The Pennsylvania State University
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ESSAYS ON CHILDHOOD NUTRITIONAL DEPRIVATION IN NEPAL AND OFF-FARM EMPLOYMENT IN THE UNITED STATES: MULTI-LEVEL AND SPATIAL ECONOMETRIC MODELING APPROACH

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by
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ABSTRACT

This dissertation, as a partial fulfillment of the requirements for the degree of Doctor of Philosophy in the dual-title program in Agricultural, Environmental and Regional Economics and Demography, is comprised of three essays that offer empirical investigations into issues of high prevalence of childhood nutritional deprivation in Nepal and into the ever-expanding off-farm employment of farm families in the United States. Essays are titled: (1) Maternal human capital and childhood stunting in Nepal: a multi-level modeling approach, (2) Community environmental contexts and childhood underweight status in Nepal: a multi-level modeling approach, and (3) Government farm payments and off-farm labor response of principal farm operators: a spatial analysis of U.S county-level data.

The first essay examines the influence of maternal human capital: maternal education, maternal health and community maternal education on childhood stunting, a form of long-term child nutritional deprivation, in Nepal. Community maternal education that captures community spillover effects of maternal education is a new innovation adopted in this study of child nutritional deprivation. This study adopts the multi-level modeling approach to account for the unobserved heterogeneity of the childhood stunting outcome at the household and community levels. Data for this study are from the Nepal Demographic and Health Survey (NDHS), 2001. Maternal own education is negatively related to childhood stunting, especially with higher levels of education. Interestingly, the spillover effect of community maternal education stands out to be negative and robust on the childhood stunting outcome, even if mothers of children are uneducated. Further,

results provide evidence of intergenerational transmission of genetic endowment from mother to child: mother’s height is negatively related to childhood stunting, regardless of mother’s educational attainment and place of residence. Key policy implications drawn from the findings, among others, are that the public health policy of alleviating long-term nutritional deprivation among children should further emphasize (1) promoting education among women and mothers, and (2) not only child nutritional health but also maternal long-term health, especially in geographically-disadvantaged areas.

The second essay also utilizes the multi-level modeling approach applied to nationally-representative NDHS data. This study focuses on community environmental contexts, especially season and altitude of current place of residence as potential determinants of childhood underweight (short-term nutritional deprivation) among preschool-age children in Nepal. These factors have been largely overlooked in past studies on childhood underweight status. Results provide unequivocal evidence of seasonal variation in childhood underweight status. The odds of children being underweight during the unfavorable season are much higher than during the favorable season. Wealthier households appear to be able to better cope with the environmental stresses associated with unfavorable season. Overall, the caste/ethnicity of household heads is found to moderate the influence of altitude on childhood underweight status. However, in urban communities, the odds of children being underweight significantly decrease with altitude. Findings suggest that public health policies towards achieving the Millennium development Goals of alleviating short-term childhood nutritional deprivation in Nepal should account for seasonal variation in prevalence of childhood underweight status.

Public health and food security interventions targeting child nutritional health should be concentrated in pre-harvest months. Similarly, lower altitude urban areas where underweight prevalence is higher should be the focus of public health and food security interventions.

The focus of the third essay is on participation and scale effects of U.S. government farm payments in total and by type on off-farm employment decisions of U.S. principal farm operators working off-farm for at least 200 days a year. Additionally, this paper for the first time ascertains if there exists a spatial dependency in off-farm employment decisions in the U.S. The paper adopts a recently-developed technique, the Feasible Generalized Spatial Two-Stage Least Squares (FGS2SLS) estimator, to address a system of equations with spatial lagged dependent variables and spatial dependency in error structure as well as endogenous explanatory variables. The county-level data are primarily from the 2002 U.S. Census of Agriculture. Results provide evidence of spatial dependency of off-farm employment among principal farm operators in the U.S., suggesting the need to correct for spatial bias in any off-farm employment studies in the U.S. Overall, participation and scale of government farm payments are negatively related to off-farm response of principal farm operators, but the extent of effects varies substantially between participation and scale of government payments. Further, different types of government payments have different impacts on the extent of off-farm response of principal farm operators. Interestingly, the off-farm employment impacts of government farm payments by type are associated with the magnitude of income transfer, suggesting policy consideration of strong caps on government farm payments.

