANEL_DTA/Z11A1C.dta
save ${DIR}landuse03.dta, replace
clear matrix
drop _all

```

```

set memory 500m
set matsize 800
mata: mata set matafavor speed, perm
use ${DIR}nlss2003/Z11A1B.dta
append using ${DIR}nlss2003/NLSS2_PANEL_DTA/Z11A1B.dta
merge 1:1 WWWW HH PNO using ${DIR}landuse03.dta
rename V11A1B_04 dist_codea
drop if PNO==.
drop _merge
rename V11A1B_03D land_unit
rename V11A1B_03A ones_place
rename V11A1B_03B seconds_place
rename V11A1B_03C threes_place
/*revenue from rent*/
rename V11A1C_11C rent_wet
rename V11A1C_11K inkind_wet
rename V11A1C_14C rent_dry
rename V11A1C_14K inkind_dry
rename V11A1C_10 use_dry
rename V11A1C_13 use_wet
rename V11A1B_09 est_value
rename V11A1B_06 irrigation
rename V11A1B_07 seasonal_irrigation
rename V11A1B_05 upland
gen year=2003
destring WWW, replace
destring HH, replace
egen WWW_HH=concat(WWW HH), punct(_)
sum WWW
save ${DIR}land_owned03.dta, replace

```

```

/*lands rented 1996 (tenant information)*/
clear matrix
drop _all

```

```

set memory 500m
set matsize 800
mata: mata set matafavor speed, perm
use ${DIR}nlss1996/Z12A2B.dta

```

```

merge 1:1 WWWHH S12A2PNO using ${DIR}nlss1996/Z12A2C.dta
drop _merge
destring WWW, replace
destring HH, replace
destring WWWHH, replace
rename S12A2PNO PNO
rename S12A205D land_unit
rename S12A205A ones_place
rename S12A205B seconds_place
rename S12A205C threes_place
rename S12A2_06 upland
rename S12A2_07 irrigation
rename S12A2_08 seasonal_irrigation

drop if land_unit==.
gen rent=1
gen year=1996
destring WWW, replace
destring HH, replace
egen WWW_HH=concat(WWW HH), punct(_)
rename S12A2_04 rent_paid
save ${DIR}land_rented96.dta, replace

/*lands rented 2003 (tenant information)*/
clear matrix
drop _all

set memory 500m
set matsize 800
mata: mata set matafavor speed, perm
use ${DIR}nlss2003/Z11A2C.dta
append using ${DIR}nlss2003/NLSS2_PANEL_DTA/Z11A2C.dta
save ${DIR}landuse_rented03.dta, replace

clear matrix
drop _all

set memory 500m
set matsize 800
mata: mata set matafavor speed, perm
use ${DIR}nlss2003/Z11A2B.dta
append using ${DIR}nlss2003/NLSS2_PANEL_DTA/Z11A2B.dta
merge 1:1 WWWHH PNO using ${DIR}landuse_rented03.dta

drop _merge

destring WWW, replace

```

```

destring HH, replace
egen WWW_HH=concat(WWW HH), punct(_)
rename V11A2B_05D land_unit
rename V11A2B_05A ones_place
rename V11A2B_05B seconds_place
rename V11A2B_05C threes_place
gen rent=1
rename V11A2B_04 rent_paid
rename V11A2B_06 upland
rename V11A2C_07 irrigation
rename V11A2C_08 seasonal_irrigation
gen year=2003
save ${DIR}land_rented03.dta, replace

```

*/*create joint data set of all lands owned, rented out, farmed, or rented*/*

```

clear matrix
drop _all

```

```

set memory 500m
set matsize 800
mata: mata set matafavor speed, perm
use ${DIR}land_owned03.dta
append using ${DIR}land_owned96.dta
append using ${DIR}land_rented03.dta
append using ${DIR}land_rented96.dta
save ${DIR}all_land9603.dta, replace

```

*/*fill in missing dist_codea numbers, particularly for land farmed that is rented land*/*

```

clear matrix
drop _all

```

```

set memory 500m
set matsize 800
mata: mata set matafavor speed, perm

```

```

use ${DIR}soc_cap_2003_match.dta
keep WWW dist_code
duplicates drop
merge 1:m WWW using ${DIR}all_land9603.dta
drop _merge

```

```

/*how many plots are there per household*/
duplicates tag WWW_HH year, gen(plot_count)
gen dist_codeab=0
replace dist_codeab=1 if dist_codea==.

```



```

egen max_dist_codea=max(dist_codea), by(WWW_HH year)
egen mean_dist_codea=mean(dist_codea), by(WWW_HH year)
egen min_dist_codea=min(dist_codea), by(WWW_HH year)
egen count_dist_codea=count(dist_codea) if dist_codea~=. , by(WWW_HH year)
egen count_dist_codeab=count(dist_codeab) if dist_codeab==1, by(WWW_HH year)
/*if renting is the only property, use district of home location for missing dist_codea
information*/
replace dist_codea=dist_code if plot_count>=0 & count_dist_codeab>=1 &
max_dist_codea==. & dist_codea==.
/*replace missing dist_codea data with the dist_codea info from the other plots in the district*/
replace dist_codea=mean_dist_code if dist_codea==. & max_dist_codea==min_dist_codea
merge m:1 dist_codea using ${DIR}cv2.dta
drop dist_code
save ${DIR}all_land9603_dist.dta, replace

/*plot size, rent revenue, rent payments, est. values*/
clear matrix
drop _all

set memory 500m
set matsize 800
mata: mata set matafavor speed, perm
use ${DIR}all_land9603_dist.dta
gen plot_size_hectare=0
replace
plot_size_hectare=(((ones_place*16+seconds_place)*4+threes_place)*85.56)*(9.290304*(10^-6)) if
land_unit==1
replace
plot_size_hectare=(((ones_place*20+seconds_place)*20+threes_place)*182.35)*(9.290304*(10^-6))
if land_unit==2
replace plot_size_hectare=(ones_place*160+seconds_place*8+threes_place)*cv_w*0.05087
///
if land_unit==3
replace plot_size_hectare=(ones_place*160+seconds_place*8+threes_place)*cv_d*0.05087 ///
if land_unit==4
drop if plot_size_hectare==0
duplicates drop
gen rent_revenue=rent_dry + inkind_dry + rent_wet + inkind_wet

save ${DIR}all_landsize9603.dta, replace

replace rent_revenue=0 if rent_revenue==.
egen total_rent_revenue=sum(rent_revenue), by(WWW_HH year dist_codea)
drop if plot_size_hectare==.
/*replace plot_size_hectare=0 if plot_size_hectare==.*/
egen total_land_hh=sum(plot_size_hectare), by(dist_codea year WWW_HH)
replace rent_paid=0 if rent_paid==.
egen total_rent_paid=sum(rent_paid), by(dist_codea year WWW_HH)

```

```

keep total_rent_revenue total_land_hh total_rent_paid ///
dist_codea year WWW_HH year
duplicates drop
duplicates tag WWW_HH year, gen(multiple_districts)

drop if multiple_districts~=0
drop multiple_districts
save ${DIR}total_land_revhha.dta, replace

clear matrix
drop _all

set memory 500m
set matsize 800
mata: mata set matafavor speed, perm
use ${DIR}all_land9603_dist.dta
gen plot_size_hectare=0
replace
plot_size_hectare=(((ones_place*16+seconds_place)*4+threes_place)*85.56)*(9.290304*(10^-6)) if
land_unit==1
replace
plot_size_hectare=(((ones_place*20+seconds_place)*20+threes_place)*182.35)*(9.290304*(10^-6))
if land_unit==2
replace plot_size_hectare=(ones_place*160+seconds_place*8+threes_place)*cv_w*0.05087
///
if land_unit==3
replace plot_size_hectare=(ones_place*160+seconds_place*8+threes_place)*cv_d*0.05087 ///
if land_unit==4
drop if plot_size_hectare==0
duplicates drop
gen rent_revenue=rent_dry + inkind_dry + rent_wet + inkind_wet

save ${DIR}all_landsize9603.dta, replace

replace rent_revenue=0 if rent_revenue==.
egen total_rent_revenue=sum(rent_revenue), by(WWW_HH year dist_codea)
drop if plot_size_hectare==.
/*replace plot_size_hectare=0 if plot_size_hectare==.*/
drop if irrigation==2
egen total_land_hh_irri=sum(plot_size_hectare), by(dist_codea year WWW_HH)
replace rent_paid=0 if rent_paid==.
egen total_rent_paid=sum(rent_paid), by(dist_codea year WWW_HH)

keep total_rent_revenue total_land_hh total_rent_paid ///
dist_codea year WWW_HH year
duplicates drop

```

```

duplicates tag WWW_HH year, gen(multiple_districts2)

drop if multiple_districts2~=0
drop multiple_districts2
save ${DIR}total_land_revhh_irrigation.dta, replace
merge m:1 WWW year using ${DIR}total_land_revhha.dta
replace total_land_hh_irri=0 if total_land_hh_irri==.
drop if _merge==1
drop _merge
save ${DIR}total_land_revhh.dta, replace

/*in the aggregate totals, we take out those lands rented out for the cost purposes,
as those lands rented do not incur costs by land owner*/

/*this land data below is only those who actually farmed--or left land fallow*/

clear matrix
drop _all

set memory 500m
set matsize 800
mata: mata set matafavor speed, perm
use ${DIR}all_landsize9603.dta
drop if use_wet==2 | use_wet==3 | use_wet==4 | use_wet==6 | use_wet==.
drop if use_dry==2 | use_dry==3 | use_dry==4 | use_dry==6 | use_dry==.
replace rent_revenue=0 if rent_revenue==.
egen total_rent_revenue=sum(rent_revenue), by(WWW_HH year dist_codea)
replace plot_size_hectare=0 if plot_size_hectare==.
egen total_land_hh=sum(plot_size_hectare), by(dist_codea year WWW_HH)
replace rent_paid=0 if rent_paid==.
egen total_rent_paid=sum(rent_paid), by(dist_codea year WWW_HH)

keep total_rent_revenue total_land_hh total_rent_paid ///
dist_codea year WWW_HH year
duplicates drop
duplicates tag WWW_HH year, gen(multiple_districts)
keep if multiple_districts==0
drop multiple_districts
save ${DIR}no_rent_total_land_revhha.dta, replace

clear matrix
drop _all

set memory 500m
set matsize 800
mata: mata set matafavor speed, perm
use ${DIR}all_landsize9603.dta
drop if use_wet==2 | use_wet==3 | use_wet==4 | use_wet==6 | use_wet==.

```

```

drop if use_dry==2 | use_dry==3 | use_dry==4 | use_dry==6 | use_dry==.
replace rent_revenue=0 if rent_revenue==.
egen total_rent_revenue=sum(rent_revenue), by(WWW_HH year dist_codea)
drop if plot_size_hectare==.
/*replace plot_size_hectare=0 if plot_size_hectare==.*/
drop if irrigation==2
egen total_land_hh_irri=sum(plot_size_hectare), by(dist_codea year WWW_HH)
replace rent_paid=0 if rent_paid==.
egen total_rent_paid=sum(rent_paid), by(dist_codea year WWW_HH)

keep total_rent_revenue total_land_hh total_rent_paid ///
dist_codea year WWW_HH year
duplicates drop
duplicates tag WWW_HH year, gen(multiple_districts)

keep if multiple_districts==0
drop multiple_districts
save ${DIR}no_rent_total_land_revhh_irrigation.dta, replace
merge m:1 WWW year using ${DIR}no_rent_total_land_revhha.dta
replace total_land_hh_irri=0 if total_land_hh_irri==.
drop if _merge==1
drop _merge
save ${DIR}no_rent_total_land_revhh.dta, replace

/*this land data below is only those who actually farmed--not including if left land fallow*/

clear matrix
drop _all

set memory 500m
set matsize 800
mata: mata set matafavor speed, perm
use ${DIR}all_landsize9603.dta
drop if use_wet==2 | use_wet==3 | use_wet==4 | use_wet==6 | use_wet==.
drop if use_dry==2 | use_dry==3 | use_dry==4 | use_dry==6 | use_dry==.
replace rent_revenue=0 if rent_revenue==.
egen total_rent_revenue=sum(rent_revenue), by(WWW_HH year dist_codea)
replace plot_size_hectare=0 if plot_size_hectare==.
egen total_land_hh=sum(plot_size_hectare), by(dist_codea year WWW_HH)
replace rent_paid=0 if rent_paid==.
egen total_rent_paid=sum(rent_paid), by(dist_codea year WWW_HH)

keep total_rent_revenue total_land_hh total_rent_paid ///
dist_codea year WWW_HH year
duplicates drop
duplicates tag WWW_HH year, gen(multiple_districts)
keep if multiple_districts==0

```

```

drop multiple_districts
save ${DIR}no_rent_no_fallow_total_land_revhha.dta, replace

clear matrix
drop _all

set memory 500m
set matsize 800
mata: mata set matafavor speed, perm
use ${DIR}all_landsize9603.dta
drop if use_wet==2 | use_wet==3 | use_wet==4 | use_wet==6 | use_wet==. | use_wet==5
drop if use_dry==2 | use_dry==3 | use_dry==4 | use_dry==6 | use_dry==. | use_dry==5
replace rent_revenue=0 if rent_revenue==.
egen total_rent_revenue=sum(rent_revenue), by(WWW_HH year dist_codea)
drop if plot_size_hectare==.
/*replace plot_size_hectare=0 if plot_size_hectare==.*/
drop if irrigation==2
egen total_land_hh_irri=sum(plot_size_hectare), by(dist_codea year WWW_HH)
replace rent_paid=0 if rent_paid==.
egen total_rent_paid=sum(rent_paid), by(dist_codea year WWW_HH)

keep total_rent_revenue total_land_hh total_rent_paid ///
dist_codea year WWW_HH year
duplicates drop
duplicates tag WWW_HH year, gen(multiple_districts)

keep if multiple_districts==0
drop multiple_districts
save ${DIR}no_rent_total_land_revhh_irrigation.dta, replace
merge m:1 WWW year using ${DIR}no_rent_total_land_revhha.dta
replace total_land_hh_irri=0 if total_land_hh_irri==.
drop if _merge==1
drop _merge
save ${DIR}no_rent_no_fallow_total_land_revhh.dta, replace

```

/*we need to generate the value of crops sold & not sold--we base assumed crop values on the home district of the household*/

```

clear matrix
drop _all

set memory 500m
set matsize 800
mata: mata set matafavor speed, perm
use ${DIR}nlss2003/Z11B1.dta
append using ${DIR}nlss2003/NLSS2_PANEL_DTA/Z11B1.dta
destring WWW, replace
destring HH, replace
drop WWWHH

```

```
egen WWW_HH=concat(WWW HH), punct( )
merge m:1 WWW using $ {DIR} soc_cap_2003_match.dta
keep if _merge==3
drop _merge
rename V11B1_03B produce_quantity
rename V11B1_03A produce_units
rename V11B1_04B market_quantity
rename V11B1_04A market_units
rename V11B1_03C landlord_quantity
rename V11B1_04C price_unit
gen year=2003
```

```
save $ {DIR} crop_values03.dta, replace
```

```
clear matrix
drop _all
```

```
set memory 500m
set matsize 800
mata: mata set matafavor speed, perm
use $ {DIR} nlss1996/Z12B1.dta
destring WWW, replace
destring HH, replace
drop WWWHH
egen WWW_HH=concat(WWW HH), punct( )
merge m:1 WWW using $ {DIR} soc_cap_2003_match.dta
keep if _merge==3
drop _merge
rename S12B103B produce_quantity
rename S12B103A produce_units
rename S12B104B market_quantity
rename S12B104A market_units
rename S12B103C landlord_quantity
rename S12B104C price_unit
rename S12B1CCD CCD
gen year=1996
save $ {DIR} crop_values96.dta, replace
append using $ {DIR} crop_values03.dta
```

```
/*make crop measurements consistent--kilograms, liters, and pieces*/
replace produce_quantity=produce_quantity*.001 if produce_units==2
replace produce_quantity=produce_quantity*37.3 if produce_units==3
replace produce_quantity=produce_quantity*72 if produce_units==5
replace produce_quantity=produce_quantity*12 if produce_units==10
replace produce_quantity=produce_quantity*4.544 if produce_units==6
replace produce_quantity=produce_quantity*0.568 if produce_units==7
replace produce_quantity=produce_quantity*0.682 if produce_units==8
```

replace market_quantity=market_quantity*.001 if market_units==2
replace market_quantity=market_quantity*37.3 if market_units==3
replace market_quantity=market_quantity*72 if market_units==5
replace market_quantity=market_quantity*12 if market_units==10
replace market_quantity=market_quantity*4.544 if market_units==6
replace market_quantity=market_quantity*0.568 if market_units==7
replace market_quantity=market_quantity/0.682 if market_units==8

replace price_unit=price_unit/.001 if market_units==2
replace price_unit=price_unit/37.3 if market_units==3
replace price_unit=price_unit/72 if market_units==5
replace price_unit=price_unit/12 if market_units==10
replace price_unit=price_unit/4.544 if market_units==6
replace price_unit=price_unit/0.568 if market_units==7
replace price_unit=price_unit/0.682 if market_units==8

gen market_unit_type=""
replace market_unit_type="weight" if market_units==1
replace market_unit_type="weight" if market_units==2
replace market_unit_type="weight" if market_units==3
replace market_unit_type="weight" if market_units==5
replace market_unit_type="pieces" if market_units==9
replace market_unit_type="pieces" if market_units==10
replace market_unit_type="liquid" if market_units==4
replace market_unit_type="liquid" if market_units==6
replace market_unit_type="liquid" if market_units==7
replace market_unit_type="liquid" if market_units==8

gen produce_unit_type=""
replace produce_unit_type="weight" if produce_units==1
replace produce_unit_type="weight" if produce_units==2
replace produce_unit_type="weight" if produce_units==3
replace produce_unit_type="weight" if produce_units==5
replace produce_unit_type="pieces" if produce_units==9
replace produce_unit_type="pieces" if produce_units==10
replace produce_unit_type="liquid" if produce_units==6
replace produce_unit_type="liquid" if produce_units==7
replace produce_unit_type="liquid" if produce_units==8
replace produce_unit_type="liquid" if produce_units==4

replace market_quantity=.89*market_quantity if market_unit_type=="liquid" & CCD==1
replace produce_quantity=.89*produce_quantity if produce_unit_type=="liquid" & CCD==1
replace market_quantity=.89*market_quantity if market_unit_type=="liquid" & CCD==2
replace produce_quantity=.89*produce_quantity if produce_unit_type=="liquid" & CCD==2

replace market_unit_type="weight" if market_unit_type=="liquid" & CCD==1
replace produce_unit_type="weight" if produce_unit_type=="liquid" & CCD==1

```
replace market_unit_type="weight" if market_unit_type=="liquid" & CCD==2
replace produce_unit_type="weight" if produce_unit_type=="liquid" & CCD==2
/*quantity of produce sold*/
```

```
replace market_quantity=0 if market_quantity==.
replace market_units=. if market_quantity==0
replace market_quantity=0 if market_units==.
gen amount_sold=0
gen non_sold=0
replace amount_sold=market_quantity if produce_unit_type==market_unit_type
```

```
replace non_sold=produce_quantity-amount_sold if produce_unit_type==market_unit_type
replace non_sold=produce_quantity if produce_unit_type~market_unit_type &
market_unit_type==""
```

```
egen price_CCD_weight=mean(price_unit) if price_unit~. & market_unit_type=="weight",
by(dist_code year)
egen price_CCD_liquid=mean(price_unit) if price_unit~. & market_unit_type=="liquid",
by(dist_code year)
egen price_CCD_pieces=mean(price_unit) if price_unit~. & market_unit_type=="pieces",
by(dist_code year)
```

```
egen max_price_CCD_weight=max(price_CCD_weight), by(dist_code year)
egen max_price_CCD_liquid=max(price_CCD_liquid), by(dist_code year)
egen max_price_CCD_pieces=max(price_CCD_pieces), by(dist_code year)
```

```
replace price_CCD_weight=max_price_CCD_weight if price_CCD_weight==.
replace price_CCD_liquid=max_price_CCD_liquid if price_CCD_liquid==.
replace price_CCD_pieces=max_price_CCD_pieces if price_CCD_pieces==.
/*in case price does not exist in the district*/
egen max_price_CCD_weight2=max(price_CCD_weight), by(year)
egen max_price_CCD_liquid2=max(price_CCD_liquid), by(year)
egen max_price_CCD_pieces2=max(price_CCD_pieces), by(year)
```

```
replace price_CCD_weight=max_price_CCD_weight2 if price_CCD_weight==. &
max_price_CCD_weight==.
replace price_CCD_liquid=max_price_CCD_liquid2 if price_CCD_liquid==. &
max_price_CCD_liquid==.
replace price_CCD_pieces=max_price_CCD_pieces2 if price_CCD_pieces==. &
max_price_CCD_pieces==.
```

```
gen value_sold=price_unit*amount_sold if produce_unit_type==market_unit_type
```

```
gen value_non_sold=0
replace value_non_sold=non_sold*price_unit if produce_unit_type==market_unit_type
```