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1. MATERNAL HUMAN CAPITAL AND CHILDHOOD STUNTING IN NEPAL: A MULTI-LEVEL MODELING APPROACH

1.1 ABSTRACT

Childhood stunting among preschool-age children stands as a serious public health problem to be addressed in Nepal. Applying the multi-level modeling approach to nationally representative data, overall, this study provides evidence that maternal education is negatively related to childhood stunting. This occurs especially for mother's higher level of education. For lower level maternal education the relationship is not as strong when household-level and community-level factors are taken into consideration, but story is just in contrast when relationships are estimated by residence. Instead, the study provides new evidence of a strong negative community externality of maternal education on childhood stunting, even if mothers of children are uneducated. Next, mother's height is negatively related to childhood stunting, regardless of mother's educational attainment and place of residence, providing evidence of intergenerational transmission of maternal health. Findings suggest that to alleviate childhood long-term nutritional deprivation, child health policy in Nepal should further emphasize the education of the mother especially focusing on geographically-disadvantaged areas. Study results also suggest that the focus should be not only on childhood nutrition but also on the mother's long-term nutritional health. Alleviation of household level poverty also appears to be important in combating the childhood long-term nutritional deprivation in Nepal.

1.2 INTRODUCTION

Childhood undernutrition[1] has been shown to have not only strong negative associations with the cognitive development of children and the productivity and economic development of nations but also a strong positive association with morbidity and mortality of people during childhood and adulthood (Martorell and Ho 1984; Senauer and Garcia 1991; WHO 2000; Case *et al.* 2002; Chang *et al.* 2002; MOH/N *et al.* 2002; United Nations 2002; Behrman and Rosenzweig 2004; Caulfield *et al*. 2004; de Onis *et al*. 2004). The seriousness of the childhood undernutrition problem is well acknowledged in the Millennium Development Goals (MDGs) both at global and national levels (United Nations 2002; United Nations Country Team of Nepal 2002). Yet, disproportionately large proportions of preschool-age children -- age below five years – living in developing countries are stunted[2]. Half of these children live in South Asia including Nepal, and Nepal ranks the second worst among South Asian countries in prevalence of stunting (UNICEF 2006). This calls for a critical understanding of factors that shape child stunting in developing countries for effective policy action.

Recently, maternal human capital as a potential determinant of childhood undernutrition has attracted considerable research interest among sociologists, demographers, economists, and many others. According to human capital theory, education and health are two key endowments. While many claim that maternal education makes a significant positive contribution to child health (Strauss 1990; Behrman and Rosenzweig 2002; Thomas *et al.* 1991), others warn that the estimated relationship may be overestimated in the absence of important community context variables (for instance, Desai and Alva

1998). Additionally, past studies have failed to capture the full effects of maternal education, such as the community-externality (spillover) of maternal education. Evidence of positive spillover effects of community maternal education on reducing fertility and mortality has recently been documented (Kravdal 2002; McNay *et al.* 2003; Moursund and Kravdal 2003; Kravdal 2004). Intergenerational transmission of maternal health, which can in part be attributed to spillover of genetic endowments, has received limited attention with a few exceptions (Strauss 1990; Thomas *et al.* 1991; Behrman and Rosenzweig 2002).

Using multi-level modeling applied to nationally-representative data from Nepal, this study examines the extent to which maternal education -- including the community externality of maternal education -- and maternal health (height) shape stunting outcomes of preschool-age children. An analysis is also extended to a restricted sample including only children from uneducated mothers to ascertain whether or not community-externality of maternal education is robust when children from educated mothers are excluded. Lastly, residential variation on the effect of maternal human capital is examined by analyzing rural and urban sub-samples.

1.3 SETTING

Stretched over an area of 147,181 square kilometers, Nepal is a landlocked county situated between China in the north and India in the south, east and west. Administratively, Nepal is divided into five developmental regions: Eastern, Central, Western, Mid-Western, and Far-Western. Similarly, the country can be divided into three agri-ecological regions: Mountains, Hills and Terai (flat land area) (Figure 1.1). Inhabited by an estimated population of 26 million (PRB 2006), the economy of Nepal is predominantly subsistence agri-based. Only about 16.1% of land in Nepal is cultivable, most of which is concentrated in the *Terai* region. The agricultural sector absorbs about 76% of the active labor force, accounting for 38% of GDP[1]. The country's per capita gross national income (purchasing power parity) was estimated to be $1,530 (2005 estimates). According to the PRB (2006) 69% percent of the populations live on below US $2 per day. Life expectancy at birth in Nepal is 62 years, which is lower than the South Central Asian average (63 years). Similarly, the infant mortality rate is 64 per 1000 live births, the same as the South Central Asian average. The percentage of population with improved sanitation greatly varies between rural and urban areas. In 2002 it was estimated to be 68% in urban areas and 20% in rural areas (PRB 2006). Food consumption in Nepal is overwhelmingly cereal based; however, food consumption patterns vary from one ethnic group to another. Food practices especially choice of animal protein are essentially influenced by culture and are ethnically-based. Despite Nepal's agriculturally-based economy, prevalence of stunting remains a major public health problem. In 2001, the prevalence of stunting was estimated at 51% (MOH/N *et al.* 2002). Similarly, wide geographical variation (east to west and north to south) in stunting is reported (FAO 1998).

[1] https://www.cia.gov/cia/publications/factbook/geos/np.html, April 2007 updates

Figure 1.1 Community-Level Prevalence of Stunting Among Preschool-Age Children, Nepal, 2001