```

    replace value_non_sold=non_sold*price_CCD_pieces if produce_unit_type=="pieces" &
produce_unit_type~=market_unit_type
    replace value_non_sold=non_sold*price_CCD_liquid if produce_unit_type=="liquid" &
produce_unit_type~=market_unit_type
    replace value_non_sold=non_sold*price_CCD_weight if produce_unit_type=="weight" &
produce_unit_type~=market_unit_type

drop if value_sold==. & value_non_sold==.
replace value_sold=0 if value_sold==.
replace value_non_sold=0 if value_non_sold==.
gen total_value=value_sold+value_non_sold
egen total_value_hh=sum(total_value), by(WWW_HH year)

gen value_landlord=0
replace value_landlord=landlord_quantity*price_unit if produce_unit_type==market_unit_type
replace value_landlord=landlord_quantity*price_CCD_weight if produce_unit_type=="weight"
& produce_unit_type~=market_unit_type
replace value_landlord=landlord_quantity*price_CCD_liquid if produce_unit_type=="liquid" &
produce_unit_type~=market_unit_type
replace value_landlord=landlord_quantity*price_CCD_pieces if produce_unit_type=="pieces"
& produce_unit_type~=market_unit_type
/*total inkind value paid to landlord or crop sharing*/
egen total_value_landlord=sum(value_landlord), by(WWW_HH year)
save ${DIR}value_crops9603.dta, replace

/*in the aggregate totals, we take out those lands rented out for the cost purposes,
as those lands rented do not incur costs by land owner*/
keep total_value_hh total_value_landlord WWW_HH year
duplicates drop
duplicates tag WWW_HH year, gen(dups_wwwhh2)
drop dups_wwwhh2
save ${DIR}overall_value.dta, replace

/*home production animal products value, not sold*/
clear matrix
drop _all

set memory 500m
set matsize 800
mata: mata set matafavor speed, perm
use ${DIR}nlss2003/Z05A.dta
append using ${DIR}nlss2003/NLSS2_PANEL_DTA/Z05A.dta
rename ITM food_item
rename V05A_07 rupees_mo
rename V05A_05 months
gen value_year=months*rupees_mo
egen dairy_home_value=sum(value_year) if food_item>030 & food_item<036, by(WWWHH)

```

```

egen meat_home_value=sum(value_year) if food_item>070 & food_item<076, by(WWWHH)
replace dairy_home_value=0 if dairy_home_value==.
replace meat_home_value=0 if meat_home_value==.
gen animal_value=dairy_home_value + meat_home_value
egen tot_animal_value=sum(animal_value), by(WWWHH)
replace tot_animal_value=0 if tot_animal_value==.
destring WWWHH, replace
destring WWW, replace
destring HH, replace
egen WWW_HH=concat(WWW HH), punct(_)
keep tot_animal_value WWWHH WWW HH WWW_HH
gen year=2003
duplicates drop
drop if tot_animal_value==.
save ${DIR}home_animal2003.dta, replace

```

```

clear matrix
drop _all

```

```

set memory 500m
set matsize 800
mata: mata set matafavor speed, perm
use ${DIR}nlss1996/Z05A.dta
rename S05A_ITM food_item
rename S05A_07 rupees_mo
rename S05A_05 months
gen value_year=months*rupees_mo
egen dairy_home_value=sum(value_year) if food_item>030 & food_item<037, by(WWWHH)
egen meat_home_value=sum(value_year) if food_item>070 & food_item<076, by(WWWHH)
replace dairy_home_value=0 if dairy_home_value==.
replace meat_home_value=0 if meat_home_value==.
gen animal_value=dairy_home_value + meat_home_value
egen tot_animal_value=sum(animal_value), by(WWWHH)
replace tot_animal_value=0 if tot_animal_value==.
destring WWWHH, replace
destring WWW, replace
destring HH, replace
egen WWW_HH=concat(WWW HH), punct(_)
keep tot_animal_value WWWHH WWW HH WWW_HH
gen year=1996
duplicates drop
drop if tot_animal_value==.
save ${DIR}home_animal1996.dta, replace
append using ${DIR}home_animal2003.dta
save ${DIR}animal_food_self_value.dta, replace

```

```

clear matrix

```

```
drop _all
```

```
set memory 500m
set matsize 800
mata: mata set matafavor speed, perm
use ${DIR}overall_value.dta
merge 1:1 WWW_HH year using ${DIR}no_rent_total_land_revhh.dta
drop if _merge~=1
drop _merge
merge 1:1 WWW_HH year using ${DIR}animal_food_self_value.dta
replace tot_animal_value=0 if tot_animal_value==.
drop _merge
save ${DIR}values_crops_revenue_land.dta, replace
```

```
/*for production costs, need to remove those plots that were rented out and farmed by
somebody else, as the owner did not
incur the costs for those plots*/
clear matrix
drop _all
```

```
set memory 500m
set matsize 800
mata: mata set matafavor speed, perm
use ${DIR}overall_value.dta

merge 1:1 WWW_HH year using ${DIR}no_rent_total_land_revhh.dta
drop if _merge~=3
drop _merge
merge 1:1 WWW_HH year using ${DIR}animal_food_self_value.dta
replace tot_animal_value=0 if tot_animal_value==.
drop _merge
save ${DIR}values_crops_nolandlords_costs_land.dta, replace
```

```
/*for production costs, need to remove those plots that were rented out and farmed by
somebody else, as the owner did not
incur the costs for those plots*/
clear matrix
drop _all
```

```
set memory 500m
set matsize 800
mata: mata set matafavor speed, perm
use ${DIR}overall_value.dta
```

```
merge 1:1 WWW_HH year using ${DIR}no_rent_no_fallow_total_land_revhh.dta
drop if _merge~=3
drop _merge
```

```

merge 1:1 WWW_HH year using ${DIR}animal_food_self_value.dta
replace tot_animal_value=0 if tot_animal_value==.
drop _merge
save ${DIR}values_crops_nolandlords_nofallow_costs_land.dta, replace

```

```

/*for production costs, need to remove those plots that were rented out and farmed by
somebody else, as the owner did not
incur the costs for those plots*/
clear matrix
drop _all

```

```

set memory 500m
set matsize 800
mata: mata set matafavor speed, perm
use ${DIR}overall_value.dta

```

```

merge 1:1 WWW_HH year using ${DIR}total_land_revhh.dta
drop if _merge~=3
drop _merge
merge 1:1 WWW_HH year using ${DIR}animal_food_self_value.dta
replace tot_animal_value=0 if tot_animal_value==.
drop _merge
save ${DIR}values_crops_landlords_land.dta, replace
merge m:1 WWW using ${DIR}www_distcodea.dta
save ${DIR}values_crops_landlords_land.dta, replace

```

```

/*www dist matching only*/
clear matrix
drop _all
set memory 500m
set matsize 800
mata: mata set matafavor speed, perm
use ${DIR}www_rural_distname0396a.dta
keep WWW dist dist_name
duplicates drop
rename dist dist_codea
drop if WWW==.
save ${DIR}www_distcodea.dta, replace

```

```

/*livestock*/
clear matrix
drop _all

```

```

set memory 500m
set matsize 800
mata: mata set matafavor speed, perm
use ${DIR}nlss1996/Z12E2.dta
rename S12E2_08 total_costs_live

```

```

rename S12E2_13 revenue_live
gen year=1996
destring WWWHH, replace
destring WWW, replace
destring HH, replace
egen WWW_HH=concat(WWW HH), punct( )
keep WWWHH WWW_HH total_costs_live revenue_live year WWW
save ${DIR}revcostslive96a.dta, replace
merge m:1 WWW using ${DIR}www_distcodea.dta
drop _merge
save ${DIR}revcostslive96.dta, replace

```

```

clear matrix
drop _all

```

```

set memory 500m
set matsize 800
mata: mata set matafavor speed, perm
use ${DIR}nlss2003/Z11E2.dta
append using ${DIR}nlss2003/NLSS2_PANEL_DTA/Z11E2.dta
rename V11E2_08 total_costs_live
rename V11E2_13 revenue_live
gen year=2003
destring WWWHH, replace
destring WWW, replace
destring HH, replace
egen WWW_HH=concat(WWW HH), punct( )
keep WWWHH WWW_HH total_costs_live revenue_live year WWW
save ${DIR}revcostslive03a.dta, replace
merge m:1 WWW using ${DIR}www_distcodea.dta
drop _merge
save ${DIR}revcostslive03.dta, replace

```

```

append using ${DIR}revcostslive96.dta
save ${DIR}revcostslive9603.dta, replace

```

```

/*totcosts totrev 96*/
clear matrix
drop _all

```

```

set memory 500m
set matsize 800
mata: mata set matafavor speed, perm
use ${DIR}nlss1996/Z12D.dta
rename S12D_23 total_costs_ag
rename S12D_08 by_product_rev

```

```

rename S12D_13 transport_costs
gen year=1996
destring WWWHH, replace
destring WWW, replace
destring HH, replace
egen WWW_HH=concat(WWW HH), punct(_)
keep total_costs_ag by_product_rev transport_costs year WWW_HH WWW HH WWWHH
merge 1:m year WWW_HH using ${DIR}revcostslive9603.dta
drop _merge
drop if year==2003
merge m:1 WWW using ${DIR}pindex9603.dta
keep if _merge==3
drop _merge
save ${DIR}revcostsag96.dta, replace

/*totrevcosts 03*/
clear matrix
drop _all

set memory 500m
set matsize 800
mata: mata set matafavor speed, perm
use ${DIR}nlss2003/Z11D.dta
append using ${DIR}nlss2003/NLSS2_PANEL_DTA/Z11D.dta
rename V11D_23 total_costs_ag
rename V11D_02 by_product_rev
rename V11D_13 transport_costs
gen year=2003
destring WWWHH, replace
destring WWW, replace
destring HH, replace
egen WWW_HH=concat(WWW HH), punct(_)
keep total_costs_ag by_product_rev transport_costs year WWW_HH WWW HH WWWHH

merge 1:m year WWW_HH using ${DIR}revcostslive9603.dta

drop _merge
drop if year==1996
merge m:1 WWW using ${DIR}pindex9603.dta
keep if _merge==3
drop _merge
save ${DIR}revcostsag03.dta, replace
append using ${DIR}revcostsag96.dta
sort WWW
/*merge m:1 WWW using ${DIR}forest_funds9603_vdc.dta
drop _merge*/

```

```

keep year transport_costs by_product_rev total_costs_ag WWW_HH WWW HH WWWHH
///
pindex total_costs_live revenue_live
duplicates drop
drop if year==.
save ${DIR}revcosts9603a.dta, replace

/*data for calculating revenue*/
clear matrix
drop _all

set memory 500m
set matsize 800
mata: mata set matafavor speed, perm
use ${DIR}revcosts9603a.dta
replace transport_costs=0 if transport_costs==.

merge 1:1 WWW_HH year using ${DIR}values_crops_nolandlords_costs_land.dta
drop _merge
merge m:1 dist_codea using ${DIR}forest_dist2.dta
drop if _merge~=3
drop _merge
save ${DIR}reveune_costs_data.dta, replace

/*calculations2*/
clear matrix
drop _all

set memory 500m
set matsize 800
mata: mata set matafavor speed, perm
use ${DIR}reveune_costs_data.dta
drop belt*

/*recall chag chfo, etc is a 10 year change....divide by 10 to get annual value*/
gen ma_land03=(ma00dist)+3*(chmad/10)*disthct
gen ma_land96=(ma00dist)-4*(chmad/10)*disthct
gen ag_land03=(ag00dist)+3*(chagd/10)*disthct
gen ag_land96=(ag00dist)-4*(chagd/10)*disthct

gen distpop=.
replace distpop=distpop2003 if year==2003
replace distpop=distpop1996 if year==1996

```

```

/*calculating costs--pcosts to adjust for inflation*/
replace total_rent_paid=0 if total_rent_paid==.
replace total_costs_ag=0 if total_costs_ag==.
replace transport_costs=0 if transport_costs==.
gen costs=total_costs_ag+total_costs_live-transport_costs
replace costs=0 if costs==.
gen costshect=costs/(total_land_hh)
gen pcosts=.
replace pcosts=costs if year==2003
replace pcosts=costs*1.475 if year==1996
replace pcosts=0 if pcosts==.

```

```

/*calculating revenue--prevenue to adjust for inflation*/
replace total_value_hh=0 if total_value_hh==.
replace tot_animal_value=0 if tot_animal_value==.
replace revenue_live=0 if revenue_live==.
gen revenue=total_value_hh+revenue_live+tot_animal_value
gen prevenue=.
replace prevenue=revenue if year==2003
replace prevenue=revenue*1.475*index if year==1996

```

```

gen maland=ma_land03
replace maland=ma_land96 if year==1996
gen malandsq=maland^2
gen malandpp=maland/(distpop)
gen malandpps=malandpp^2
gen agland=ag_land03
replace agland=ag_land96 if year==1996
gen aglandsq=agland^2
gen aglandpp=agland/(distpop/1)
gen aglandpps=aglandpp^2
gen aglandppcu=aglandpp^3

```

```

/*land per household---total_land_hh*/

```

```

gen landhh=total_land_hh
gen landhhsq=landhh^2
gen landhhcu=landhh^3
gen distpopsq=distpop^2
gen distpopden=distpop/disthect

```

```

/*year dummy*/
gen year1=0
replace year1=1996 if year==1996
save ${DIR}reveune_costs_datab.dta, replace

```



```

clear matrix
drop _all

set memory 500m

set matsize 800
mata: mata set matafavor speed, perm
use ${DIR}reveune_costs_datab.dta
drop if landhh==0
drop if landhh==.
gen prevenue2=revenue
replace prevenue2=0 if revenue==.
replace prevenue2=revenue*1.475 if year==1996
replace prevenue2=revenue if year==2003
gen prevland=prevenue2/(landhh)
gen pcosts2=.
replace pcosts2=costs if year==2003
replace pcosts2=costs*1.475*pindex if year==1996
replace pcosts2=0 if pcosts==. & landhh~=0
duplicates drop

save ${DIR}reveune_costs_datad.dta, replace

drop if landhh==.
duplicates tag WWW_HH, gen(panel)
drop if landhh==.
xtset WWWHH year
gen disthctsq=disthct^2

reg prevland aglandpp aglandppsq malandpp malandppsq ///
distpop year if prevland<1000000 & landhh<5 , robust

gen inter2=malandpp*aglandpp
gen panel196=0
replace panel196=1 if year==1996 & panel==1
egen dist_prevland=mean(prevland) if prevland<200000000, by(dist_codea year)
save ${DIR}reveune_costs_analysis.dta, replace

clear matrix
drop _all

set memory 500m
set matsize 800
mata: mata set matafavor speed, perm
use ${DIR}reveune_costs_analysis.dta

```

```

reg pcosts2 landhh landhhsq landhhcu malandpp malandppsqsq distpop if panel196~=1 &
pcosts<300000, robust nocons
keep dist_prevland distpop distpopsq agland aglandpp aglandsq malandpp distpopden disthct
///
aglandppsqsq dist_codea year roadden_dist maland ma90dist ma00dist ter mnt nokat hil kat
duplicates drop
drop if dist_prevland==.
tsset dist_codea year
gen yeard=0
replace yeard=1 if year==2003
gen malandsq=maland^2

xtreg dist_prevland agland distpop disthct if agland<200000, fe
est store fe
xtreg dist_prevland agland distpop disthct if agland<200000, re
est store re
hausman fe re, sigmamore
xtoverid

/*testing endogeneity of agland*/
xtivreg2 dist_prevland (agland=roadden maland malandsq ter mnt nokat) distpop disthct if
agland<200000, fe endog(agland)

```

Appendix B Sample Maple Code

This is code used to analyze the Hill Belt with a high growth rate and high carrying capacity.

restart;

Where *g* is population growth, *j* is the factor increase of current population to reach carrying capacity

This is *g*=.018(high growth rate) and *j*=2 (for high carrying capacity)

unassign('g','j')

assign(g = .018, j = 2) :

Defining the carrying capacity, where *hillk* is current, starting population, *k* is carrying capacity.

hillk := 11068150 :

k := hillk·j : := hillk·j :

Land Area of Hills Region

Land := 6084096 :

State equation

$$Fdot := \left(-\frac{10441.63}{Land} - .03 \cdot (diff(D(t), t) \cdot A(t)) - .013 \cdot (Land - A(t) \cdot D(t) - F(t)) + 3675 + 1271 \right) :$$

Population Growth

$$Ddot := g \cdot D(t) \cdot \left(1 - \frac{D(t)}{k} \right) :$$

Cost Function

$$CostsA := \left((At) \cdot (6369.3 - 579.96 \cdot At + 12.6 \cdot At \cdot At) + \frac{Ft}{Dt} \cdot \left(-2488.94 + \frac{215.48 \cdot Ft}{Dt} \right) + Dt \cdot (.006) \right) :$$

Revenue Function

$$RevA2 := At \cdot (.43 \cdot Dt - Dt \cdot At \cdot (2.44) + .53 \cdot Land + 100533) :$$

Discount factor and rate

$$discount := \exp(-r \cdot t) :$$

(1)

r := .15 :

$$Hamiltonian := discount \cdot (RevA2 - CostsA) + lambda \cdot (Fdot) :$$

First order conditions

$$Ha := diff(Hamiltonian, At) :$$

$$Hf := diff(Hamiltonian, Ft) :$$

$$Hat := subs(At = A(t), Ft = F(t), DtAt = (Dt \cdot A(t)), Dt = D(t), lambda = lambda(t), Ha) :$$

$$Hft := subs(At = A(t), Ft = F(t), Dt = D(t), DtAt = (Dt \cdot A(t)), lambda = lambda(t), Hf) :$$

(2)

$$fdott := subs(At = A(t), Ft = F(t), Dt = D(t), DtAt = (Dt \cdot A(t)), lambda = lambda(t), Fdot) :$$

$$Ddott := subs(At = A(t), Ft = F(t), Dt = D(t), lambda = lambda(t), Ddot) :$$

$$lambda1 := solve(Hat = 0, lambda(t)) :$$

$$Hfilambda := subs(lambda(t) = lambda1, Hft) :$$

(3)

```
diffHat := diff(Hat, t) :
Adot := solve(subs(diff(lambda(t), t) = -Hft, diff(F(t), t) = fdott, lambda(t) = lambda1, diffHat = 0),
diff(A(t), t)) :
```

Solving for steady state

```
Adot2 := solve(subs(D(t) = k, Adot = 0), A(t))
Adot2 gives two solutions. First choice is unrealistic, so second choice is used to get the F steady state.
Fsteady1 := solve(subs(A(t) = Adot2[2], diff(D(t), t) = 0, D(t) = k, fdott = 0), F(t)) :
AsteadyHH := solve(subs(F(t) = Fsteady1, Adot2[2] = A(t)), A(t)) :
FsteadyHH := subs(A(t) = AsteadyHH, Fsteady1) :
```

Prepare ODEs to be solved. P(t) is population, F(t) is aggregate forest, A(t) is per capita agriculture land

```
difD2 := subs(D(t) = P(t), Ddott) :
differ2 := subs(D(t) = P(t), fdott) :
diffF := diff(F(t), t) = differ2 :
diffP := diff(P(t), t) = difD2 :
diffa2 := subs(D(t) = P(t), Adot) :
diffA := diff(A(t), t) = differa2 :
```

Backward shooting method, solve negative values of ODEs. Use steady states as starting values. The solution will get hung up at the carrying capacity, so need to choose population slightly below carrying capacity (or population steady state value).

```
resultHH := dsolve([-diffA, -diffF, -diffP, P(0) = k - 10000, A(0) = AsteadyHH, F(0)
= FsteadyHH], numeric, method = rosenbrock)
```

proc(x_rosenbrock) ... end proc (4)

Find the negative time period where current population is found. This becomes the starting value.

hillk

11068150 (5)

resultHH(-428)

[t = -428., A(t) = 0.149623395072558, F(t) = 3.60927795859798 10⁶, P(t) = 1.10570513628526 10⁷] (6)

Ensure the boundary of the land area is not exceeded.

```
landsize := subs(resultHH(-428), (Land - (F(t) + P(t)·A(t))))
```

8.20424477000354 10⁵ (7)

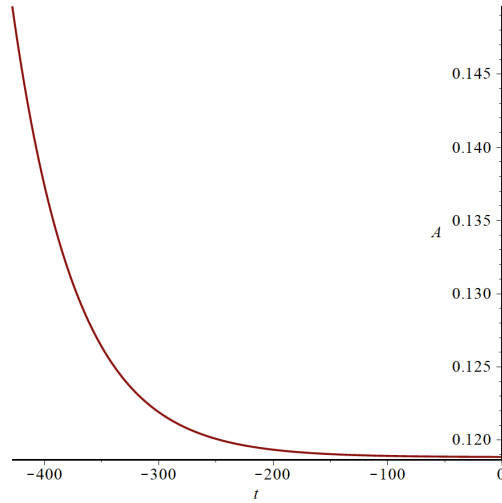
View Plot of Agriculture time Path

```
plotA := plots[odeplot](resultHH, [t, A(t)], t = -428..0)
```

PLOT(...) (8)

```
with(plots) :
```

```
display(plotA)
```

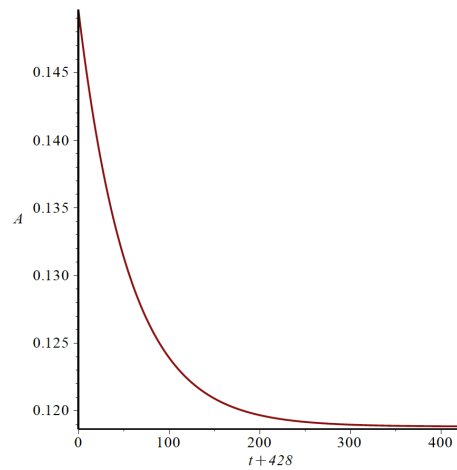


Forward Plot

```
plotA2 := plots[odeplot](resultHH, [t + 428, A(t)], t = -428..0)
PLOT(...)
```

(9)

display(plotA2)



SECTION 1 - DEMOGRAPHICS: Read - "I would now like to ask you a few questions on the composition of your household"

1.1 - What is the number of persons living in your household? ____ please list below by first name starting with the head of the HH and complete table for each member

A household is defined as a group of people currently living and eating together "under the same roof" (or in same compound if the HH has 2 structures)

Household Member code	1.2	1.3	1.4	1.5	1.6	1.7	1.8	1.9	1.10
	First name	Gender	Relationship to Head	Age	Marital Status	Current level of Education	Schooling status of Children 6-14	If attending School	
								Did [name] miss School for at least 1 week in the last month	What was the reason for missing
	<i>Do not record full name, but only an identifying first name to refer to the household member</i>	1 = Male 2 = Female	1 = Head 2 = Spouse 3 = Child 4 = Parent 5 = Sibling 6 = Grandchild 7 = Grandparent 8 = Orphan taken care of 9 = Other relative 10 = No relation	<i>for children < 6 months, write 0 (below 5 years in</i>	1 = Married 2 = Divorced 3 = Living apart not divorced 4 = Widow or widower 5 = Not married	1 = No Schooling 2 = Some Primary 3 = Completed Primary 4 = Some Secondary 5 = Completed Secondary 6 = Vocational 7 = Some University 8 = Completed University 99 = N/A	1 = Attend Primary 2 = Attend Secondary 3 = Not attending school (Skip to Section 1.11)	1 = Yes 2 = No	1 = Sickness 2 = Work 3 = Household Work 4 = Take care of Siblings 5 = Long Distance to School 6 = School fee not paid 7 = Insecurity 8 = Refuse to go
0									
1									

1.11 Any members of your household chronically ill or disabled?

1 = Yes 2 = No **(Go To Section 2)**

1.11a If yes, how many?

_____ Members

1.12 The Caste/Ethnicity of your household is:

1. Brahmin / Chhetri (specify___) 2. Janjati (Specify:___) 3. Dalit (Specify:___)

SECTION 2 – MIGRATION

2.1 -	Are there any members of your household living or working outside the community?	1 Yes	2 No → Section 3
2.2 -	If yes, then how many people?	_____ persons.	
2.3 -	Where are they currently living/working? CIRCLE ALL THAT APPLY	1 Nepal	2 India
		3 Other (specify) _____	
2.4 -	Is one of these persons the head of household?	1 Yes	2 No
2.5 -	Approximately how much money did this household receive in the last 12 months from all of these persons?	NRs. _____	
2.6	Approximately how many months in a year are members of your household away from the community?	1 = Less than 1 month a year 2 = Between 1 and 3 months a year 3 = Between 3 and 6 months a year 4 = Between 6 and 9 months a year 5 = More than 9 months a year	
2.7	Who are the members of your HH who have migrated in search of employment? CIRCLE ALL THAT APPLY	1__ Boys below the age of 18 years 2__ Men between the ages of 18 and 30 years 3__ Men between the ages of 30 and 50 years 4__ Men above the age of 50 years 5__ Girls below the age of 18 years 6__ Women between the ages of 18 & 30 years 7__ Women between the ages of 30 & 50 years 8__ Women above the age of 50 years	

SECTION 3 – HOUSING AND FACILITIES

3.1 -	Do you or your household own or rent this dwelling?	1 Own → 3.3	2 Don't own but live for free → 3.3
		3 Rent	
3.2 -	How much do you pay per month (in NRs.)	_____ NRs.	
3.3 -	How many units/ rooms does your household occupy?	Units/Rooms _ _	
3.4 -	How many people usually sleep in this dwelling?	_ _ persons	
3.5 -	What is the major construction material of the outside walls?	1 Cement bonded bricks / stones	2 Mud bonded bricks / stones
		3 Wood . Bamboo	

	OBSERVE & RECORD. DO NOT ASK THIS QUESTION	4 Concrete
		5 Other, specify _____
3.6 -	What is the major material of the roof? OBSERVE & RECORD. DO NOT ASK THIS QUESTION	1 Straw / thatch
		2 Earth / mud
		3 Concrete
		4 Tiles / slate
		5 CGI sheet
		6 Other, specify _____
3.7-	What is the major material of the floor? OBSERVE & RECORD. DO NOT ASK THIS QUESTION	1 Earth
		2 Wood
		3 Cement / Stone / Brick
		4 Other, specify _____
3.8 -	What is the main type of household facility your household uses?	1 Flush latrine
		2 Traditional pit latrine
		3 Open pit (no walls)
		4 Communal Latrine
		5 None/bush
3.9	What is the main source of lighting for this house?	1 Electricity
		2 Kerosene, oil or gas lamp, candles
		3 Battery flashlights/fluorescent lights/tube light
		4 Solar panels
		5 No lighting → Section 3.11
		6 Other ____
3.10 -	How much do you pay for lighting per month?	NR _____ s _____
3.11 -	What is your main source of cooking fuel?	1 Cylinder Gas
		2 Bio-gas
		3 Electricity
		4 Wood
		5 Dung
		6 Kerosene
		7 Other, specify _____
3.12 -	How much do you pay for cooking fuel per month?	NR _____ s _____

3.13 -	<p>What is the main source of water for your household?</p> <p>1 = Public tap 6 = Pond, lake, river or stream</p> <p>2 = Tubewell/borehole with pump 7 = Tanker</p> <p>3 = Protected dug well or spring 8 = vendor</p> <p>4 = Unprotected well or spring 9 = Other, specify</p> <p>5 = Rain water</p>	
3.14 -	<p>How far is the main source of water for your household?</p> <p><i>Record both time in minutes and distance in km to access source Write 888 if water on premises, Write 999 if don't know</i></p>	_____ Minutes

SECTION 4 – HOUSEHOLD ASSETS, PRODUCTIVE ASSETS AND ACCESS TO CREDIT

4.1 -	<p>Does your household own any of the following assets?</p> <p>Circle all that apply</p>	<table border="1"> <tr> <td>1</td> <td>Bed</td> <td>7</td> <td>Refrigerator</td> </tr> <tr> <td>2</td> <td>Table</td> <td>8</td> <td>Bicycle</td> </tr> <tr> <td>3</td> <td>Fans / heaters</td> <td>9</td> <td>Motorcycle</td> </tr> <tr> <td>4</td> <td>Radio/Tape</td> <td>10</td> <td>Automobile</td> </tr> <tr> <td>5</td> <td>Television</td> <td>11</td> <td>Bullock cart</td> </tr> <tr> <td>6</td> <td>Sewing machine</td> <td>12</td> <td>Hoes, axes, shovels, spades</td> </tr> </table>	1	Bed	7	Refrigerator	2	Table	8	Bicycle	3	Fans / heaters	9	Motorcycle	4	Radio/Tape	10	Automobile	5	Television	11	Bullock cart	6	Sewing machine	12	Hoes, axes, shovels, spades
1	Bed	7	Refrigerator																							
2	Table	8	Bicycle																							
3	Fans / heaters	9	Motorcycle																							
4	Radio/Tape	10	Automobile																							
5	Television	11	Bullock cart																							
6	Sewing machine	12	Hoes, axes, shovels, spades																							
4.2	<p>Do you have access to a place to borrow money?</p> <p>Circle all that apply</p>	<table border="1"> <tr> <td>1</td> <td>YES – relatives / friends</td> </tr> <tr> <td>2</td> <td>YES – charities / NGOs</td> </tr> <tr> <td>3</td> <td>YES – local lender</td> </tr> <tr> <td>4</td> <td>YES - bank</td> </tr> <tr> <td>5</td> <td>YES – Co-operatives</td> </tr> <tr> <td>6</td> <td>No access to credit (skip to 4.5)</td> </tr> </table>	1	YES – relatives / friends	2	YES – charities / NGOs	3	YES – local lender	4	YES - bank	5	YES – Co-operatives	6	No access to credit (skip to 4.5)												
1	YES – relatives / friends																									
2	YES – charities / NGOs																									
3	YES – local lender																									
4	YES - bank																									
5	YES – Co-operatives																									
6	No access to credit (skip to 4.5)																									
4.3	<p>Do you often purchase food on credit or borrow money to purchase food?</p>	<table border="1"> <tr> <td>1</td> <td>YES</td> <td>2</td> <td>NO → Section 4.5</td> </tr> </table>	1	YES	2	NO → Section 4.5																				
1	YES	2	NO → Section 4.5																							
4.4	<p>If yes, in the last 3 months how often did you use credit or borrow money to purchase food?</p>	<p>1 = On one occasion 2 = On two occasions</p> <p>3 = On three occasions</p> <p>4 = On more than three occasions</p>																								
4.5	<p>Does your household own any farm-animals?</p>	<table border="1"> <tr> <td>1</td> <td>YES</td> <td>2</td> <td>NO → Section</td> </tr> </table>	1	YES	2	NO → Section																				
1	YES	2	NO → Section																							

		5
4.6	<p>If yes, then how many of each of the following animals do you own?</p> <p>(Please circle the animals applicable and note the number beside it)</p>	<p>1. Cows / Bullocks : _____</p> <p>2. Buffaloes : _____</p> <p>3. Goats / Sheep : _____</p> <p>4. Poultry: _____</p> <p>5. Yak / Nak: _____</p> <p>6. Horses / Donkey: _____</p> <p>7. Pig _____</p> <p>8. Other: _____</p>
SECTION 5 – AGRICULTURE		
<i>Please use the following codes for this section:</i>		
Land Access Codes:		
1 = Inherited 2 = Rent 3 = Share-cropping 4 = Bought from private person 5= Other (specify)_____		
Production Codes: 1 = wheat 2 = maize 3 = barley 4 = rice 5 = millets 6 = vegetables 7 = potatoes 8 = fruits 9 = other_____		
5.1a: Do you have access to agricultural land? 1 = YES 2 = NO (<i>Skip to 5.6a</i>)		
5.1b: What is the size of this land (<i>in Kattha or Ropani</i>)? _____ Kattha / Ropani (circle whichever applicable) _____ Hectares		
5.1c: How did you or members of your household acquire this land? (<i>Use Land Access Codes</i>) 5.1c1 _ 5.1c2 _		
5.1d : What is the main source of water for your land? 1 = rainfed 2 = irrigated – Canals/dam 3 = irrigated – Pump 4 = irrigated – river 5 = other_____		
5.2a: With respect to field crop farming, what crops do you cultivate on your land? (<i>See Production codes above</i>) 5.2a1 _ 5.2a2 _ 5.2a3 _ 5.2a4 _		
5.3: For your field crop farming, what is the main source of seeds? (<i>Circle one</i>) 1 = purchase 2 = own stock 3 = Government 4 = purchase and own stock 5 = NGOs/INGOs 6 = Borrow / Exchange		
5.4a: For your field crop farming, what type of fertilizers do you use? 1 = Chemical Fertilizers 2 = Natural Fertilizers → (skip to 5.5a) 3 = None → (skip to 5.5a)		

5.4b: For your **field crop** farming, what is the main source of chemical fertilizer? (*Circle one*)

- 1 = purchase 2 = own stock
 3 = Government 4 = purchase and own stock
 5 = NGOs/INGOs

5.5a Do you use chemical pesticides/herbicides?

- 1 = Yes 2 = No → **skip to 5.6a**

5.5b What are the main sources of chemical pesticides/herbicides (same codes as fertiliser)

- 1 = purchase 2 = own stock
 3 = Government 4 = purchase and own stock
 5 = NGOs/INGOs

5.6a: Do you have a Kitchen garden:

- 1 = YES 2 = NO → **Section 6**

5.6b: What do you produce on this Kitchen garden? (*See codes above*)

5.6b1 |_| **5.6b2** |_| **5.6b3** |_|

SECTION 6 – INCOME

Please complete the following table one activity at the time, using the codes below

		a. - What is your household's [rank] income activity? (use activity code)	b. Who participates in this activity? (use participant code)	c. Of the food consumed by this HH, how much is obtained directly from this activity?(%)
6.1	<u>Main</u>	_ _	_	_ _ _ %
6.2	<u>Second</u>	_ _	_	_ _ _ %
6.3	<u>Third</u>	_ _	_	_ _ _ %
6.4	<u>Fourth</u>	_ _	_	_ _ _ %
		<u>Income activity codes</u>	<u>Participant codes</u>	
		1 = Agriculture and Sales of Crops	1 = Head of the Household only	
		2 = Livestock and Sales of Animals	2 = Spouse of the head of the Household only	
		3 = Brewing	3 = Men only	
		4 = Fishing	4 = Women only	
		5 = Unskilled Wage Labour	5 = Adults only	
		6 = Skilled Labour		

	<p>7 = Handicrafts /Artisan</p> <p>8 = Use of natural. resources (firewood, charcoal, bricks, grass, wild foods, honey...)</p> <p>9 = Petty trading</p> <p>10 = Seller, commercial activity</p> <p>11 = Remittances</p> <p>12 = Salaries, Wages (employees)</p> <p>13. Porter</p> <p>14 = Begging, assistance</p> <p>15 = Government allowance (pension, disability benefit)</p> <p>16 = Others, specify_____</p>	<p>6 = Children only</p> <p>7 = Women & children</p> <p>8 = Men & children</p> <p>9 = Everybody</p>								
6.5 -	Using proportional piling or 'divide the pie' methods, please estimate the relative contribution to total income of each activity (%)	<table border="1"> <tr> <td>1</td> <td>_____ %</td> </tr> <tr> <td>2</td> <td>_____ %</td> </tr> <tr> <td>3</td> <td>_____ %</td> </tr> <tr> <td>4</td> <td>_____ %</td> </tr> </table>	1	_____ %	2	_____ %	3	_____ %	4	_____ %
1	_____ %									
2	_____ %									
3	_____ %									
4	_____ %									

SECTION 7 – EXPENDITURE

In the Past MONTH , how much money have you spent on each of the following items or service? <i>Use the following table, write 0 if no expenditure.</i>		a. - Spent on previous month 1 = Yes 2 = No <i>(if no, go to next item)</i>	b. - Estimated Expenditure in Cash during the last month (NRs.)	c. - Estimated Expenditure in Credit during the last month (NRs.)
7.1 -	Maize	_		
7.2 -	Wheat	_		
7.3 -	Millet	_		
7.4 -	Barley	_		
7.5 -	Rice/Paddy	_		
7.6 -	Roots and tubers <i>(potatoes, yam)</i>	_		
7.7 -	Pulses / Lentils	_		
7.8 -	Vegetables	_		
7.9 -	Milk / Yogurt / Milk products	_		
7.10 -	Fresh fruits / Nuts	_		
7.11 -	Fish	_		
7.12 -	White meat - poultry	_		
7.13 -	Pork	_		
7.14 -	Red meat - goat, sheep	_		
7.15 -	Red meat - Buffalo	_		
7.16 -	Eggs	_		
7.17 -	Oil / Butter / Ghee	_		
7.18 -	Sugar / Salt	_		
7.19 -	Alcohol and tobacco	_		
7.20 -	Soap	_		
7.21 -	Transport	_		
7.22 -	Firewood / charcoal	_		

7.23 -	Kerosene	_		
In the Past 6 MONTHS (semester), how much money have you spent on each of the following items or service? <i>Use the following table, write 0 is no expenditure.</i>				
		NRs.		NRs.
7.24 -	Equipment, tools, seeds		7.30 -	Celebrations, social events, funerals, weddings
7.25-	Hiring labour		7.31 -	Fines / Taxes
7.26 -	Medical expenses, health care		7.32 -	Debts
7.27 -	Education, school fee		7.33 -	Construction, house repair
7.28 -	Clothing, shoes		7.34 -	Other Long term expenditure, specify
7.29	Veterinary expenses			

SECTION 8 - FOOD SOURCES AND CONSUMPTION

Could you please tell me how many **days** in the past week your household has eaten the following foods and what the source was (*use codes on the right, write 0 for items not eaten over the last 7 days and if several sources, write all*)

	Food Item	# of days eaten last 7 days	Food Source (write all)	Food Source codes
8.1a-	Maize	_	_ , _ , _	Food Source codes 1 = Own production (crops, animals) 2 = hunting, fishing 3 = gathering 4 = borrowed 5 = purchase with wages 6 = exchange labor for food 7 = exchange items for food 8 = gift (food) from family relatives 9 = food aid (NGOs etc.) 10 = Other (specify: _____)
8.1b-	Rice/Paddy	_	_ , _ , _	
8.1c	Millet	_	_ , _ , _	
8.1d-	Roots and tubers (potatoes, yam)	_	_ , _ , _	
8.1e-	Wheat / Barley	_	_ , _ , _	
8.1f-	Fish	_	_ , _ , _	
8.1g-	White meat - poultry	_	_ , _ , _	
8.1h-	Pork	_	_ , _ , _	
8.1i-	Red meat - goat, sheep	_	_ , _ , _	
8.1j-	Red meat -Buffalo	_	_ , _ , _	
8.1k-	Eggs	_	_ , _ , _	
8.1l-	Pulses / Lentils	_	_ , _ , _	
8.1m	Vegetables	_	_ , _ , _	

-			
8.1n-	Oil / Ghee / Butter	_	_ , _ , _
8.1o-	Fresh fruits	_	_ , _ , _
8.1p-	Sugar / Salt	_	_ , _ , _
8.1q-	Milk / Curd	_	_ , _ , _
8.2 -	Has any member of your household received food aid in the last 6 months?	1 yes	2 No → 8.4
8.3 -	If yes, please specify the type of program and the number of beneficiary in your household? circle all that apply and specify number of beneficiaries in the last column	1 School feeding	_ _
		2 Food for work/for assets	_ _
		3 Supplementary feeding	_ _
		4 Other, specify _____	_ _
8.4-	Has any member of your household received any other type of external assistance beside food aid in the last 6 months?	1 Yes	2 No → Section 9
8.5-	If yes, from whom? Circle all that apply	1 World Food Programme	
		2 SAPPROSC / DEPROSC	
		3 Save the Children	
		4 UNICEF	
		5 GT2 / SNV / DFID	
		6 French Cooperation	
		7 The government	
		8 Other, specify _____	
8.6-	If yes, what type of assistance? Circle all that apply	1 Food products	
		2 Money allowances / loans	
		3 For education (fee, books, uniforms)	
		4 For medical services	
		5 Construction material, building	
		6 Agricultural assistance (tools / seeds)	
		7 Other, specify _____	

SECTION 9 – SHOCKS AND FOOD SECURITY (IF NO SHOCKS GO TO SECTION 10)

9.1- By order of importance, what were the 4 main problems / shocks you faced in the last 12 months?
Do not read options, write number in front of the identified cause by order of importance

_	A. Drought/irregular rains / Hailstorms	_	G. Unusually high level of human disease	_	L. Serious illness or accident of household member
_	B. Floods	_	H. Unavailability of food	_	M. Death of a working household member
_	C. Landslides, erosion	_	I. High costs of agric. inputs (seed, fertilizer, etc.)	_	N. Death of other household member
_	D. Unusually high level of crop pests & disease	_	J. Loss of employment for a household member	_	P. Theft of Animals
_	E. Unusually high level of livestock diseases	_	K. Reduced income of a household member	_	Q. Conflict
_	F. Lack of employment	_	G. Bandh	_	

For the four main shocks above, please complete the following table using the codes below. Please be consistent in the ranking. Complete one line at the time.

Rank & Cause (copy code from above the four main causes)	9.2- Did [cause] create a decrease or loss for your household of: 1 = Income & in-kind receipts 2 = Assets (e.g. livestock, cash savings) 3 = Both income and assets 4 = No change (Write number)	9.3- Did [cause] create a decrease in your household's ability to produce or purchase enough food to eat for a period of time (not including the annual 'lean season')? 1 = Yes 2 = No 3 = Don't know	9.4- What did the household do to compensate or resolve these decreases or losses of income and/or assets caused by shocks <i>Use codes below, record all used</i>	9.5 - Has the household recovered from the decrease in income or assets or both from the shocks. 1 = Not recovered at all 2 = Partially recovered 3 = Completely recovered
1. _____	_	_	1. _ _, 2. _ _,	_
2. _____	_	_	1. _ _, 2. _ _,	_
3. _____	_	_	1. _ _, 2. _ _,	_
4. _____	_	_	1. _ _, 2. _ _,	_

01 = Rely on less preferred, less expensive food
02 = Borrowed food, helped by relatives
03 = Purchased food on credit
04 = Consumed seed stock held for next season
05 = Reduced the proportions of the meals
06 = Reduced number of meals per day
07 = Skipped days without eating
08 = Some HH members migrated temporarily (< 6 months)
09 = Some HH members migrated (> 6 months)
10 = Reduced expenditures on health and education
11 = Spent savings
12 = Borrowed money
13 = Sold HH articles (utensils, blankets) or jewelry

14 = Sold agricultural tools, seeds, ...
15 = Sold building materials
16 = Sold HH furniture
17 = Sold HH poultry,
18 = Sold small animals – goats, cheep
19 = Sold big animals – oxen, cow, bulls
20 = Rented out land
21 = Sold land
22 = Worked for food only
23 = Other, specify _____
24 = Other, specify _____

Appendix D GIS Technical Guidance

GIS Buffer Analysis—Technical Guide/Steps

This approach was used in analyzing the impact of vegetation coverage in Nepal on household food security. Also, this was used to analyze the impact of district level and vdc level conflict and road density on household food security. The steps of each are provided here (the ARC GIS commands are in bold).

I. Vegetation Analysis

Steps:

- 1) **Add data:** Bring in VDC map of Nepal
- 2) **Geoprocessing—Buffer:** Create buffers using this tool, indicate the distance around the VDC that is needed. This produces buffers around the border of the VDC, but also includes the VDC.

Buffers around districts could also be created.

- 3) **Clipped:** After creating buffers, I clipped those buffers that go beyond the Nepal borders. Leaving them would be okay, but one would need to ignore this area when calculating the land cover type in that area.
- 4) **Add data:** Bring in raster images of land use, and be sure to check the properties are what is expected
- 5) **(Third Party Program) GME IsectPoly (or Zonal Statistics** within ARCMAP which requires the correct license): Use this program to get a profile of land cover in each of the VDCs. A previous tool, Hawth's tool, was replaced by the GME program. This can be downloaded, with instructions, for free (<http://www.spataleecology.com/gme/>)
Use the analysis tool for each geographic area—VDC, and each buffer. This may need to be done separately for each area. Note: Sometimes the GME tool requires the path to the buffer shapefile to be somewhat short. So, copy the necessary files directly into the D folder before running the analysis—the analysis could take over night
Be sure to click “True” for thematic raster image (such as the vegetation raster)
Here is sample code used to analyze the 10 km vdc buffers