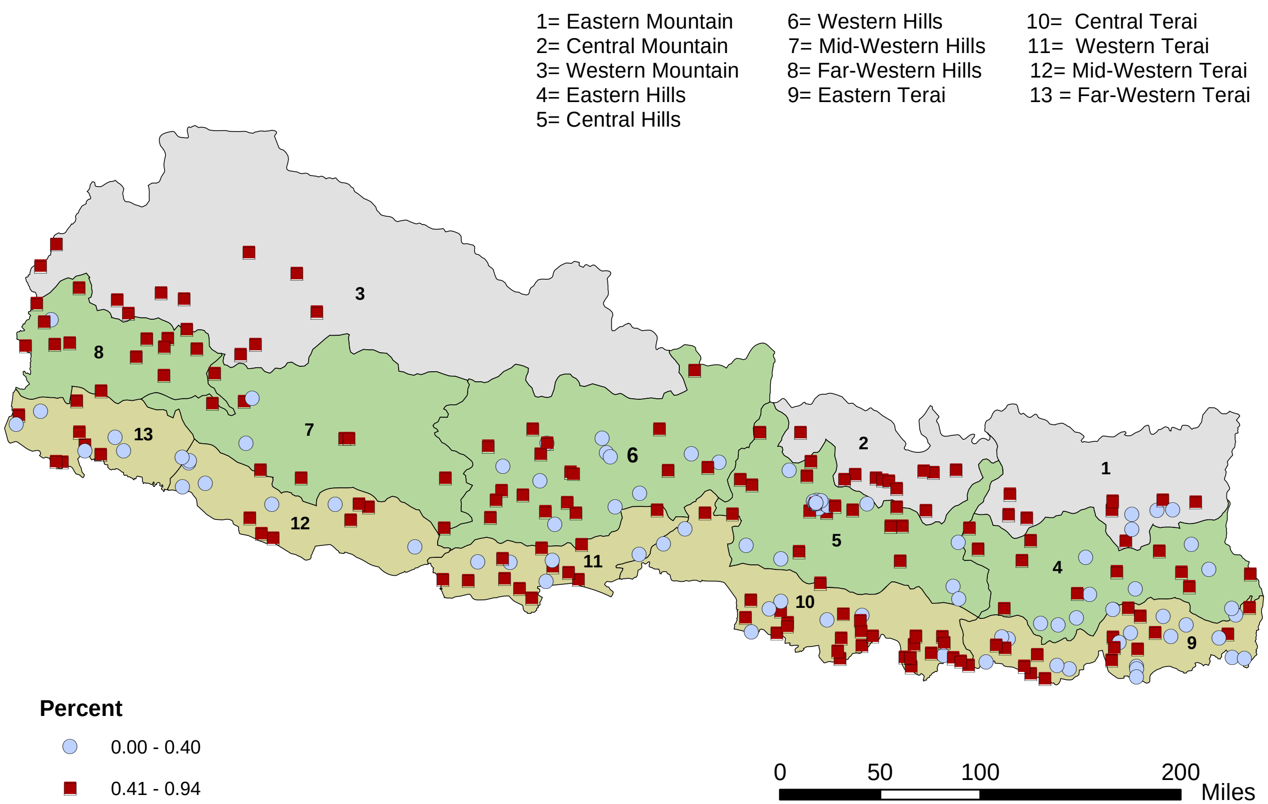


Figure 1.1 illustrates the community-level pattern of the childhood stunting prevalence in Nepal. While very few communities have no record of stunted children at all, many experience staggering proportions of stunted children with a percentage as high as 94%. Communities with solid red squares on the map exceed the cut-off (40%) for a serious long-term public health problem as defined by the WHO (1995). Communities with solid blue circles, on the other hand, are relatively better-off, yet the prevalence is substantial. By development region, children in Eastern Nepal are nutritionally better-off compared with those in other parts of Nepal, especially Far-Western Nepal, showing an apparent regional variation in prevalence. Similarly, greater proportions of children in the Mountain regions seem to be stunted compared with those in the Hills and Terai regions. However, it is not clear in Figure 1.1 whether this pattern corresponds to altitude of community, a key element of ecological domain.

1.4 PAST STUDIES

Maternal education and health constitute key human capital endowments. Maternal education as a potential determinant and mechanisms through which it influences child health have been widely studied by economists, demographers and other social scientists (Caldwell 1979; Grossman and Kaestner 1997; Handa 1999; Variyam *et al.* 1999; Pongou *et al.* 2006). According to household production theory, maternal education positively affects child health through greater allocative efficiency. More educated mothers are more able to acquire and process health information than less educated ones (Grossman and Kaestner 1997). Cowell (2006) provides three broad explanations of how education influences health behavior among adults. These include efficiency mechanism, unobserved heterogeneity, and future opportunity costs. The same explanations may also explain the link between maternal education and child health. In terms of efficiency mechanism, as mentioned by Grossman and Kaestner (1997), educated persons allocate their resources more efficiently to obtain better health. According to the unobserved heterogeneity explanation, education affects health because education proxies unobserved variables such as time preference. Finally, the future opportunity cost explanation posits that any utility improving future outcomes such as income can affect current behavior. Higher future income of healthier behavior signals a disincentive for more educated people to adopt unhealthy behavior. The education of parents not only directly affects the health production function of children but also indirectly affects child health through increased wages and income (Kassouf and Senauer 1996). Caldwell (1979) argues that education improves the ability of mothers to manipulate the world such as seeking health services, and secures greater access to resources for investment in child health and nutrition. Similarly, Pongou *et al.* (2006) state that education provides mothers the power to depart from traditional practices, including taboos regarding breast feeding and dietary intake.