```
isectpolrst(in="D:\Steve\Buffers\clip10.shp", raster="D:\Steve\2000\2000lc.img",  
prefix="buf10", thematic=TRUE);
```

The output will be added as new columns to the attribute table of your shapefile.

- 6) **Export** attribute table for the shapefile that was analyzed. Then, it will be ready to save as a csv file, which can be brought into Stata.

Non-GIS Steps for analyzing “rings”

- 7) There will be a count of raster cells for each category, or theme of the data. The buffer produced includes the area of the vdc being analyzed. To get the % of the area of a certain theme type, simply divide the raster cells of that theme by the total raster cells counted.

- 8) If the interest is the vegetation quality in the area outside of the vdc (say the 10km ring around the vdc), it is necessary to subtract the count of the vdc raster cells from the buffer raster cells. The example below considers theme 1 in a 10 km ring around the vdc.

A) Count of theme 1 in 10 km ring around VDC = raster cells of theme 1 in the buffer – raster cells of theme 1 in the VDC.

Now, to get a percentage of theme one in ring, it is necessary to divide by the total number of raster cells counted in the shapefile. But again, subtract the total of the vdc raster cells from the buffer raster cells. I considered both primary and secondary forest.

B) Count of all raster cells in 10 km ring around VDC = total raster cells in the buffer – total raster cells in the VDC.

Now, to get the % of theme one in the ring, divide the result from A) by the result from B)

C) % of theme 1 in 10 km ring = Count of theme 1 in 10 km ring around VDC / Count of all raster cells in 10 km ring around VDC

II. Other GIS attributes at VDC and District level

Road Density

To calculate the road density, the same steps were followed as above. Using the GME program, I analyzed the quantity of roads (by type or theme) in each VDC. I also did this for the district level. Following the steps above, I subtracted quantity of roads at the VDC level from that of the VDC. I included all roads (except railway and footpaths). Then, I did a similar analysis for footpaths only. By dividing by the geographic area, I had the road density.

Violence

To calculate the violence, I added up the total number of persons killed in the area of interest (VDC and District). When analyzing the effects of violence beyond the VDC where the household observation resides, I subtracted the total deaths in the vdc from the total deaths at the district level.

Appendix E Household Food Security Stata Code

Stata code from the econometric analysis. This includes combining data from the World Food Program, GIS, conflict data, and NLSS data.

```
/*Forest vegetation data
first: bring in 1990 forest data merge with 2000 data*/
clear all
clear matrix
drop _all
set memory 500m
set matsize 800
global DIR "D:\Data\users\sarchambault\dissertation_data\"

use ${DIR}forest_buff_1990.dta
merge 1:1 vdcdistfixc100 using ${DIR}forest_buff_2000.dta
drop _merge
/*deforestation*/
/*NO BUFFER
0      unidentified, 1 Mature, 2 secondary, 3 degraded, 4 farmland,
5 bareland, 6 cloud and snow, 7 unidentified*/
/*total area of VDC and individual buffers--adding up area of all land cover types*/
gen vdc_sum=t2000_1+t2000_2+t2000_3+t2000_4+t2000_5
gen vdc5_sum=(t1_5+t2_5+ t3_5+ t4_5+ t5_5)
gen vdc10_sum=(t1_10+t2_10+ t3_10+ t4_10+ t5_10)
gen vdc20_sum=(t1_20+t2_20+ t3_20+ t4_20+ t5_20)
gen vdc30_sum=t1_30+t2_30+ t3_30+ t4_30+ t5_30
gen vdc40_sum=t1_40+t2_40+ t3_40+ t4_40+ t5_40
gen vdc50_sum=t1_50+t2_50+ t3_50+ t4_50+ t5_50
/*% vegetation cover: vdc, 10km, 20km, 30km*/
gen forest_vdc=(t2000_1+t2000_2)/vdc_sum
gen forest_vdc10=(t2_10+t1_10)/vdc10_sum
gen forest_vdc20=(t2_20+t1_20)/vdc20_sum
gen forest_vdc30=(t2_30+t1_30)/vdc30_sum

/*subtracting out vdc deforestation, and subtracting out each additional buffer--10, 20, 30
to create "donoughts"*/
gen forest_vdc10a=(t2_10+t1_10-(t2000_1+t2000_2))/(vdc10_sum-vdc_sum)
gen forest_vdc20b=(t2_20+t1_20-(t1_10+t2_10))/(vdc20_sum-vdc10_sum)
gen forest_vdc30b=(t2_30+t1_30-(t1_20+t2_20))/(vdc30_sum-vdc20_sum)
gen vdistrict=lower(vdc_dist2)
destring v40, replace
save ${DIR}forest_buff_20001990.dta, replace
/*Social Capital Index*/
clear all
clear matrix
drop _all
set memory 500m
set matsize 800
```

```

/*first I brought in the rural household id file*/
use ${DIR}rural/R1A1.dta
ren S1A1_WNO wardno
ren S1A1_01 hhsward
ren S1A1_02 popward
ren S1A1_VDC vdcname
/*this merges to my nlss_match with dist names....you may have your own file*/
merge 1:1 WWW using ${DIR}nlss_match.dta
drop _merge
save ${DIR}rural_ward_data2.dta, replace
/*now brining in social capital data--I only have used the 2003 data*/
clear all
clear matrix
drop _all
set memory 500m
set matsize 800
use ${DIR}rural/R1A1.dta
ren S1A1_WNO wardno
ren S1A1_01 hhsward
ren S1A1_02 popward
ren S1A1_VDC vdcname
merge 1:1 WWW using ${DIR}nlss_match.dta
drop _merge
save ${DIR}rural_ward_identifiers.dta, replace
/*now brining in social capital data*/
clear all
clear matrix
drop _all
set memory 500m
set matsize 800
use ${DIR}rural/R5B2.dta
merge m:1 WWW using ${DIR}rural_ward_identifiers.dta
drop _merge
/*type of group*/
gen type_text=S5B2_09
destring type_text, replace
/*replace missing group categories*/
replace type_text=3 if S5B2_08=="FORESTRY USER"
replace type_text=4 if S5B2_08=="CREDIT GROUP"
replace type_text=1 if S5B2_08=="FARMERS GROUP"
replace S5B2_10B=0 if S5B2_10B==.
rename S5B2_12 perc_women
rename S5B2_13 meet_no
replace perc_women=0 if perc_women==.
replace meet_no=0 if meet_no==.
replace perc_women=perc_women/100
gen per_of_hhs=(S5B2_11/hhsward)
gen ageyears=S5B2_10A+(S5B2_10B/12)

```

```

replace ageyears=0 if ageyear==.
gen ag_type=0
replace ag_type=1 if type_text==1
gen forest_type=0
replace forest_type=1 if type_text==3
gen credit_type=0
replace credit_type=1 if type_text==4
gen water_type=0
replace water_type=1 if type_text==2
gen women_type=0
replace women_type=1 if type_text==5
gen other_type=0
replace other_type=1 if type_text==6
replace per_of_hhs=0 if per_of_hhs==.
gen for_age=forest_type*ageyears
gen for_perhhs=forest_type*per_of_hhs
gen for_perwo=forest_type*perc_women
gen for_meet=forest_type*meet_no
gen water_age=water_type*ageyears
gen water_perhhs=water_type*per_of_hhs
gen water_perwo=water_type*perc_women
gen water_meet=water_type*meet_no
gen credit_age=credit_type*ageyears
gen credit_perhhs=credit_type*per_of_hhs
gen credit_perwo=credit_type*perc_women
gen credit_meet=credit_type*meet_no
gen women_age=women_type*ageyears
gen women_perhhs=women_type*per_of_hhs
gen women_perwo=women_type*perc_women
gen women_meet=women_type*meet_no
gen other_age=other_type*ageyears
gen other_perhhs=other_type*per_of_hhs
gen other_perwo=other_type*perc_women
gen other_meet=other_type*meet_no
gen ag_age=ag_type*ageyears
gen ag_perhhs=ag_type*per_of_hhs
gen ag_perwo=ag_type*perc_women
gen ag_meet=ag_type*meet_no
rename dist_code distric2
egen num_HHs_www_sample=count(distric2), by(distric2)
egen for_ages=sum(for_age),by(distric2)
egen for_perhhs=sum(for_perhhs),by(distric2)
egen for_perwos=sum(for_perwo),by(distric2)
egen for_meets=sum(for_meet),by(distric2)
egen water_ages=sum(water_age),by(distric2)
egen water_perhhs=sum(water_perhhs),by(distric2)
egen water_perwos=sum(water_perwo),by(distric2)
egen water_meets=sum(water_meet),by(distric2)

```



```

egen credit_ages=sum(credit_age),by(district2)
egen credit_perhss=sum(credit_perhhs),by(district2)
egen credit_perwos=sum(credit_perwo),by(district2)
egen credit_meets=sum(credit_meet),by(district2)
egen women_ages=sum(women_age),by(district2)
egen women_perhss=sum(women_perhhs),by(district2)
egen women_perwos=sum(women_perwo),by(district2)
egen women_meets=sum(women_meet),by(district2)
egen other_ages=sum(other_age),by(district2)
egen other_perhss=sum(other_perhhs),by(district2)
egen other_perwos=sum(other_perwo),by(district2)
egen other_meets=sum(other_meet),by(district2)
egen ag_ages=sum(ag_age),by(district2)
egen ag_perhss=sum(ag_perhhs),by(district2)
egen ag_perwos=sum(ag_perwo),by(district2)
egen ag_meets=sum(ag_meet),by(district2)
keep devreg belt district2 dist_name ag_ages ag_perhss ag_perwos ///
ag_meets other_ages other_perhss other_perwos other_meets women_ages ///
women_perhss women_perwos women_meets credit_ages credit_perhss ///
credit_perwos credit_meets water_ages water_perhss water_perwos ///
water_meets for_ages for_perhss for_perwos for_meets
duplicates drop
/*want to know how districts stack up to one another*/
egen year_max_for=max(for_age)
egen year_min_for=min(for_age)
egen hhs_max_for=max(for_perhhs)
egen hhs_min_for=min(for_perhhs)
egen wo_min_for=min(for_perwo)
egen wo_max_for=max(for_perwo)
egen meets_max_for=max(for_meet)
egen meets_min_for=min(for_meet)
egen year_max_water=max(water_age)
egen year_min_water=min(water_age)
egen hhs_max_water=max(water_perhhs)
egen hhs_min_water=min(water_perhhs)
egen wo_min_water=min(water_perwo)
egen wo_max_water=max(water_perwo)
egen meets_max_water=max(water_meet)
egen meets_min_water=min(water_meet)
egen year_max_ag=max(ag_age)
egen year_min_ag=min(ag_age)
egen hhs_max_ag=max(ag_perhhs)
egen hhs_min_ag=min(ag_perhhs)
egen wo_min_ag=min(ag_perwo)
egen wo_max_ag=max(ag_perwo)
egen meets_max_ag=max(ag_meet)
egen meets_min_ag=min(ag_meet)
egen year_max_other=max(other_age)

```

egen year_min_other=min(other_age)
 egen hhs_max_other=max(other_perhhs)
 egen hhs_min_other=min(other_perhhs)
 egen wo_min_other=min(other_perwo)
 egen wo_max_other=max(other_perwo)
 egen meets_max_other=max(other_meet)
 egen meets_min_other=min(other_meet)
 egen year_max_women=max(women_age)
 egen year_min_women=min(women_age)
 egen hhs_max_women=max(women_perhhs)
 egen hhs_min_women=min(women_perhhs)
 egen wo_min_women=min(women_perwo)
 egen wo_max_women=max(women_perwo)
 egen meets_max_women=max(women_meet)
 egen meets_min_women=min(women_meet)
 egen year_max_credit=max(credit_age)
 egen year_min_credit=min(credit_age)
 egen hhs_max_credit=max(credit_perhhs)
 egen hhs_min_credit=min(credit_perhhs)
 egen wo_min_credit=min(credit_perwo)
 egen wo_max_credit=max(credit_perwo)
 egen meets_max_credit=max(credit_meet)
 egen meets_min_credit=min(credit_meet)
 gen foryears=((for_age-year_min_for)^1)/(year_max_for-year_min_for)
 gen forhhsd=((for_perhhs-hhs_min_for)^1)/(hhs_max_for-hhs_min_for)
 gen forwosd=((for_perwo-wo_min_for)^1)/(wo_max_for-wo_min_for)
 gen formeetsd=((for_meet-meets_min_for)^1)/(meets_max_for-meets_min_for)
 gen agyears=((ag_age-year_min_ag)^1)/(year_max_ag-year_min_ag)
 gen aghhsd=((ag_perhhs-hhs_min_ag)^1)/(hhs_max_ag-hhs_min_ag)
 gen agwosd=((ag_perwo-wo_min_ag)^1)/(wo_max_ag-wo_min_ag)
 gen agmeetsd=((ag_meet-meets_min_ag)^1)/(meets_max_ag-meets_min_ag)
 gen womenyears=((women_age-year_min_women)^1)/(year_max_women-year_min_women)
 gen womenhhsd=((women_perhhs-hhs_min_women)^1)/(hhs_max_women-hhs_min_women)
 gen womenwosd=((women_perwo-wo_min_women)^1)/(wo_max_women-wo_min_women)
 gen womenmeetsd=((women_meet-meets_min_women)^1)/(meets_max_women-meets_min_women)
 gen credityears=((credit_age-year_min_credit)^1)/(year_max_credit-year_min_credit)
 gen credithhsd=((credit_perhhs-hhs_min_credit)^1)/(hhs_max_credit-hhs_min_credit)
 gen creditwosd=((credit_perwo-wo_min_credit)^1)/(wo_max_credit-wo_min_credit)
 gen creditmeetsd=((credit_meet-meets_min_credit)^1)/(meets_max_credit-meets_min_credit)
 gen othereyears=((other_age-year_min_other)^1)/(year_max_other-year_min_other)
 gen otherhhsd=((other_perhhs-hhs_min_other)^1)/(hhs_max_other-hhs_min_other)
 gen otherwosd=((other_perwo-wo_min_other)^1)/(wo_max_other-wo_min_other)
 gen othermeetsd=((other_meet-meets_min_other)^1)/(meets_max_other-meets_min_other)
 gen wateryears=((water_age-year_min_water)^1)/(year_max_water-year_min_water)
 gen waterhhsd=((water_perhhs-hhs_min_water)^1)/(hhs_max_water-hhs_min_water)
 gen waterwosd=((water_perwo-wo_min_water)^1)/(wo_max_water-wo_min_water)
 gen watermeetsd=((water_meet-meets_min_water)^1)/(meets_max_water-meets_min_water)

```

egen waterindex=sum(wateryears+waterhh+d+waterwod+watermeetsd), by(district)
egen forindex=sum(foryears+forhh+d+forwod+formeetsd), by(district)
egen womenindex=sum(womenyears+womenhh+d+womenwod+womenmeetsd), by(district)
egen creditindex=sum(credityears+credithh+d+creditwod+creditmeetsd), by(district)
egen otherindex=sum(othereyears+otherhh+d+otherwod+othermeetsd), by(district)
egen agindex=sum(agyyears+aghh+d+agwod+agmeetsd), by(district)
egen totindex=sum(waterindex+forindex+womenindex+creditindex+otherindex+agindex),
by(district)
egen totindex_no=sum(waterindex+forindex+womenindex+creditindex+otherindex+agindex),
by(district)
egen agwatforindex=sum(waterindex+forindex+agindex), by(district)
save ${DIR}soc_cap_index.dta, replace
/*newspaper data*/
clear all
clear matrix
drop _all
set memory 500m
set matsize 800
use ${DIR}Z06A.dta
destring WWW, replace
destring WWWHH, replace
destring HH, replace
gen newspapers=0
replace newspapers=1 if ITM==234
merge m:1 WWW using ${DIR}nlss_match.dta
replace newspapers=0 if _merge==2
drop _merge
egen newspapers_dist=count(newspapers), by(dist_name)
keep newspapers_dist dist_name
duplicates drop
merge 1:1 dist_name using ${DIR}soc_cap_index.dta
drop _merge
save ${DIR}newspapers_index.dta, replace
/*now brining in total fuelwood data*/
clear all
clear matrix
drop _all
set memory 500m
set matsize 800
use ${DIR}Z02D.dta
merge m:m WWWHH using ${DIR}Z18B/Z02D.dta
drop _merge
merge m:1 WWW using ${DIR}nlss_match.dta
drop _merge
destring WWW, replace
destring WWWHH, replace
destring HH, replace
gen woodbasket=0

```

```

replace woodbasket=1 if V02D_03A==1
replace V02D_03B=0 if V02D_03B==.
gen wood_basket_month=woodbasket*V02D_03B
egen month_wood=mean(wood_basket_month), by(dist_name)
keep dist_name month_wood
duplicates drop
replace month_wood=0 if month_wood==.
merge 1:1 dist_name using ${DIR}newspapers_index.dta
drop _merge
replace distric2=69 if dist_name=="Achham"
replace distric2=64 if dist_name=="Kalikot"
replace distric2=41 if dist_name=="Manang"
keep dist_name month_wood newspapers_dist distric2 ///
totindex waterindex agindex forindex womenindex creditindex otherindex
duplicates drop
/*gen mean values for those districts without data*/
egen month_wooda=mean(month_wood)
egen newspapers_dista=mean(newspapers_dist)
egen forindexa=mean(forindex)
egen agindexa=mean(agindex)
egen waterindexa=mean(waterindex)
egen otherindexa=mean(otherindex)
egen creditindexa=mean(creditindex)
egen womenindexa=mean(womenindex)
egen totindexa=mean(totindex)
save ${DIR}soc_cap_index2.dta, replace
/*prices of food*/
clear all
clear matrix
drop _all
set memory 500m
set matsize 800
use ${DIR}Z05A.dta
destring WWW, replace
destring WWWHH, replace
destring HH, replace
merge m:1 WWW using ${DIR}nlss_match.dta
drop _merge
keep if ITM==12 & V05A_01==1
/*pathi to kilo*/
replace V05A_03A=V05A_03A*3.7 if V05A_03B==6
/*price rice per kilo*/
gen price_rice_www=V05A_04/V05A_03A
egen price_riced=mean(price_rice_www), by(dist_name)
keep price_riced dist_name
duplicates drop
egen pricea=mean(price_riced)
replace price_riced=pricea if price_riced==.

```

```

merge 1:1 dist_name using ${DIR}soc_cap_index2.dta
drop _merge
gen dist_code=distric2
save ${DIR}soc_cap_index_prices.dta, replace
/*Bring in WFP DATA*/
clear all
clear matrix
drop _all
set memory 500m
set matsize 800
/*combine WFP HH Data*/
insheet using ${DIR}variables hh.csv
destring vdc_code, replace
sort vdc_code
save sort_nepal_hh_1, replace
clear all
clear matrix
drop _all
set memory 100m
set matsize 800
insheet using ${DIR}nepal_hh_2.csv
destring vdc_code, replace
sort vdc_code
save sort_nepal_hh_2, replace
merge 1:1 quest using sort_nepal_hh_1
drop _merge
sort vdc_code
egen vdistrict=concat(vdcs2 distric2), punct("_")
sort vdistrict
save nepal_1_2_merged, replace
clear matrix
drop _all
set memory 100m
set matsize 800
insheet using ${DIR}individual_nepala.csv
drop if s1_14==.
drop if truefalse=="TRUE"
merge m:1 quest using nepal_1_2_merged
drop _merge
save ${DIR}nepal_hh_indva.dta, replace
drop _all
set memory 100m
set matsize 800
insheet using ${DIR}conflict_one.csv
egen vdistrict=concat(vdcs2 distric2), punct("_")
merge 1:m vdc_code using ${DIR}nepal_hh_indva.dta
drop _merge
egen distkill =sum(totkill), by(distid)

```

```

sum distkill
save ${DIR}nepal_conflict_merge.dta, replace
/*clean up VDC and District Names so data matches up*/
rename vdc2 vname
gen vdc_dist=vdc2
rename vname vname_temp
gen vname=strupper(vname_temp)
replace vname=upper(vname)
replace vdc_dist=upper(vdc_dist)
replace distric2="SINDHUPALCHOK" if vdc_dist=="MANKHA_KUNCHOK"
replace distric2="CHITAWAN" if distric2=="CHITWAN"
replace distric2="ILAM" if distric2=="ILAM"
replace distric2="dhanusa" if distric2=="dhanusha"
replace distric2="DOTI" if vdc_dist=="LADAGADA_DOTI"
replace vname="BHIMMAPUR" if vdc_dist=="BHIMAPUR_BARDIA"
replace vname="ARBAN" if vdc_dist=="AARUARBANG_GORKHA"
replace vname="ANKHIBHUI" if vdc_dist=="ANKHIBHUI_SANKHUWASABHA"
replace vname="BALTHALI" if vdc_dist=="BALTING_KAVRE"
replace vname="WANTA" if vdc_dist=="WANGLA_ARGHAKHANCHI"
replace vname="WANTA" if vdc_dist=="WANGLA_ARGHAKHANCHI"
replace vname="DHATAN" if vdc_dist=="GHATAN_MYAGDI"
replace vname="BAMANGAMA KATTI" if vdc_dist=="BAMANGAMAKATTI_SAPTARI"
replace vname="BELDANA" if vdc_dist=="BELDANDI_KANCHANPUR"
replace vname="BETINI" if vdc_dist=="BETENI_NUWAKOT"
replace vname="BHAKIMLI" if vdc_dist=="BHAKIMLI_MYAGDI"
replace vname="BHIMMAPUR" if vdc_dist=="BHIMAPUR_BARDIYA"
replace vname="BHUMISTHAN" if vdc_dist=="BHUMESTHAN_DHADING"
replace vname="BHUMLINCHOK" if vdc_dist=="BHUMLICHOK_GORKHA"
replace vname="PIPALTARI" if vdc_dist=="BITALAWAPIPALTARI_PARBAT"
replace vname="BHUDHABARE" if vdc_dist=="BUDHABARE_JHAPA"
replace vname="CHAMAITA" if vdc_dist=="CHAMETA_ILAM"
replace vname="PHIKKAL BAZAR" if vdc_dist=="PHIKALBAZAR_ILAM"
replace vname="BARBOTA" if vdc_dist=="BARBOTE_ILAM"
replace vname="CHAUKHAM" if vdc_dist=="CHAUKHAM_BAITADI"
replace vname="CHHUSAN" if vdc_dist=="CHHUSANG_MUSTANG"
replace vname="DARSIN DAHATHUM" if vdc_dist=="DARSINGDAHATHUM_SYANGJA"
replace vname="DHANUSAGHAM" if vdc_dist=="DHANUSADHAM_DHANUSA"
replace vname="DHANAWANG" if vdc_dist=="DHANWANG_SALYAN"
replace vname="DHIKUREPOKHARI" if vdc_dist=="DHIKUREPOKHARI_KASKI"
replace vname="DHITAR" if vdc_dist=="DHITAL_KASKI"
replace vname="DODHAR" if vdc_dist=="DODHARA_KANCHANPUR"
replace vname="DUBIDADA" if vdc_dist=="DUBIDANDA_ROLPA"
replace vname="PHAGAUM" if vdc_dist=="FAGAAM_ROLPA"
replace vname="PHAKHEL" if vdc_dist=="FAKHEL_MAKWANPUR"
replace distric2="makawanpur" if distric2=="makwanpur"
replace vname="PADAM POKHARI" if vdc_dist=="PADAMPOKHARI_MAKWANPUR"
replace vname="LEKHGAU" if vdc_dist=="LEKHGAUN_BAJHANG"
replace vname="KOTBHAIRAB" if vdc_dist=="KOT_BHAIRAB_BAJHANG"

```

replace vname="SHIKHARPUR" if vdc_dist=="SIKHARPUR_BAITADI"
 replace vname="SHANKARPUR" if vdc_dist=="SANKARPUR_DARCHAULA"
 replace vname="panchkhuwa deurali" if vdc_dist=="PANCHKHUWADEURALI_GORKHA"
 replace vname="pratappur paltuwa" if vdc_dist=="PRATAPPURPALTUWA_RAUTAHAT"
 replace vname="pokhari bhanjyang" if vdc_dist=="POKHARI BHANJYANG_TANAHU"
 replace distric2="tanahun" if distric2=="tanahu"
 replace vname="GARJYANGKOT" if vdc_dist=="GARJYANGKOT_JUMLA"
 replace vname="JIRMALA" if vdc_dist=="JIRMALE_ILAM"
 replace vname="HARINAGARA" if vdc_dist=="HARINAGAR_SUNSARI"
 replace vname="HEMJA" if vdc_dist=="HEMAJA_KASKI"
 replace vname="JYMARUKOT" if vdc_dist=="JAMARKOT_MYAGDI"
 replace vname="MANANG (W)" if vdc_dist=="MANANG_MANANG"
 replace distric2="manang" if vdc_dist=="MANANG_MANANG"
 replace vname="KADEM" if vdc_dist=="KADEL_BAJHANG"
 replace vname="KHAHAREPAGU" if vdc_dist=="KHAHAREPANGU_KAVRE"
 replace vname="MAJHATHANA" if vdc_dist=="MAJHATHANA_KASKI"
 replace vname="LADAGADA" if vdc_dist=="LADAGADA_DOTI"
 replace vname="LIBAN" if vdc_dist=="LIWANG_ROLPA"
 replace vname="LWANG GHALAIL" if vdc_dist=="LWANGGHALE_KASKI"
 replace vname="BAKOHUWA" if vdc_dist=="LOHAJARA_SAPTARI(AVG)"
 replace vname="BAKOHUWA" if vdc_dist=="LOHAJARA_SAPTARI"
 replace distric2="SAPTARI" if vdc_dist=="LOHAJARA_SAPTARI(AVG)"
 replace vname="NAKAISIN" if vdc_dist=="MAKAISING_GORKHA"
 replace vname="MALAKHET" if vdc_dist=="MALAKHETI_KAILALI"
 replace vname="MALIKATHAT" if vdc_dist=="MALIKATHOTA_JUMLA"
 replace vname="KARKI MANAKAMANA" if vdc_dist=="MANAKAMANA_NUWAKOT"
 replace vname="SHIKH" if vdc_dist=="SHIKHA_MYAGDI"
 replace vname="MAKHA" if vdc_dist=="MANKHA_KUNCHOK"
 replace vname="MUDEGAU" if vdc_dist=="MUDHEGAU_DOTI"
 replace vname="NAUWAKHIR" if vdc_dist=="NAUWAKHORPRASHAHI_DHANUSA"
 replace vname="SARANKOT" if vdc_dist=="SARANGKOT_KASKI"
 replace vname="NAVADURGA" if vdc_dist=="NAWADURGA_DADELDHURA"
 replace vname="PASANG" if vdc_dist=="PISANG_MANANG"
 replace vname="SHANKARPUR" if vdc_dist=="SANKARPUR_DARCHAULA"
 replace vname="PAKBADI" if vdc_dist=="PAKWADI_SYANGJA"
 replace vname="THULOSIRBARI" if vdc_dist=="THULOSIRUBARI_SINDHUPALCHOWK"
 replace vname="PIPALE" if vdc_dist=="PIPLE_CHITWAN"
 replace vname="SIPALE CHILAUNE" if vdc_dist=="SIPALICHILAUNE_KAVRE"
 replace vname="SUBHAN" if vdc_dist=="SUMANG_PANCHTHAR"
 replace vname="TINLA" if vdc_dist=="TINGLA_SOLUKHUMBU"
 replace vname="ELADI" if vdc_dist=="YALADI_SYANGJA"
 replace vname="NAKAISIN" if vdc_dist=="BARBOTA_KANCHANPUR"
 replace vname="DHANUSAGHAM" if vdc_dist=="DHANUSHADHAM_DHANUSA"
 replace vname="MALIKATHAT" if vdc_dist=="DHIKUPOKHARI_KASKI "
 replace vname="KARKI MANAKAMANA" if vdc_dist=="GARJYANGKOT_Jumla"
 replace vname="MAKHA" if vdc_dist=="LADAGADA_Doti"
 replace vname="NAUWAKHIR" if vdc_dist=="YAGYABHUMI_DHANUSA"
 replace vname="NAUWAKHIR" if vdc_dist=="khimdada_Arghakhanchi"


```

replace vname="SORAHAWA" if vdc_dist=="SORHAWA_BARDIA"
replace distric2="bardiya" if distric2=="Bardia"
replace vname="KHIMDADA" if vdc_dist=="Arghakhanchi_KEEMADADA"
replace distric2="ARGHAKHANCHI" if distric2=="arghakhanchi"
replace vname="SONOGAMA" if vdc_dist=="SONIGAMA_DHANUSA"
replace vname="YAGYA BHUMI" if vdc_dist=="YAGYABHUMI_DHANUSA"
replace distric2="DHANUSHA" if distric2=="DHANUSA"
replace distric2="DHANUSA" if vdc_dist=="YADUKUHA_DHANUSA"
replace vname="YADUKOHA" if vdc_dist=="YADUKUHA_DHANUSA"
replace distric2="darchula" if distric2=="Darchaula"
replace vname="MAKHA" if vdc_dist=="MANKHA_SINDHUPALCHOWK"
replace distric2="SINDHUPALCHOK" if distric2=="Sindhupalchowk"
rename vdistrict vdistrictcode
replace vname=lower(vname)
/*rename district districttemp*/
rename district districtfirst
gen district=lower(district2)
egen vdistrict=concat(vname district), punct("_")
merge m:1 vdistrict using ${DIR}forest_buff_20001990.dta
drop _merge
destring vdc_code, replace
sort vdc_code
/*distance to water*/
gen waterdist=s3_314
replace waterdist=0 if s3_314==888
replace waterdist=3.85 if s3_314==999
gen waterdistmin=waterdist/60

/*food index*/
/* We first calculate the number of days each of the food types are consumed,
based on the hh survey data: starch, beans, milk, eggs, fruit, veg etc. The raw data presents the
number
of days all sub-categories of food are consumed (starch=rice, maized, etc) multiplied by the weight
for that group. So, we have to generate
the days such that they max out at 7. First, this requires dividing the "raw category" by the weight, to
get number of days */
gen staples_re=staples/2
replace staples_re=7 if staples_re>=7 & staples_re~=.
gen meat_re=meat/4
replace meat_re=7 if meat_re>=7 & meat_re~=.
gen beans_re=beans/3
replace beans_re=7 if beans_re>=7 & beans_re~=.
gen fru_re=fruit
replace fru_re=7 if fru_re>=7 & fru_re~=.
gen veg_re=veg
replace veg_re=7 if veg_re>=7 & veg_re~=.
gen sug_re=sugar
replace sug_re=7 if sug_re>=7 & sug_re~=.

```



```

gen oil_re=oil
replace oil_re=7 if oil_re>=7 & oil_re~=
gen dairy_re=dairy/4
replace dairy_re=7 if dairy_re>=7 & dairy_re~=
rename foodindx foodindex
/*next, we recalculate the food consumption score, our food index, as follows. The mean of each
category of food security is very close
to those values presented in the WFP report, so we feel this approach is accurate*/
/*foodindx represents the correct food score data*/
gen
foodindx=(2*staples_re+3*beans_re+4*meat_re+1*fru_re+1*veg_re+dairy_re*4+sug_re*.5+oil_re
*.5)
drop if foodindx==.
/*household size*/
gen hhsz = s1_1
/*replace hhsz=0 if hhsz==.*/
destring hhsz, replace
/*education*/
tabulate s1_17
gen educ_years=s1_17
replace educ_years=0 if s1_17==.
replace educ_years=0 if s1_17==99
/*caste*/
gen brahmin=0
gen janjati=0
gen dalit=0
gen other_caste=0
destring s1cast, replace
replace brahmin=1 if s1cast==1
replace janjati=1 if s1cast==2
replace dalit=1 if s1cast==3
replace other_caste=1 if s1cast==4
/*geographic belt*/
gen belt_1=0 /*Mountain*/
gen belt_2=0 /*Hills*/
replace belt_1=1 if belt==1
replace belt_2=1 if belt==2
gen belt_3=0 /*Terai*/
replace belt_3=1 if belt==3
/*region*/
gen farwest=0
replace farwest=1 if region_n==1
gen midwest=0
replace midwest=1 if region_n==2
gen western=0
replace western=1 if region_n==3
gen central=0
replace central=1 if region_n==4

```

```

gen eastern=0
replace eastern=1 if region_n==5
/*access to credit*/
gen credit_bank =s4_42_4
gen credit_no=s4_42_6
gen credit_local=s4_42_3
gen credit_ngo=s4_42_2
gen credit_family=s4_42_1
gen credit_coop=s4_42_5
gen credit=0
replace credit=1 if credit_bank==1
replace credit=1 if credit_ngo==1
replace credit=1 if credit_local==1
replace credit=1 if credit_coop==1
/*animal ownership*/
gen cownum=s4_46_1
gen bufnum=s4_46_2
gen goatnum=s4_46_3
gen poultnum=s4_46_4
gen yaknum=s4_46_5
gen donkeynum=s4_46_6
gen pignum=s4_46_7
gen othernum=s4_46_8
/*land size*/
destring s5_51b2, replace
replace s5_51b2=0 if s5_51b2==.
gen landsize=s5_51b2
/*percent of income from agriculture*/
gen agric1=0
replace agric1=1 if s6_61a==1
gen agric2=0
replace agric2=1 if s6_62a==1
gen agric3=0
replace agric3=1 if s6_63a==1
gen agric4=0
replace agric4=1 if s6_64a==1

/*1-4 are the identified main sources of income---in percent of total income*/
gen agricper1=s6_65_1*agric1
gen agricper2=s6_65_2*agric2
gen agricper3=s6_65_3*agric3
gen agricper4=s6_65_4*agric4
gen agricper=agricper1+agricper2+agricper3+agricper4
/*population density*/
gen popden=popsiz/area_rd
/*district level conflict deaths minus vdc level deaths*/
gen distkillnov=distkill-totkill
/*remittances*/

```

```

gen rem_income1=s2_25
save ${DIR}food_forest_spatial, replace

clear all
clear matrix
drop _all
set memory 500m
set matsize 800
use ${DIR}food_forest_spatial.dta
rename distric2 dist_name
rename districtfirst distric2
save ${DIR}food_forest_spatial2.dta, replace
merge m:1 distric2 using ${DIR}soc_cap_index_prices.dta
drop if _merge==2
drop _merge
merge m:1 distric2 using /data_6_2009/data/soc_cap_nlss2b.dta
drop _merge
merge m:1 distric2 using ${DIR}devprojs_2003b.dta
drop if foodindx==.
/*replacing district level variables with mean values
if the observation is in a district where no district data was available*/
egen creditindexam=mean(creditindex)
replace creditindex=creditindexam if creditindex==.
egen otherindexam=mean(otherindex)
replace otherindex=creditindexam if otherindex==.
egen womenindexam=mean(womenindex)
replace womenindex=womenindexam if womenindex==.
egen forindexam=mean(forindex)
replace forindex=forindexam if forindex==.
egen agindexam=mean(agindex)
replace agindex=agindexam if agindex==.
egen waterindexam=mean(waterindex)
replace waterindex=waterindexam if waterindex==.
egen totindexam=mean(totindex)
replace totindex=totindexam if totindex==.
egen pricem=mean(price_riced)
replace price_riced=pricem if price_riced==.

/*km of roads non foot*/
drop roadsum
gen roadsum=(main+gravel+hiway+metal+high_grav)/1000
egen dist_area=sum(area_rd), by(districtc50)
/*convert to km^2*/
replace dist_area=dist_area/(1000*1000)
replace area_rd=area_rd/(1000*1000)
gen dist_areanov1=dist_area-area_rd
egen roadsum_dist=sum(roadsum), by(districtc50)
egen foot_dist=sum(foot), by(districtc50)

```

```

gen roadden=(roadsum)/(area_rd)
gen dist_roadden=(roadsum_dist)/(dist_area)
gen distroadsumnov=roadsum_dist-roadsum
gen distroaddenov=distroadsumnov/dist_areanov

gen foodindx10=foodindx/10
gen remhh=((rem_income1)/hhsiz)
gen totkill100=totkill/10
gen poultnum100=poultnum/100
gen price100=price_riced/100
sum price100
replace rem_income1=rem_income1/10000
gen landsizehh=10*(landsiz/hhsiz)
gen foodaide=0
replace foodaide=1 if s8_82==1

/*instruments*/
egen migrantsam=mean(migrants_dist)
replace migrants_dist=migrantsam if migrants_dist==.
replace popden=popden/10
gen footden=(foot/1000)/area_rd
rename migrants_dist migrants
egen newspapers_distam=mean(newspapers_dist)
replace newspapers_dist=newspapers_distam if newspapers_dist==.
egen month_woodam=mean(month_wood)
replace month_wood=month_woodam if month_wood==.
/*district level data*/
gen distkill100nov=distkillnov/100
gen forest_vdc100=forest_vdc*100
gen forest_vdc101=forest_vdc10*100
gen forest_vdc10a1=forest_vdc10a*100
gen forest_vdc201=forest_vdc20*100
gen forest_vdc20a1=forest_vdc20a*100
gen forest_vdc20b1=forest_vdc20b*100
gen forest_vdc301=forest_vdc30*100
gen forest_vdc30a1=forest_vdc30a*100
gen forest_vdc30b1=forest_vdc30b*100
gen forest_vdc401=forest_vdc40*100
gen forest_vdc40a1=forest_vdc40a*100
gen forest_vdc40b1=forest_vdc40b*100
replace remhh=remhh/1000
sum foodindx10 hhsiz landsizehh agricper educ_years poultnum100 belt_1 belt_2 ///
roadden distroaddenov price100 waterdistmin forest_vdc100 forest_vdc10a1 ///
forest_vdc20b1 forest_vdc30b1 dalit janjati other_caste agindex ///
waterindex forindex womenindex remhh credit foodaid totindex totkill100 distkill100nov ///
month_wood midwest footden migrants farwest newspapers_dist, separator(0)
eststo clear
eststo: ivreg2 foodindx10 landsizehh hhsiz agricper educ_years ///

```

```

poultnum100 belt_1 belt_2 roadden price100 [pweight=weights]
quietly: ivreg2 foodindx10 landsizehh hhszize agricper educ_years ///
poultnum100 belt_1 belt_2 roadden price100
ivhettest
/*general forest*/
eststo: ivreg2 foodindx10 landsizehh hhszize agricper educ_years ///
poultnum100 belt_1 belt_2 waterdistmin roadden price100 forest_vdc100 ///
[pweight=weights]
quietly: ivreg2 foodindx10 forest_vdc100 landsizehh hhszize agricper educ_years ///
poultnum100 belt_1 belt_2 popden waterdistmin roadden price100
ivhettest
eststo: ivreg2 foodindx10 landsizehh hhszize agricper educ_years poultnum100 ///
belt_1 belt_2 roadden waterdistmin price100 (forest_vdc100 =month_wood midwest popden) ///
[pweight=weights], endog(forest_vdc100)
quietly: ivreg2 foodindx10 landsizehh hhszize agricper educ_years poultnum100 ///
belt_1 belt_2 roadden waterdistmin price100 poultnum100 (forest_vdc100=month_wood midwest
popden)
ivhettest
/*general capital */
eststo: ivreg2 foodindx10 totindex landsizehh hhszize agricper educ_years poultnum100 ///
janjati dalit other_caste belt_1 belt_2 roadden waterdistmin price100 ///
(forest_vdc100=month_wood midwest popden) [pweight=weights], endog(forest_vdc100)
quietly: ivreg2 foodindx10 landsizehh hhszize agricper educ_years totindex poultnum100 ///
janjati dalit other_caste belt_1 belt_2 roadden waterdistmin price100 ///
(forest_vdc100=month_wood midwest popden)
ivhettest
eststo: ivreg2 foodindx10 landsizehh hhszize agricper educ_years poultnum100 ///
janjati dalit other_caste belt_1 belt_2 roadden waterdistmin price100 ///
(forest_vdc100 totindex =month_wood midwest popden newspapers_dist footden) ///
[pweight=weights], endog(totindex)

ivreg2 foodindx10 landsizehh hhszize agricper educ_years poultnum100 ///
janjati dalit other_caste belt_1 belt_2 roadden waterdistmin price100 ///
(forest_vdc100 totindex =month_wood midwest popden newspapers_dist footden) ///
[pweight=weights], robust endog(forest_vdc100)
quietly: ivreg2 foodindx10 landsizehh hhszize agricper educ_years poultnum100 ///
janjati dalit other_caste belt_1 belt_2 roadden waterdistmin price100 ///
(forest_vdc100 totindex =month_wood midwest popden newspapers_dist footden)
ivhettest
/*conflict*/
eststo: ivreg2 foodindx10 landsizehh hhszize agricper educ_years totkill100 poultnum100 ///
janjati dalit other_caste totindex belt_1 belt_2 roadden waterdistmin price100 ///
(forest_vdc100 =month_wood midwest popden) [pweight=weights], endog(forest_vdc100)
quietly: ivreg2 foodindx10 landsizehh hhszize agricper educ_years totkill100 poultnum100 ///
janjati dalit other_caste totindex belt_1 belt_2 roadden waterdistmin price100 ///
(forest_vdc100 =month_wood midwest popden)
ivhettest
eststo: ivreg2 foodindx10 landsizehh hhszize agricper educ_years poultnum100 ///