Although past studies have documented a negative relationship between mother's education and long-term nutritional deprivation, these studies are limited to the mother's individual education. Above and beyond the mother's education, the education of others including the community-level education of mothers may play an important role. Other social scientists have put forth diffusion theory to explain the community externalities that may affect individual fertility behavior and child mortality (Montgomery and Casterline 1993, 1996; Kravdal 2004). According to diffusion theory, the diffusion of innovative ideas takes place through social influence and social learning. Peer pressure and authority constitute the key elements of the social influence mechanism that is believed to affect the behavior of others. The social learning may occur due to interpersonal interactions and learning by observation.

There is no study, to the best of our knowledge, analyzing the effect of community-level education on child stunting. Kravdal (2004) has demonstrated the limitation of taking an individual-level perspective on education and argues that the individual-level perspective fails to encompass the full impact of education on child mortality in India. The inability to capture the full effect of education is likely to arise from the heterogeneity in community settings. The beneficial impact of education of mothers in the community above and beyond individual education on child health arises from peer or spillover effects. For instance, an uneducated mother can benefit from educated mothers in the community. Similarly, less educated mothers can benefit from more educated mothers in the community regarding good health behaviors. The community-effect of education on child health can have stronger effects in a developing country context, where only a small share of women has formal education and where social interaction among community members is strong.

Recently, the community-level effect of education has been examined on fertility (Kravdal 2002), contraceptive use (McNay *et al.* 2003, Moursund and Kravdal 2003) and mortality (Kravdal 2004). Although maternal community-level effect of education has been ignored in the child health literature, the relevance of community-level unobserved factors is pointed out by Desai and Alva (1998). They show that even the incorporation of location of residence (rural/urban) variables weakens the effect of education on child nutrition; this effect is further weakened if a community-fixed effect is incorporated, demonstrating that the effect of education without considering community contexts is biased. However, their study does not take into account the potential effect of community-level education of mothers on child health. This study aims to fill this gap.

It should be noted that the effect of community-level of maternal education may proxy community-level economic status, as economically prosperous communities are more likely to have more educated mothers. Therefore, the measured community-externality of maternal education may be overestimated if the community-level factors, such as economic status of community, are not accounted for.

Studies focusing on the effect of the nutritional status of the mother on child health are limited. Kebebe (2005) mentions that a nutrition spillover from mother to child can occur in part through sharing the genetic endowment or through behavioral effects, yet many studies on child health and its socioeconomic determinants ignore parent's health in the specification of models. The health economics literature considers that genetic endowment and behavior can substitute or complement the production of health (Ganz 2001). The fundamental role of genetic endowments on the production of child health is also recognized in other social science fields including economics (Haughton and Haughton 1997; Black *et al.* 2005; Kebede 2005). Haughton and Haughton (1997) warn that nutrition studies ignoring parental anthropometric variables should be taken with caution. Similarly, Kebede (2005) emphasizes that the genetic inheritance of child health should not be ignored, especially in the context where parents and children are exposed to the same disease environment and there exists low cross-sectional variation in nutritional status and disease conditions.

In the economics literature, height is a commonly used measure of health. Most economists have used parents' heights to capture the intergenerational transmission of genetic endowments and their unobserved family background characteristics including the investment in health and human capital not picked up by the education variable (Strauss 1990; Kassouf and Senauer 1996). Burgard (2002) also notes that mother's height reflects genetic endowments and nutritional status in childhood and adolescence. Similarly, Kebede (2005) states that in addition to the sharing of genetic endowments, parents' health influences child health through the behavioral effects. For this reason, the heights of parents are also important in accounting for unobserved personal endowments of parent and family backgrounds. The estimated impact of education while ignoring parents' health is, therefore, argued to be overestimated (Behrman and Wolfe 1987). Kebede (2005) states that even the effect of income may be biased due to unobserved heterogeneity originating from parent's health. Given that mother's height in part reflects her own socioeconomic background, inclusion of it as one of the explanatory variables in the model helps measure the independent effect of education instead of serving as a proxy measure of her socioeconomic background (Burgard 2000).