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```

janjati dalit other_caste totindex belt_1 belt_2 roadden waterdistmin price100 ///
(forest_vdc100 totkill100 =month_wood midwest footden migrants) ///
[pweight=weights], endog(totkill100)
ivreg2 foodindx10 landsizehh hhsiz e agricper educ_years poultnum100 ///
janjati dalit other_caste totindex belt_1 belt_2 roadden waterdistmin price100 ///
(forest_vdc100 totkill100 =month_wood midwest footden migrants) ///
[pweight=weights], endog(forest_vdc100)
quietly: ivreg2 foodindx10 landsizehh hhsiz e agricper educ_years poultnum100 ///
janjati dalit other_caste totindex belt_1 belt_2 roadden waterdistmin price100 ///
(forest_vdc100 totkill100 =month_wood midwest footden migrants)
ivhettest
/*coping*/
eststo: ivreg2 foodindx10 landsizehh hhsiz e agricper educ_years totindex totkill100 poultnum100
///
janjati dalit other_caste remhh foodaid credit belt_1 belt_2 roadden waterdistmin price100 ///
(forest_vdc100 =month_wood midwest popden) [pweight=weights], endog(forest_vdc100)
quietly: ivreg2 foodindx10 landsizehh hhsiz e agricper educ_years totindex totkill100 poultnum100
///
janjati dalit other_caste remhh foodaid credit belt_1 belt_2 roadden waterdistmin price100 ///
(forest_vdc100 =month_wood midwest popden)
ivhettest
eststo: ivreg2 foodindx10 landsizehh hhsiz e agricper educ_years totindex totkill100 poultnum100
///
janjati dalit other_caste remhh credit belt_1 belt_2 roadden waterdistmin price100 ///
(forest_vdc100 foodaid =month_wood midwest footden popden farwest migrants) ///
[pweight=weights], endog(foodaid)
ivreg2 foodindx10 landsizehh hhsiz e agricper educ_years totindex totkill100 poultnum100 ///
janjati dalit other_caste remhh credit belt_1 belt_2 roadden waterdistmin price100 ///
(forest_vdc100 foodaid=month_wood midwest footden popden farwest migrants) ///
[pweight=weights], endog(forest_vdc100)
quietly: ivreg2 foodindx10 landsizehh hhsiz e agricper educ_years totindex totkill100 poultnum100
///
janjati dalit other_caste remhh credit belt_1 belt_2 roadden waterdistmin price100 ///
(forest_vdc100 foodaid =month_wood midwest footden popden farwest migrants)
ivhettest
estadd beta : *
label variable foodindx FOODSEC
label variable educ_years EDUC
label variable agricper AGRICINC
label variable poultnum100 POULTNUM
label variable hhsiz e HHSIZE
label variable landsizehh LAND
label variable totkill100 CONFLICT
label variable janjati JANJATI
label variable dalit DALIT
label variable other_caste OTHCASTE
label variable waterdist WATERDIST
label variable forest_vdc100 VDCFOREST

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```

label variable totindex SOCIALCAPALL
label variable waterdistmin WATERDIST
label variable credit CREDIT
label variable roadden ROADDEN
label variable belt_1 MOUNT
label variable belt_2 HILLS
label variable foodaide FOODAID
label variable price100 PRICES
label variable remhh REMIT
esttab using ${DIR}tables_foodmain.csv, replace wide modelwidth(8) ///
label cells("b(fmt(3) star)" se(par("(" " ")))) order(_cons landsizehh hhszize agricper educ_years
poultnum100 ///
belt_1 belt_2 roadden price100 waterdistmin forest_vdc100 dalit janjati other_caste totindex
totkill100 remhh credit foodaide) ///
stats(N ll chi2 aic bic r2 pr2 se F) starlevels(* 0.10 ** 0.05 *** 0.01)
/*for beta coefficients*/
esttab using ${DIR}tables_foodmain_beta.csv, replace wide modelwidth(8) ///
label cells("beta(fmt(3) star)") order(_cons landsizehh hhszize agricper educ_years poultnum100 ///
belt_1 belt_2 roadden price100 waterdistmin forest_vdc100 dalit janjati other_caste totindex
totkill100 remhh credit foodaide) ///
stats(N ll chi2 aic bic r2 pr2 se) starlevels(* 0.10 ** 0.05 *** 0.01)
eststo clear
/*these are the regressions for each of the community group types*/
/*agindex*/
eststo: ivreg2 foodindx10 agindex landsizehh hhszize agricper educ_years poultnum100 ///
janjati dalit other_caste belt_1 belt_2 roadden waterdistmin price100 ///
(forest_vdc100=month_wood midwest popden) ///
[pweight=weights], endog(forest_vdc100)
quietly: ivreg2 foodindx10 agindex landsizehh hhszize agricper educ_years poultnum100 ///
janjati dalit other_caste belt_1 belt_2 roadden waterdistmin price100 ///
(forest_vdc100=month_wood midwest popden)
ivhettest
eststo: ivreg2 foodindx10 landsizehh hhszize agricper educ_years poultnum100 ///
janjati dalit other_caste belt_1 belt_2 roadden waterdistmin price100 ///
(forest_vdc100 agindex =month_wood midwest footden popden newspapers_dist) ///
[pweight=weights], endog(agindex)

ivreg2 foodindx10 landsizehh hhszize agricper educ_years poultnum100 ///
janjati dalit other_caste belt_1 belt_2 roadden waterdistmin price100 ///
(forest_vdc100 agindex =month_wood midwest footden popden newspapers_dist) ///
[pweight=weights], endog(forest_vdc100)
quietly: ivreg2 foodindx10 landsizehh hhszize agricper educ_years poultnum100 ///
janjati dalit other_caste belt_1 belt_2 roadden waterdistmin price100 ///
(forest_vdc100 agindex =month_wood midwest footden popden newspapers_dist),
ivhettest

/*waterindex*/
eststo: ivreg2 foodindx10 landsizehh hhszize agricper educ_years poultnum100 waterindex ///

```



```

janjati dalit other_caste belt_1 belt_2 roadden waterdistmin price100 ///
(forest_vdc100=month_wood midwest popden) ///
[pweight=weights], endog(forest_vdc100)
quietly: ivreg2 foodindx10 landsizehh hhsiz e agricper educ_years waterindex poultnum100 ///
janjati dalit other_caste belt_1 belt_2 roadden waterdistmin price100 ///
(forest_vdc100=month_wood midwest popden)
ivhettest
eststo: ivreg2 foodindx10 landsizehh hhsiz e agricper educ_years poultnum100 ///
janjati dalit other_caste belt_1 belt_2 roadden waterdistmin price100 ///
(forest_vdc100 waterindex =month_wood midwest footden popden newspapers_dist) ///
[pweight=weights], endog(waterindex)

ivreg2 foodindx10 landsizehh hhsiz e agricper educ_years poultnum100 ///
janjati dalit other_caste belt_1 belt_2 roadden waterdistmin price100 ///
(forest_vdc100 waterindex =month_wood midwest footden popden newspapers_dist) ///
[pweight=weights], endog(forest_vdc100)
quietly: ivreg2 foodindx10 landsizehh hhsiz e agricper educ_years poultnum100 ///
janjati dalit other_caste belt_1 belt_2 roadden waterdistmin price100 ///
(forest_vdc100 waterindex =month_wood midwest footden popden newspapers_dist)
ivhettest
/*forest*/
eststo: ivreg2 foodindx10 landsizehh hhsiz e agricper educ_years poultnum100 forindex ///
janjati dalit other_caste belt_1 belt_2 roadden waterdistmin price100 ///
(forest_vdc100=month_wood midwest popden) ///
[pweight=weights], endog(forest_vdc100)
quietly: ivreg2 foodindx10 landsizehh hhsiz e agricper educ_years forindex poultnum100 ///
janjati dalit other_caste belt_1 belt_2 roadden waterdistmin price100 ///
(forest_vdc100=month_wood midwest popden)
ivhettest
eststo: ivreg2 foodindx10 landsizehh hhsiz e agricper educ_years poultnum100 ///
janjati dalit other_caste belt_1 belt_2 roadden waterdistmin price100 ///
(forest_vdc100 forindex =month_wood midwest footden popden newspapers_dist) ///
[pweight=weights], endog(forindex)

ivreg2 foodindx10 landsizehh hhsiz e agricper educ_years poultnum100 ///
janjati dalit other_caste belt_1 belt_2 roadden waterdistmin price100 ///
(forest_vdc100 forindex =month_wood midwest footden popden newspapers_dist) ///
[pweight=weights], endog(forest_vdc100)
quietly: ivreg2 foodindx10 landsizehh hhsiz e agricper educ_years poultnum100 ///
janjati dalit other_caste belt_1 belt_2 roadden waterdistmin price100 ///
(forest_vdc100 forindex =month_wood midwest footden popden newspapers_dist),
ivhettest

/*womenindex*/
eststo: ivreg2 foodindx10 landsizehh hhsiz e agricper educ_years poultnum100 womenindex ///
janjati dalit other_caste belt_1 belt_2 roadden waterdistmin price100 ///
(forest_vdc100=month_wood midwest popden) [pweight=weights], endog(forest_vdc100)
quietly: ivreg2 foodindx10 landsizehh hhsiz e agricper educ_years womenindex poultnum100 ///

```



```

janjati dalit other_caste belt_1 belt_2 roadden waterdistmin price100 ///
(forest_vdc100=month_wood midwest popden)
ivhettest
eststo: ivreg2 foodindx10 landsizehh hhsizе agricper educ_years poultnum100 ///
janjati dalit other_caste belt_1 belt_2 roadden waterdistmin price100 ///
(forest_vdc100 womenindex =month_wood midwest popden migrants) ///
[pweight=weights], endog(womenindex)

ivreg2 foodindx10 landsizehh hhsizе agricper educ_years poultnum100 ///
janjati dalit other_caste belt_1 belt_2 roadden waterdistmin price100 ///
(forest_vdc100 womenindex =month_wood midwest popden migrants) ///
[pweight=weights], endog(forest_vdc100)
quietly: ivreg2 foodindx10 landsizehh hhsizе agricper educ_years poultnum100 ///
janjati dalit other_caste belt_1 belt_2 roadden waterdistmin price100 ///
(forest_vdc100 womenindex =month_wood midwest popden migrants)
ivhettest
/*totindex*/
eststo: ivreg2 foodindx10 landsizehh hhsizе agricper educ_years poultnum100 totindex ///
janjati dalit other_caste belt_1 belt_2 roadden waterdistmin price100 ///
(forest_vdc100=month_wood midwest popden) ///
[pweight=weights], endog(forest_vdc100)
quietly: ivreg2 foodindx10 landsizehh hhsizе agricper educ_years totindex poultnum100 ///
janjati dalit other_caste belt_1 belt_2 roadden waterdistmin price100 ///
(forest_vdc100=month_wood midwest popden),
ivhettest
eststo: ivreg2 foodindx10 landsizehh hhsizе agricper educ_years poultnum100 ///
janjati dalit other_caste belt_1 belt_2 roadden waterdistmin price100 ///
(forest_vdc100 totindex =month_wood midwest footden popden newspapers_dist) ///
[pweight=weights], endog(totindex)

ivreg2 foodindx10 landsizehh hhsizе agricper hhsizе educ_years poultnum100 ///
janjati dalit other_caste belt_1 belt_2 roadden waterdistmin price100 ///
(forest_vdc100 totindex =month_wood midwest footden popden newspapers_dist) ///
[pweight=weights], endog(forest_vdc100)
quietly: ivreg2 foodindx10 landsizehh hhsizе agricper hhsizе educ_years poultnum100 ///
janjati dalit other_caste belt_1 belt_2 roadden waterdistmin price100 ///
(forest_vdc100 totindex =month_wood midwest footden popden newspapers_dist)
ivhettest
estadd beta : *
esttab using ${DIR} tables_soccap.csv, replace wide modelwidth(8) ///
label cells("b(fmt(3) star)" se(par("(" " ")))) order(_cons landsizehh hhsizе agricper educ_years
poultnum100 ///
belt_1 belt_2 roadden price100 waterdistmin hhsizе forest_vdc100 dalit janjati other_caste agindex
waterindex forindex womenindex totindex) ///
stats(N ll chi2 aic bic r2 pr2 se F) starlevels(* 0.10 ** 0.05 *** 0.01)
esttab using ${DIR} tables_soccap_beta.csv, replace wide modelwidth(8) ///
label cells("beta(fmt(3) star)") order(_cons landsizehh hhsizе agricper educ_years poultnum100 ///
belt_1 belt_2 roadden price100 waterdistmin hhsizе forest_vdc100 dalit janjati ///

```

```

other_caste agindex waterindex forindex womenindex totindex) starlevels(* 0.10 ** 0.05 *** 0.01)
/*estimating forest_vdc, to take care of endogeneity problems in the programming analysis
--where 10a is 10 km buffer minus the vdc area. 20b is the 20 km buffer minus the 10km buffer.
30b is the 30 km buffer minus the 20 km buffer*/
eststo clear
ivreg2 forest_vdc100 ///
belt_1 belt_2 popden roadden price100 janjati dalit other_caste ///
totindex totkill100 month_wood midwest footden popden [pweight=weights]
predict forest_pred1
ivreg2 forest_vdc10a1 landsizehh hhszic agricper educ_years totindex totkill100 poultnum100 ///
janjati dalit other_caste remhh credit belt_1 belt_2 roadden waterdistmin price100 ///
foodaid month_wood midwest footden popden migrants [pweight=weights]
predict forest_pred10
ivreg2 forest_vdc20b1 landsizehh hhszic agricper educ_years totindex totkill100 poultnum100 ///
janjati dalit other_caste remhh credit belt_1 belt_2 roadden waterdistmin price100 ///
foodaid month_wood midwest footden popden migrants [pweight=weights]
predict forest_pred20
ivreg2 forest_vdc30b1 landsizehh hhszic agricper educ_years totindex totkill100 poultnum100 ///
janjati dalit other_caste remhh credit belt_1 belt_2 roadden waterdistmin price100 ///
foodaid month_wood midwest footden popden migrants [pweight=weights]
predict forest_pred30
/*note we use the predicted values for the forest data.
Also, we only include a limited number of explanatory variables to ensure convergence*/

```

```

capture program drop simplemle
program simplemle
    args lnL a0 a1 a2 a3 a4 a5 a6 a7 a8 a9 a10 a11 a12 b eta
    tempvar xb sigma
    quietly gen double `xb'=`a0'+ `a1'*landsizehh + `a2'*hhszic+ `a3'*agricper+ `a4'*educ_years
    ///
    + `a5'*poultnum100+ `a6'*belt_1+ `a7'*belt_2 +
`a8'*roadden+ `a9'*price100+ `a10'*waterdistmin ///
    + `a11'*totindex + `a12'*totkill100 + `b'*(forest_pred1)
    quietly gen double `sigma'=exp(`eta')
    quietly replace `lnL'=-.5*ln(2*_pi)-.5*ln((`sigma')^2)-.5*(foodindx10-`xb')^2/(`sigma')^2
end
ml model lf simplemle (a0:) (a1:) (a2:) (a3:) (a4:) (a5:) (a6:) ///
(a7:) (a8:) (a9:) (a10:) (a11:) (a12:) (b:) (eta:)
ml search
ml maximize

```

```

capture program drop simplemle
program simplemle
    args lnL a0 a1 a2 a3 a4 a5 a6 a7 a8 a9 a10 a11 a12 b eta kappa
    tempvar lambda xb sigma
    quietly gen double `lambda'=exp(`kappa')/(1+exp(`kappa'))
    quietly gen double `xb'=`a0'+ `a1'*landsizehh + `a2'*hhszic+ `a3'*agricper+ `a4'*educ_years
    ///

```

```

+`a5*poultnum100+`a6*belt_1+`a7*belt_2 +
`a8*roadden+`a9*price100+`a10*waterdistmin ///
+`a11*totindex +`a12*totkill100 +`b*(forest_pred1+`lambda*forest_pred10)
quietly gen double `sigma'=exp(`eta)
quietly replace `lnL'=-.5*ln(2*_pi)-.5*ln((`sigma')^2)-.5*(foodindx10-`xb')^2/(`sigma')^2
end
ml model lf simplemle (a0:) (a1:) (a2:) (a3:) (a4:) (a5:) (a6:) ///
(a7:) (a8:) (a9:) (a10:) (a11:) (a12:) (b:) (eta:) (kappa:)
ml search
ml maximize

```

```

capture program drop simplemle
program simplemle
args lnL a0 a1 a2 a3 a4 a5 a6 a7 a8 a9 a10 a11 a12 b eta kappa
tempvar lambda xb sigma
quietly gen double `lambda'=exp(`kappa)/(1+exp(`kappa))
quietly gen double `xb'=`a0'+`a1*landsizehh +`a2*hhsz+`a3*agricper+`a4*educ_years
///
+`a5*poultnum100+`a6*belt_1+`a7*belt_2 +
`a8*roadden+`a9*price100+`a10*waterdistmin ///
+`a11*totindex +`a12*totkill100
+`b*(forest_pred1+`lambda*forest_pred10+(`lambda'^2)*forest_pred20)
quietly gen double `sigma'=exp(`eta)
quietly replace `lnL'=-.5*ln(2*_pi)-.5*ln((`sigma')^2)-.5*(foodindx10-`xb')^2/(`sigma')^2
end
ml model lf simplemle (a0:) (a1:) (a2:) (a3:) (a4:) (a5:) (a6:) ///
(a7:) (a8:) (a9:) (a10:) (a11:) (a12:) (b:) (eta:) (kappa:)
ml search
ml maximize

```

```

capture program drop simplemle
program simplemle
args lnL a0 a1 a2 a3 a4 a5 a6 a7 a8 a9 a10 a11 a12 b eta kappa
tempvar lambda xb sigma
quietly gen double `lambda'=exp(`kappa)/(1+exp(`kappa))
quietly gen double `xb'=`a0'+`a1*landsizehh +`a2*hhsz+`a3*agricper ///
+`a4*educ_years +`a5*poultnum100+`a6*belt_1+`a7*belt_2 + ///
`a8*roadden+`a9*price100+`a10*waterdistmin ///
+`a11*totindex +`a12*totkill100 +`b*(forest_pred1+`lambda*forest_pred10 ///
+(`lambda'^2)*forest_pred20+`lambda'^3*forest_pred30)
quietly gen double `sigma'=exp(`eta)
quietly replace `lnL'=-.5*ln(2*_pi)-.5*ln((`sigma')^2)-.5*(foodindx10-`xb')^2/(`sigma')^2
end
ml model lf simplemle (a0:) (a1:) (a2:) (a3:) (a4:) (a5:) (a6:) ///
(a7:) (a8:) (a9:) (a10:) (a11:) (a12:) (b:) (eta:) (kappa:)
ml search
ml maximize

```

```

capture program drop simplemle
program simplemle
    args lnL a0 a1 a2 a3 a4 a5 a6 a7 a8 a9 a10 a11 a12 b eta kappa kappa2
    tempvar lambda lambda2 xb sigma
    quietly gen double `lambda'=exp(`kappa')/(1+exp(`kappa'))
    quietly gen double `lambda2'=exp(`kappa2')/(1+exp(`kappa2'))
    quietly gen double `xb'=`a0'+ `a1'*landsizehh + `a2'*hhsz + `a3'*agricper ///
+ `a4'*educ_years + `a5'*poultnum100 + `a6'*belt_1+ `a7'*belt_2 + ///
`a8'*(roadden+ `lambda2'*distroaddenov) + `a9'*price100+ `a10'*waterdistmin ///
+ `a11'*totindex + `a12'*(totkill100+ `lambda2'*distkill100nov) ///
+ `b'*(forest_pred1+ `lambda*forest_pred10 ///
+ `lambda'^2*forest_pred20+ `lambda'^3*forest_pred30)
    quietly gen double `sigma'=exp(`eta')
    quietly replace `lnL'=-.5*ln(2*_pi)-.5*ln((`sigma')^2)-.5*(foodindx10-`xb')^2/(`sigma')^2
end
ml model lf simplemle (a0:) (a1:) (a2:) (a3:) (a4:) (a5:) (a6:) (a7:) (a8:) (a9:) (a10:) (a11:) (a12:) ///
(b:) (eta:) (kappa:) (kappa2:)
ml search
ml maximize

```

Appendix F Emergency Food Aid Stata Code

```
clear all
clear matrix
drop _all
set memory 500m
set matsize 800
mata: mata set matafavor speed, perm
use ${DIR}data_food_281.dta
merge 1:m year country_name using ${DIR}aid_fao.dta
drop _merge
gen lngdp=ln(gdpcap*pop_tot)
gen gdptot=(gdpcap*pop_tot)
gen lnpop=ln(pop_tot)
replace pop_tot=(pop_tot/10000)
replace lnpop=ln(pop_tot)
gen lngdpcap=ln((gdptot)/(pop_tot))
egen id_code2=group(country_name)
tsset id_code2 year
replace pop_tot=1*pop_tot if pop_tot==.
gen lncrop_prod_index= ln(crop_prod_index+1)
gen lnfood_prod_index= ln(food_prod_index+1)
gen emer_total=emer_aid_gr
gen emer_totalb=emer_non_cereal+emer_aid
gen lncerealnnon=ln(emer_non_cereal+1)
gen cerealnnonpp=(emer_non_cereal/pop_tot)
gen lncerealnnonpp=ln(cerealnnonpp+1)
replace eastasi=1 if country_name=="Timor-Leste"
gen cerealpp=(cereal_prod_1000)/(pop_tot)
gen lncerealpp=ln(cerealpp+1)
gen lncereal=ln((cereal_prod_1000)+1)
gen emer_totalbpp=emer_totalb/pop_tot
gen lnemer_totalbpp=ln(emer_totalb+1)
drop if country_name==" " & year==.
gen lncereal_prod_1000=ln(cereal_prod_1000+1)

sort country_name year
gen free=14-(cl_1+pr_1)
gen lncl=ln(8-cl_1+1)
gen lnpr=ln(8-pr_1+1)
gen lnfree=ln(free+1)
by country_name: replace sum_polity_pos = sum(polity_pos) if year>1969
by country_name: gen sum_free = sum(free) if year>1969
gen lnfreesum =ln(sum_free+1)
gen lnpolity2sum =ln(sum_polity_pos+1)

sort id_code_id year
```

```

drop if year==2011
drop if id_code_id==.
tsset id_code_id year
replace emer_total=0 if emer_total==. & year>1987
replace fastdis=0 if fastdis==. & slowdis~=.
replace slowdis=0 if slowdis==. & fastdis~=.
gen totdis=slowdis+fastdis
replace totdis=0 if fastdis~=. & totdis==.
replace totdis=0 if slowdis~=. & totdis==.

replace emer_total=emer_total
gen lnemertot=ln(emer_total+1)
gen lnemertotb=ln(emer_totalb+1)
gen emertotcap=emer_total/(pop_tot)
gen lnemertotcap=ln(emertotcap+1)
gen emertotcapb=emer_totalb/(pop_tot)
gen lnemertotcapb=ln(emertotcapb+1)

gen lnfastdis=ln(fastdis+1)
gen lnslowdis=ln(slowdis+1)
gen fastdispp=fastdis/(pop_tot)
gen lnfastdispp=ln(fastdispp+1)
gen slowdispp=slowdis/(pop_tot)
gen lnslowdispp=ln(slowdispp+1)

gen lntotdis=ln(totdis+1)
gen totdispp=totdis/(pop_tot)
gen lntotdispp=ln(totdispp+1)

gen hostidp=host+idp
gen lnhostidp=ln(hostidp+1)
gen hostidpcap=hostidp/(pop_tot)
gen lnhostidpcap=ln((hostidpcap)+1)
gen laglnfastdispp=l.lnfastdispp
gen laglnslowdispp=l.lnslowdispp
gen laglnemertotcap=l.lnemertotcap
gen laglnfastdis=l.lnfastdis
gen laglnslowdis=l.lnslowdis
gen laglnemertot=l.lnemertot
gen lnpolity2=ln(polity2+11)
gen lntrade=ln(trade+1)
gen lnstockgdp=ln((stockpergdp*gdpcap*pop_tot)+1)
gen lnstockpergdp=ln(stockpergdp+1)
replace lncereal=ln(1+(cereal_prod_1000))

gen lnfood=ln(food_prod_index+1)

gen lncrop=ln(crop_prod_index+1)

```

```

gen lnexp=ln((export_value/gdpcap*pop_tot)+1)
gen lnfood_index=ln(food_index)
gen lnfood_index_capita=ln(food_index_capita)
replace lnemertot=0 if lnemertot==.
replace lnemertotcap=0 if lnemertotcap==.
replace lnemertot=. if year<1988
replace lnemertotcap=. if year<1988

gen lntelepp=ln(tele100+1)
gen lnlele=ln((tele100*(pop_tot/100))+1)
gen stockpp=((stockpergdp/100)*(gdptot))/pop_tot
gen lnstockpp=ln(stockpp+1)
gen lnstock=ln((stockpergdp/100)*gdptot)
replace lnslowdispp=0 if lnslowdispp==. & lnfastdispp~=.
replace lnfastdispp=0 if lnfastdispp==. & lnslowdispp~=.
replace lnslowdis=0 if lnslowdis==. & lnfastdis~=.
replace lnfastdis=0 if lnfastdis==. & lnslowdis~=.
replace lntotdispp=0 if lntotdispp==. & lnslowdispp~=.
replace lntotdis=0 if lntotdis==. & lnslowdis~=.

gen lnexport_value=ln(export_value+1)
gen lnexport_valuepp=ln((export_value/pop_tot)+1)
gen lntotalac=ln(totalac+1)
gen lnper14=ln(per_pop_14)
gen lnprural=ln((rural_pop/pop_tot)*100000)
gen lnfdi=ln(fdi_in+1)
gen casi=0
replace casi=1 if eur==0 & eucasi==1

gen asia=0
replace asia=1 if southasi==1
replace asia=1 if eastasi==1
replace asia=1 if casi==1
replace afri=1 if country_name=="Algeria"
replace afri=1 if country_name=="Egypt, Arab Rep."
replace afri=1 if country_name=="Tunisia"
replace afri=1 if country_name=="Morocco"
replace afri=1 if country_name=="Libya"
gen subafri=0
replace subafri=1 if midna~=1 & afri==1
replace asia=1 if midna==1 & afri~=1
/*lower income countries--per capita--Table 4-4*/
eststo b15:xtabond2 lnemertotcap l(1).lnemertotcap lngdpcap l(0).lnfastdispp l(0).lnslowdispp ///
l(0).lncrealpp lnpop lnpolity2 lntrade yr1987-yr2009 ocn afri eur nam asia ///
if upper_inc==0 & year>1987 & year<2010, gmm(l(1).lnemertotcap , laglimits(2 10) collapse) ///
gmm(lnfastdispp lnslowdispp, laglimits(1 10) collapse) ///
gmm(lngdpcap l(0).lncrealpp , laglimits(2 10) collapse) ///
iv(yr1987-yr2009 ocn afri eur nam asia, eq(level)) ///

```

```

iv(lnpolity2 lnpop lntrade ocn afri eur nam asia ) robust small twostep ar(3) orthog
eststo b25:xtabond2 lnemertotcap l(1/2).lnemertotcap lngdpcap l(0).lnfastdispp l(0).lnslowdispp
///
l(0).lncerealpp lnpop lnpolity2 lntrade yr1987-yr2009 ocn afri eur nam asia ///
if upper_inc==0 & year>1987 & year<2010, gmm(l(1).lnemertotcap , laglimits(2 10) collapse) ///
gmm(lnfastdispp lnslowdispp, laglimits(1 10) collapse) ///
gmm(lngdpcap l(0).lncerealpp , laglimits(2 10) collapse) ///
iv(yr1987-yr2009 ocn afri eur nam asia, eq(level)) ///
iv(lnpolity2 lnpop lntrade l(2).lnemertotcap ocn afri eur nam asia ) robust small twostep ar(3)
orthog
eststo b35:xtabond2 lnemertotcap l(1/2).lnemertotcap lngdpcap l(0/1).lnfastdispp
l(0/1).lnslowdispp ///
l(0).lncerealpp lnpop lnpolity2 lntrade yr1987-yr2009 ocn afri eur nam asia ///
if upper_inc==0 & year>1987 & year<2010, gmm(l(1).lnemertotcap , laglimits(1 10) collapse) ///
gmm(lnfastdispp lnslowdispp l(1).lnslowdispp l.lnfastdispp, laglimits(1 10) collapse) ///
gmm(lngdpcap l(0).lncerealpp , laglimits(2 10) collapse) ///
iv(yr1987-yr2009 ocn afri eur nam asia , eq(level)) ///
iv(lnpolity2 lnpop lntrade l(2).lnemertotcap ) robust small twostep ar(3) orthog
eststo b45:xtabond2 lnemertotcap l(1/2).lnemertotcap lngdpcap lnhostidpcap l(0/1).lnfastdispp
l(0/1).lnslowdispp ///
l(0).lncerealpp lnpop lnpolity2 lntrade yr1987-yr2009 ocn afri eur nam asia ///
if upper_inc==0 & year>1987 & year<2010, gmm(l(1).lnemertotcap , laglimits(1 10) collapse) ///
gmm(lnfastdispp lnslowdispp l(1).lnslowdispp l.lnfastdispp, laglimits(1 10) collapse) ///
gmm(lngdpcap l(0).lncerealpp , laglimits(2 10) collapse) ///
iv(yr1987-yr2009 ocn afri eur nam asia , eq(level)) ///
iv(lnpolity2 lnhostidpcap lnpop lntrade l(2).lnemertotcap ) robust small twostep ar(3) orthog
eststo b55:xtabond2 lnemertotcap l(1/2).lnemertotcap lngdpcap lnhostidpcap l(0/1).lntotdispp
///
l(0).lncerealpp lnpop lnpolity2 lntrade yr1987-yr2009 ocn afri eur nam asia ///
if upper_inc==0 & year>1987 & year<2010, gmm(l(1).lnemertotcap , laglimits(1 10) collapse) ///
gmm(l(0/1).lntotdispp , laglimits(1 10) collapse) ///
gmm(lngdpcap l(0).lncerealpp , laglimits(2 10) collapse) ///
iv(yr1987-yr2009 ocn afri eur nam asia , eq(level)) ///
iv(lnpolity2 lnhostidpcap lnpop lntrade l(2).lnemertotcap ) robust small twostep ar(3) orthog
/*sensitivity analysis (reduced instruments) lower income countries--per capita Table 4-5*/
eststo b45a:xtabond2 lnemertotcap l(1/2).lnemertotcap lngdpcap lnhostidpcap l(0/1).lnfastdispp
l(0/1).lnslowdispp ///
l(0).lncerealpp lnpop lnpolity2 lntrade yr1987-yr2009 ocn afri eur nam asia ///
if upper_inc==0 & year>1987 & year<2010, gmm(l(1).lnemertotcap , laglimits(1 8) collapse) ///
gmm(lnfastdispp lnslowdispp l(1).lnslowdispp l.lnfastdispp , laglimits(1 8) collapse) ///
gmm(lngdpcap l(0).lncerealpp , laglimits(2 8) collapse) ///
iv(yr1987-yr2009 ocn afri eur nam asia , eq(level)) ///
iv(lnpolity2 lnhostidpcap lnpop lntrade l(2).lnemertotcap ) robust small twostep ar(3) orthog
eststo b45b:xtabond2 lnemertotcap l(1/2).lnemertotcap lngdpcap lnhostidpcap l(0/1).lnfastdispp
l(0/1).lnslowdispp ///
l(0).lncerealpp lnpop lnpolity2 lntrade yr1987-yr2009 ocn afri eur nam asia ///
if upper_inc==0 & year>1987 & year<2010, gmm(l(1).lnemertotcap , laglimits(1 4) collapse) ///
gmm(lnfastdispp lnslowdispp l(1).lnslowdispp l(1).lnfastdispp, laglimits(1 4) collapse) ///

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gmm(lngdpcap l(0).lncerealpp , laglimits(2 4) collapse) ///
iv(yr1987-yr2009 ocn afri eur nam asia , eq(level)) ///
iv(lnpolity2 lnhostidpcap lnpop ltrade l(2).lnemertotcap ) robust small twostep ar(3) orthog
eststo b45c:xtabond2 lnemertotcap l(1/2).lnemertotcap lngdpcap lnhostidpcap l(0/1).lnfastdispp
l(0/1).lnslowdispp ///
l(0).lncerealpp lnpop lnpolity2 ltrade yr1987-yr2009 ocn afri eur nam asia ///
if upper_inc==0 & year>1987 & year<2010, gmm(l(1).lnemertotcap , laglimits(1 2) collapse) ///
gmm(lnfastdispp lnslowdispp l(1).lnslowdispp l(1).lnfastdispp, laglimits(1 2) collapse) ///
gmm(lngdpcap l(0).lncerealpp , laglimits(2 2) collapse) ///
iv(yr1987-yr2009 ocn afri eur nam asia , eq(level)) ///
iv(lnpolity2 lnhostidpcap lnpop ltrade l(2).lnemertotcap ) robust small twostep ar(3) orthog
eststo b55a:xtabond2 lnemertotcap l(1/2).lnemertotcap lngdpcap lnhostidpcap l(0/1).lntotdispp
///
l(0).lncerealpp lnpop lnpolity2 ltrade yr1987-yr2009 ocn afri eur nam asia ///
if upper_inc==0 & year>1987 & year<2010, gmm(l(1).lnemertotcap , laglimits(1 8) collapse) ///
gmm(l(0/1).lntotdispp , laglimits(1 8) collapse) ///
gmm(lngdpcap l(0).lncerealpp , laglimits(2 8) collapse) ///
iv(yr1987-yr2009 ocn afri eur nam asia , eq(level)) ///
iv(lnpolity2 lnhostidpcap lnpop ltrade l(2).lnemertotcap ) robust small twostep ar(3) orthog
eststo b55b:xtabond2 lnemertotcap l(1/2).lnemertotcap lngdpcap lnhostidpcap l(0/1).lntotdispp
///
l(0).lncerealpp lnpop lnpolity2 ltrade yr1987-yr2009 ocn afri eur nam asia ///
if upper_inc==0 & year>1987 & year<2010, gmm(l(1).lnemertotcap , laglimits(1 4) collapse) ///
gmm(l(0/1).lntotdispp , laglimits(1 4) collapse) ///
gmm(lngdpcap l(0).lncerealpp , laglimits(2 4) collapse) ///
iv(yr1987-yr2009 ocn afri eur nam asia , eq(level)) ///
iv(lnpolity2 lnhostidpcap lnpop ltrade l(2).lnemertotcap ) robust small twostep ar(3) orthog
eststo b55c:xtabond2 lnemertotcap l(1/2).lnemertotcap lngdpcap lnhostidpcap l(0/1).lntotdispp
///
l(0).lncerealpp lnpop lnpolity2 ltrade yr1987-yr2009 ocn afri eur nam asia ///
if upper_inc==0 & year>1987 & year<2010, gmm(l(1).lnemertotcap , laglimits(1 2) collapse) ///
gmm(l(0/1).lntotdispp , laglimits(1 2) collapse) ///
gmm(lngdpcap l(0).lncerealpp lnhostidpcap, laglimits(2 2) collapse) ///
iv(yr1987-yr2009 ocn afri eur nam asia , eq(level)) ///
iv(lnpolity2 lnpop ltrade l(2).lnemertotcap ) robust small twostep ar(3) orthog
/*all income countries--per capita--Table 4-6*/
eststo bb15:xtabond2 lnemertotcap l(1).lnemertotcap lngdpcap l(0).lnfastdispp l(0).lnslowdispp
///
l(0).lncerealpp lnpop lnpolity2 ltrade yr1987-yr2009 ocn afri eur nam asia ///
if year>1987 & year<2010, gmm(l(1).lnemertotcap , laglimits(1 10) collapse) ///
gmm(lnfastdispp lnslowdispp, laglimits(1 10) collapse) ///
gmm(lngdpcap l(0).lncerealpp , laglimits(2 10) collapse) ///
iv(yr1987-yr2009 ocn afri eur nam asia , eq(level)) ///
iv(lnpolity2 lnpop ltrade ) robust small twostep ar(3) orthog
eststo bb25:xtabond2 lnemertotcap l(1/2).lnemertotcap lngdpcap l(0).lnfastdispp l(0).lnslowdispp
///
l(0).lncerealpp lnpop lnpolity2 ltrade yr1987-yr2009 ocn afri eur nam asia ///
if year>1987 & year<2010, gmm(l(1).lnemertotcap , laglimits(1 10) collapse) ///

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gmm(lfastdispp lnslowdispp, laglimits(1 10) collapse) ///
gmm(lngdpcap l(0).lncerealpp , laglimits(2 10) collapse) ///
iv(yr1987-yr2009 ocn afri eur nam asia, eq(level)) ///
iv(lnpolity2 lnpop ltrade l(2).lnemertotcap ) robust small twostep ar(3) orthog
eststo bb35:xtabond2 lnemertotcap l(1/2).lnemertotcap lngdpcap l(0/1).lfastdispp
l(0/1).lnslowdispp ///
l(0).lncerealpp lnpop lnpolity2 ltrade yr1987-yr2009 ocn afri eur nam asia ///
if year>1987 & year<2010, gmm(l(1).lnemertotcap , laglimits(1 10) collapse) ///
gmm(lfastdispp lnslowdispp l(1).lnslowdispp l.lfastdispp, laglimits(1 10) collapse) ///
gmm(lngdpcap l(0).lncerealpp , laglimits(2 10) collapse) ///
iv(yr1987-yr2009 ocn afri eur nam asia , eq(level)) ///
iv(lnpolity2 lnpop ltrade l(2).lnemertotcap ) robust small twostep ar(3) orthog
eststo bb45:xtabond2 lnemertotcap l(1/2).lnemertotcap lngdpcap lnhostidpcap l(0/1).lfastdispp
l(0/1).lnslowdispp ///
l(0).lncerealpp lnpop lnpolity2 ltrade yr1987-yr2009 ocn afri eur nam asia ///
if year>1987 & year<2010, gmm(l(1).lnemertotcap , laglimits(1 10) collapse) ///
gmm(lfastdispp lnslowdispp l(1).lnslowdispp l.lfastdispp, laglimits(1 10) collapse) ///
gmm(lngdpcap l(0).lncerealpp , laglimits(2 10) collapse) ///
iv(yr1987-yr2009 ocn afri eur nam asia , eq(level)) ///
iv(lnpolity2 lnhostidpcap lnpop ltrade l(2).lnemertotcap ) robust small twostep ar(3) orthog
eststo bb55:xtabond2 lnemertotcap l(1/2).lnemertotcap lngdpcap lnhostidpcap l(0/1).lntotdispp
///
l(0).lncerealpp lnpop lnpolity2 ltrade yr1987-yr2009 ocn afri eur nam asia ///
if year>1987 & year<2010, gmm(l(1).lnemertotcap , laglimits(1 10) collapse) ///
gmm(l(0/1).lntotdispp , laglimits(1 10) collapse) ///
gmm(lngdpcap l(0).lncerealpp , laglimits(2 10) collapse) ///
iv(yr1987-yr2009 ocn afri eur nam asia , eq(level)) ///
iv(lnpolity2 lnhostidpcap lnpop ltrade l(2).lnemertotcap ) robust small twostep ar(3) orthog

/*all income countries--per capita--sensitivity analysis--Table 4-7*/
eststo bb45a:xtabond2 lnemertotcap l(1/2).lnemertotcap lngdpcap lnhostidpcap l(0/1).lfastdispp
l(0/1).lnslowdispp ///
l(0).lncerealpp lnpop lnpolity2 ltrade yr1987-yr2009 ocn afri eur nam asia ///
if year>1987 & year<2010, gmm(l(1).lnemertotcap , laglimits(1 8) collapse) ///
gmm(lfastdispp lnslowdispp l(1).lnslowdispp l.lfastdispp , laglimits(1 8) collapse) ///
gmm(lngdpcap l(0).lncerealpp , laglimits(2 8) collapse) ///
iv(yr1987-yr2009 ocn afri eur nam asia , eq(level)) ///
iv(lnpolity2 lnhostidpcap lnpop ltrade l(2).lnemertotcap ) robust small twostep ar(3) orthog
eststo bb45b:xtabond2 lnemertotcap l(1/2).lnemertotcap lngdpcap lnhostidpcap l(0/1).lfastdispp
l(0/1).lnslowdispp ///
l(0).lncerealpp lnpop lnpolity2 ltrade yr1987-yr2009 ocn afri eur nam asia ///
if year>1987 & year<2010, gmm(l(1).lnemertotcap , laglimits(1 4) collapse) ///
gmm(lfastdispp lnslowdispp l(1).lnslowdispp l(1).lfastdispp, laglimits(1 4) collapse) ///
gmm(lngdpcap l(0).lncerealpp , laglimits(2 4) collapse) ///
iv(yr1987-yr2009 ocn afri eur nam asia , eq(level)) ///
iv(lnpolity2 lnhostidpcap lnpop ltrade l(2).lnemertotcap ) robust small twostep ar(3) orthog
eststo bb45c:xtabond2 lnemertotcap l(1/2).lnemertotcap lngdpcap lnhostidpcap l(0/1).lfastdispp
l(0/1).lnslowdispp ///

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l(0).lncerealpp lnpop lnpolity2 lntrade yr1987-yr2009 ocn afri eur nam asia ///
if year>1987 & year<2010, gmm(l(1).lnemertotcap , laglimits(1 2) collapse) ///
gmm(lnfastdispp lnslowdispp l(1).lnslowdispp l(1).lnfastdispp, laglimits(1 2) collapse) ///
gmm(lngdpcap l(0).lncerealpp , laglimits(2 2) collapse) ///
iv(yr1987-yr2009 ocn afri eur nam asia , eq(level)) ///
iv(lnpolity2 lnhostidpcap lnpop lntrade l(2).lnemertotcap ) robust small twostep ar(3) orthog
eststo bb55a:xtabond2 lnemertotcap l(1/2).lnemertotcap lngdpcap lnhostidpcap l(0/1).lntotdispp
///
l(0).lncerealpp lnpop lnpolity2 lntrade yr1987-yr2009 ocn afri eur nam asia ///
if year>1987 & year<2010, gmm(l(1).lnemertotcap , laglimits(1 8) collapse) ///
gmm(l(0/1).lntotdispp , laglimits(1 8) collapse) ///
gmm(lngdpcap l(0).lncerealpp , laglimits(2 8) collapse) ///
iv(yr1987-yr2009 ocn afri eur nam asia , eq(level)) ///
iv(lnpolity2 lnhostidpcap lnpop lntrade l(2).lnemertotcap ) robust small twostep ar(3) orthog
eststo bb55b:xtabond2 lnemertotcap l(1/2).lnemertotcap lngdpcap lnhostidpcap l(0/1).lntotdispp
///
l(0).lncerealpp lnpop lnpolity2 lntrade yr1987-yr2009 ocn afri eur nam asia ///
if year>1987 & year<2010, gmm(l(1).lnemertotcap , laglimits(1 4) collapse) ///
gmm(l(0/1).lntotdispp , laglimits(1 4) collapse) ///
gmm(lngdpcap l(0).lncerealpp lnhostidpcap, laglimits(2 4) collapse) ///
iv(yr1987-yr2009 ocn afri eur nam asia , eq(level)) ///
iv(lnpolity2 lnpop lntrade l(2).lnemertotcap ) robust small twostep ar(3) orthog
eststo bb55c:xtabond2 lnemertotcap l(1/2).lnemertotcap lngdpcap lnhostidpcap l(0/1).lntotdispp
///
l(0).lncerealpp lnpop lnpolity2 lntrade yr1987-yr2009 ocn afri eur nam asia ///
if year>1987 & year<2010, gmm(l(1).lnemertotcap , laglimits(1 2) collapse) ///
gmm(l(0/1).lntotdispp , laglimits(1 2) collapse) ///
gmm(lngdpcap l(0).lncerealpp lnhostidpcap , laglimits(2 2) collapse) ///
iv(yr1987-yr2009 ocn afri eur nam asia , eq(level)) ///
iv(lnpolity2 lnpop lntrade l(2).lnemertotcap ) robust small twostep ar(3) orthog
/*lower income countries--non per capita--Table 4-8*/
eststo a15:xtabond2 lnemertot l(1).lnemertot lngdp l(0).lnfastdis l(0).lnslowdis ///
l(0).lncereal lnpop lnpolity2 lntrade yr1987-yr2009 ocn afri eur nam asia ///
if upper_inc==0 & year>1987 & year<2010, gmm(l(1).lnemertot , laglimits(1 10) collapse) ///
gmm(lnfastdis lnslowdis, laglimits(1 10) collapse) ///
gmm(lngdp l(0).lncereal , laglimits(2 10) collapse) ///
iv(yr1987-yr2009 ocn afri eur nam asia , eq(level)) ///
iv(lnpolity2 lnpop lntrade) robust small twostep ar(3) orthog
eststo a25:xtabond2 lnemertot l(1/2).lnemertot lngdp l(0).lnfastdis l(0).lnslowdis ///
l(0).lncereal lnpop lnpolity2 lntrade yr1987-yr2009 ocn afri eur nam asia ///
if upper_inc==0 & year>1987 & year<2010, gmm(l(1).lnemertot , laglimits(2 10) collapse) ///
gmm(lnfastdis lnslowdis, laglimits(1 10) collapse) ///
gmm(lngdp l(0).lncereal , laglimits(2 10) collapse) ///
iv(yr1987-yr2009 ocn afri eur nam asia , eq(level)) ///
iv(lnpolity2 lnpop lntrade l(2).lnemertot) robust small twostep ar(3) orthog
eststo a35:xtabond2 lnemertot l(1/2).lnemertot lngdp l(0/1).lnfastdis l(0/1).lnslowdis ///
l(0).lncereal lnpop lnpolity2 lntrade yr1987-yr2009 ocn afri eur nam asia ///
if upper_inc==0 & year>1987 & year<2010, gmm(l(1).lnemertot , laglimits(1 10) collapse) ///

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gmm(lfastdis lnslowdis l(1).lnslowdis l.lfastdis, laglimits(1 10) collapse) ///
gmm(lngdp l(0).lncereal , laglimits(2 10) collapse) ///
iv(yr1987-yr2009 ocn afri eur nam asia , eq(level)) ///
iv(lnpolity2 lnpop lntrade l(2).lnemertot) robust small twostep ar(3) orthog
eststo a45:xtabond2 lnemertot l(1/2).lnemertot lngdp lnhostidp l(0/1).lfastdis l(0/1).lnslowdis
///
l(0).lncereal lnpop lnpolity2 lntrade yr1987-yr2009 ocn afri eur nam asia ///
if upper_inc==0 & year>1987 & year<2010, gmm(l(1).lnemertot , laglimits(1 10) collapse ) ///
gmm(lfastdis lnslowdis l(1).lnslowdis l.lfastdis, laglimits(1 10) collapse) ///
gmm(lngdp l(0).lncereal , laglimits(2 10) collapse) ///
iv(yr1987-yr2009 ocn afri eur nam asia , eq(level)) ///
iv(lnpolity2 lnhostidp lnpop lntrade l(2).lnemertot) robust small twostep ar(3) orthog
eststo a55: xtabond2 lnemertot l(1/2).lnemertot lngdp lnhostidp l(0/1).lntotdis ///
l(0).lncereal lnpop lnpolity2 lntrade yr1987-yr2009 ocn afri eur nam asia ///
if upper_inc==0 & year>1987 & year<2010, gmm(l(1).lnemertot , laglimits(1 10) collapse ) ///
gmm(lntotdis l.lntotdis, laglimits(1 10) collapse) ///
gmm(lngdp l(0).lncereal , laglimits(2 10) collapse) ///
iv(yr1987-yr2009 ocn afri eur nam asia , eq(level)) ///
iv(lnpolity2 lnhostidp lnpop lntrade l(2).lnemertot) robust small twostep ar(3) orthog

/*sensitivity analysis (reduced instruments) lower income countries--non per capita Table 4-9*/
eststo a45a:xtabond2 lnemertot l(1/2).lnemertot lngdp lnhostidp l(0/1).lfastdis l(0/1).lnslowdis
///
l(0).lncereal lnpop lnpolity2 lntrade yr1987-yr2009 ocn afri eur nam asia ///
if upper_inc==0 & year>1987 & year<2010, gmm(l(1).lnemertot , laglimits(1 8) collapse ) ///
gmm(lfastdis lnslowdis l(1).lnslowdis ///
l.lfastdis , laglimits(1 8) collapse) ///
gmm(lngdp l(0).lncereal , laglimits(2 8) collapse) ///
iv(yr1987-yr2009 ocn afri eur nam asia , eq(level)) ///
iv(lnpolity2 lnhostidp lnpop lntrade l(2).lnemertot ) robust small twostep ar(3) orthog
eststo a45b:xtabond2 lnemertot l(1/2).lnemertot lngdp lnhostidp l(0/1).lfastdis l(0/1).lnslowdis
///
l(0).lncereal lnpop lnpolity2 lntrade yr1987-yr2009 ocn afri eur nam asia ///
if upper_inc==0 & year>1987 & year<2010, gmm(l(1).lnemertot , laglimits(1 4) collapse ) ///
gmm(lfastdis lnslowdis l(1).lnslowdis ///
l.lfastdis, laglimits(1 4) collapse) ///
gmm(lngdp l(0).lncereal , laglimits(2 4) collapse) ///
iv(yr1987-yr2009 ocn afri eur nam asia , eq(level)) ///
iv(lnpolity2 lnhostidp lnpop lntrade l(2).lnemertot) robust small twostep ar(3) orthog
eststo a45c:xtabond2 lnemertot l(1/2).lnemertot lngdp lnhostidp l(0/1).lfastdis l(0/1).lnslowdis
///
l(0).lncereal lnpop lnpolity2 lntrade yr1987-yr2009 ocn afri eur nam asia ///
if upper_inc==0 & year>1987 & year<2010, gmm(l(1).lnemertot , laglimits(1 2) collapse ) ///
gmm(lfastdis lnslowdis l(1).lnslowdis ///
l.lfastdis, laglimits(1 2) collapse) ///
gmm(lngdp l(0).lncereal , laglimits(2 2) collapse) ///
iv(yr1987-yr2009 ocn afri eur nam asia , eq(level)) ///
iv(lnpolity2 lnhostidp lnpop lntrade l(2).lnemertot) robust small twostep ar(3) orthog

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eststo a55a: xtabond2 lnemertot l(1/2).lnemertot lngdp lnhostidp l(0/1).lntotdis ///
l(0).lncereal lnpop lnpolity2 lntrade yr1987-yr2009 ocn afri eur nam asia ///
if upper_inc==0 & year>1987 & year<2010, gmm(l(1).lnemertot , laglimits(1 8) collapse) ///
gmm(lntotdis l.lntotdis, laglimits(1 8) collapse) ///
gmm(lngdp l(0).lncereal , laglimits(2 8) collapse) ///
iv(yr1987-yr2009 ocn afri eur nam asia , eq(level)) ///
iv(lnpolity2 lnhostidp lnpop lntrade l(2).lnemertot) robust small twostep ar(3) orthog
eststo a55b: xtabond2 lnemertot l(1/2).lnemertot lngdp lnhostidp l(0/1).lntotdis ///
l(0).lncereal lnpop lnpolity2 lntrade yr1987-yr2009 ocn afri eur nam asia ///
if upper_inc==0 & year>1987 & year<2010, gmm(l(1).lnemertot , laglimits(1 4) collapse) ///
gmm(lntotdis l.lntotdis, laglimits(1 4) collapse) ///
gmm(lngdp l(0).lncereal , laglimits(2 4) collapse) ///
iv(yr1987-yr2009 ocn afri eur nam asia , eq(level)) ///
iv(lnpolity2 lnhostidp lnpop lntrade l(2).lnemertot) robust small twostep ar(3) orthog
eststo a55c: xtabond2 lnemertot l(1/2).lnemertot lngdp lnhostidp l(0/1).lntotdis ///
l(0).lncereal lnpop lnpolity2 lntrade yr1987-yr2009 ocn afri eur nam asia ///
if upper_inc==0 & year>1987 & year<2010, gmm(l(1).lnemertot , laglimits(1 2) collapse) ///
gmm(lntotdis l.lntotdis, laglimits(1 2) collapse) ///
gmm(lngdp l(0).lncereal , laglimits(2 2) collapse) ///
iv(yr1987-yr2009 ocn afri eur nam asia , eq(level)) ///
iv(lnpolity2 lnhostidp lnpop lntrade l(2).lnemertot) robust small twostep ar(3) orthog

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/*all income countries--non per capita--Table 4-10*/

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eststo aa15:xtabond2 lnemertot l(1).lnemertot lngdp l(0).lnfastdis l(0).lnslowdis ///
l(0).lncereal lnpop lnpolity2 lntrade yr1987-yr2009 ocn afri eur nam asia ///
if year>1987 & year<2010, gmm(l(1).lnemertot , laglimits(1 10) collapse) ///
gmm(lnfastdis lnslowdis, laglimits(1 10) collapse) ///
gmm(lngdp l(0).lncereal , laglimits(2 10) collapse) ///
iv(yr1987-yr2009 ocn afri eur nam asia , eq(level)) ///
iv(lnpolity2 lnpop lntrade) robust small twostep ar(3) orthog
eststo aa25:xtabond2 lnemertot l(1/2).lnemertot lngdp l(0).lnfastdis l(0).lnslowdis ///
l(0).lncereal lnpop lnpolity2 lntrade yr1987-yr2009 ocn afri eur nam asia ///
if year>1987 & year<2010, gmm(l(1).lnemertot , laglimits(1 10) collapse) ///
gmm(lnfastdis lnslowdis, laglimits(1 10) collapse) ///
gmm(lngdp l(0).lncereal , laglimits(2 10) collapse) ///
iv(yr1987-yr2009 ocn afri eur nam asia , eq(level)) ///
iv(lnpolity2 lnpop lntrade l(2).lnemertot) robust small twostep ar(3) orthog
eststo aa35:xtabond2 lnemertot l(1/2).lnemertot lngdp l(0/1).lnfastdis l(0/1).lnslowdis ///
l(0).lncereal lnpop lnpolity2 lntrade yr1987-yr2009 ocn afri eur nam asia ///
if year>1987 & year<2010, gmm(l(1).lnemertot , laglimits(1 10) collapse) ///
gmm(lnfastdis lnslowdis l(1).lnslowdis l.lnfastdis, laglimits(1 10) collapse) ///
gmm(lngdp l(0).lncereal , laglimits(2 10) collapse) ///
iv(yr1987-yr2009 ocn afri eur nam asia , eq(level)) ///
iv(lnpolity2 lnpop lntrade l(2).lnemertot) robust small twostep ar(3) orthog
eststo aa45:xtabond2 lnemertot l(1/2).lnemertot lngdp lnhostidp l(0/1).lnfastdis l(0/1).lnslowdis
///
l(0).lncereal lnpop lnpolity2 lntrade yr1987-yr2009 ocn afri eur nam asia ///
if year>1987 & year<2010, gmm(l(1).lnemertot , laglimits(1 10) collapse) ///

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gmm(lnfastdis lnslowdis l(1).lnslowdis l.lnfastdis, laglimits(1 10) collapse) ///
gmm(lngdp l(0).lncereal , laglimits(2 10) collapse) ///
iv(yr1987-yr2009 ocn afri eur nam asia , eq(level)) ///
iv(lnpolity2 lnhostidp lnpop lntrade l(2).lnemertot) robust small twostep ar(3) orthog
eststo aa55: xtabond2 lnemertot l(1/2).lnemertot lngdp lnhostidp l(0/1).lntotdis ///
l(0).lncereal lnpop lnpolity2 lntrade yr1987-yr2009 ocn afri eur nam asia ///
if year>1987 & year<2010, gmm(l(1).lnemertot , laglimits(1 10) collapse) ///
gmm(lntotdis l.lntotdis, laglimits(1 10) collapse) ///
gmm(lngdp l(0).lncereal , laglimits(2 10) collapse) ///
iv(yr1987-yr2009 ocn afri eur nam asia , eq(level)) ///
iv(lnpolity2 lnhostidp lnpop lntrade l(2).lnemertot) robust small twostep ar(3) orthog

/*all income countries--non per capita--sensitivity analysis--Table 4-11*/
eststo aa45a:xtabond2 lnemertot l(1/2).lnemertot lngdp lnhostidp l(0/1).lnfastdis
l(0/1).lnslowdis l(0).lncereal lnpop lnpolity2 lntrade yr1987-yr2009 ocn afri eur nam asia ///
if year>1987 & year<2010, gmm(l(1).lnemertot , laglimits(1 8) collapse) ///
gmm(lnfastdis lnslowdis l(1).lnslowdis l.lnfastdis , laglimits(1 8) collapse) ///
gmm(lngdp l(0).lncereal , laglimits(2 8) collapse) iv(yr1987-yr2009 ocn afri eur nam
asia , eq(level)) iv(lnpolity2 lnhostidp lnpop lntrade l(2).lnemertot) robust small twostep ar(3) orthog
eststo aa45b:xtabond2 lnemertot l(1/2).lnemertot lngdp lnhostidp l(0/1).lnfastdis
l(0/1).lnslowdis l(0).lncereal lnpop lnpolity2 lntrade yr1987-yr2009 ocn afri eur nam asia ///
if year>1987 & year<2010, gmm(l(1).lnemertot , laglimits(1 4) collapse) gmm(lnfastdis ///
lnslowdis l(1).lnslowdis l.lnfastdis, laglimits(1 4) collapse) gmm(lngdp l(0).lncereal , laglimits(2 4) ///
collapse) iv(yr1987-yr2009 ocn afri eur nam asia , eq(level)) ///
iv(lnpolity2 lnhostidp lnpop lntrade l(2).lnemertot) robust small twostep ar(3) orthog
eststo aa45c:xtabond2 lnemertot l(1/2).lnemertot lngdp lnhostidp l(0/1).lnfastdis
l(0/1).lnslowdis l(0).lncereal lnpop lnpolity2 lntrade yr1987-yr2009 ocn afri eur nam asia ///
if year>1987 & year<2010, gmm(l(1).lnemertot , laglimits(1 2) collapse) ///
gmm(lnfastdis lnslowdis l(1).lnslowdis l.lnfastdis, laglimits(1 2) collapse) ///
gmm(lngdp l(0).lncereal , laglimits(2 2) collapse) iv(yr1987-yr2009 ocn afri eur nam asia ///
, eq(level)) iv(lnpolity2 lnhostidp lnpop lntrade l(2).lnemertot) robust small twostep ar(3) orthog
eststo aa55a: xtabond2 lnemertot l(1/2).lnemertot lngdp lnhostidp l(0/1).lntotdis ///
l(0).lncereal lnpop lnpolity2 lntrade yr1987-yr2009 ocn afri eur nam asia ///
if year>1987 & year<2010, gmm(l(1).lnemertot , laglimits(1 8) collapse) ///
gmm(lntotdis l.lntotdis, laglimits(1 8) collapse) ///
gmm(lngdp l(0).lncereal , laglimits(2 8) collapse) ///
iv(yr1987-yr2009 ocn afri eur nam asia , eq(level)) ///
iv(lnpolity2 lnhostidp lnpop lntrade l(2).lnemertot) robust small twostep ar(3) orthog
eststo aa55b: xtabond2 lnemertot l(1/2).lnemertot lngdp lnhostidp l(0/1).lntotdis ///
l(0).lncereal lnpop lnpolity2 lntrade yr1987-yr2009 ocn afri eur nam asia ///
if year>1987 & year<2010, gmm(l(1).lnemertot , laglimits(1 4) collapse) ///
gmm(lntotdis l.lntotdis, laglimits(1 4) collapse) ///
gmm(lngdp l(0).lncereal , laglimits(2 4) collapse) ///
iv(yr1987-yr2009 ocn afri eur nam asia , eq(level)) ///
iv(lnpolity2 lnhostidp lnpop lntrade l(2).lnemertot) robust small twostep ar(3) orthog
eststo aa55c: xtabond2 lnemertot l(1/2).lnemertot lngdp lnhostidp l(0/1).lntotdis ///
l(0).lncereal lnpop lnpolity2 lntrade yr1987-yr2009 ocn afri eur nam asia ///
if year>1987 & year<2010, gmm(l(1).lnemertot , laglimits(1 2) collapse) ///

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gmm(lntotdis l.lntotdis, laglimits(1 2) collapse) ///
gmm(lngdp l(0).lncereal , laglimits(2 2) collapse) ///
iv(yr1987-yr2009 ocn afri eur nam asia , eq(level)) ///
iv(lnpolity2 lnhostidp lnpop lntrade l(2).lnemertot) robust small twostep ar(3) orthog
esttab a15 a25 a35 a45 a55 a45a a45b a45c a55a a55b a55c aa15 aa25 aa35 ///
aa45 aa55 aa45a aa45b aa45c aa55a aa55b aa55c using ${DIR}output_inc.csv, ///
style(tex) cells(b(star fmt(3)) se(par) ll) star(* 0.10 ** 0.05 *** 0.01) order(_cons L.lnemertot
L2.lnemertot) ///
lnpop lnpolity2 lntrade lngdp lncereal ///
lnfastdis L.lnfastdis lnslowdis L.lnslowdis lntotdis L.lntotdis lnhostidp afri asia ocn eur nam) ///
nogaps replace
esttab b15 b25 b35 b45 b55 b45a b45b b45c b55a b55b b55c bb15 bb25 bb35 bb45 bb55 bb45a
bb45b bb45c bb55a bb55b bb55c ///
using ${DIR}output_inc_cap.csv, ///
style(tex) cells(b(star fmt(3)) se(par) ll) star(* 0.10 ** 0.05 *** 0.01) order(_cons L.lnemertotcap
L2.lnemertotcap) ///
lnpop lnpolity2 lntrade lngdpcap lncerealpp ///
lnfastdispp L.lnfastdispp lnslowdispp L.lnslowdispp ///
lntotdispp L.lntotdispp lnhostidpcap ocn eur nam afri asia) ///
nogaps replace

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