Kassouf and Senauer (1996), based on an analysis of data from the 1989 National Health and Nutritional Survey of Brazil for children aged 2-5 years, found that mother's and father's standardized height-for-age positively and significantly contributed to child height-for-age. Similarly, using 1996 Brazil Demographic and Health Survey (DHS) data for children aged 6 to 59 months, Burgard (2002) found that children of mothers who are 10 centimeters taller (height unstandardized) are 36% less likely to be stunted. Another study, based on five Sub-Saharan African counties, showed that height and weight-for-age of parents positively contributed to height-for-age of children aged 1 to 35 months, showing the intergenerational chain of poor nutrition (Madise *et al.* 1999). The notion that taller parents are likely to have taller children is also confirmed by a longitudinal study based on the Russian Living Standard Measurement Survey (1992-2001) (Fedorov and Sahn 2005). Fedorov and Sahn (2005) found similar effects for mother's and father's heights; however, Glick and Sahn (1998) found that the effect of mother's height was higher than father's in South Africa. A study of children below 6 years of age using the 1985 Living Standard Measurement Survey of Cote d'Ivoire showed that the effect of log of mother's standardized height was significant on height-for-age of children. A study using data from Vietnam showed that taller parents have taller children (Haughton and Haughton 1997); this study showed that the log of heights of mother and father had the same impact, confirming the expectation of biological reasoning. These studies generally do not account for unobserved heterogeneity at higher levels and important community characteristics including community education of mothers.

1.5 CONCEPTUAL FRAMEWORK

The conceptual framework for this study is drawn from the nutrition model used by Behrman and Deolalikar (1988), which is based on the Becker's (1981) household economic model. Most variables used in the specification are based on the Mosley and Chen (1984) framework, which is designed to explain child survival in developing countries. Nevertheless, it is equally applicable to explain childhood stunting in developing countries.

It is assumed that a household aims to maximize the following joint utility function

$$U_j = U(H, C, l) \tag{1}$$

where U_j is the joint utility function of the j^th household with mother and father. The utility parents derive is dependent on the nutritional health status of a child (*H*), the consumption of goods and services from the market (*C*) and amount of leisure time (*l*). The household maximizes the joint utility function subject to the full-income constraint that includes budget and time constraints and the i^th child's health production function (H_i). The health of child is considered as a household-produced good. The health production function of an individual child is specified as

$$H_i = H(I_i, G_i, Ch_i; \phi, \theta, \psi_h, \psi_c) \tag{2}$$

where H_i represents the health outcome of the i^{th} child. The I_i is the child health input including dietary intake, child care time by parents, and the medical care provided when the child is sick; G_i is the child's health endowment, which is unobservable but is proxied by parent's health; Ch_i is the child's observable characteristics including age, birth order, size at birth and sex; ϕ represents observable household characteristics including maternal education, mother's height, age, father's education, household wealth, ethnicity and household size; θ *is* community characteristics including access to health services, market price of consumption goods and services, micro-environmental conditions such as altitude, geographical location such as regions and community-level education of mothers; ψ_h is the unobserved household attributes such as quality of parenting, household public goods such as floor space and level of sanitation. These attributes are common to children within the household; whereas ψ_c represents community attributes such as sanitation condition, exposure to infection, and community location, which are common to children in households within the same community. In the child health production function (eq. 2), the quality and quantity of health input is influenced by the parent's health investment decision such as investment in dietary supplies and in medical care when the child is ill and time devoted to child care. This nurturing behavior of parents depends, among other variables, on education of mother and father. The mechanisms through which education of mother is hypothesized to affect nurturing behavior have been discussed.

Equation 3 provides the budget constraint faced by the household, that is

$$pC + p'I^h = wL + M \tag{3}$$

where p is the vector of prices of market goods and services and p' is the price of health inputs. The I^h represents amount of health inputs. The household income comprises of income from wage earnings (wL) at wage rate w and non-wage income (M). The time constraint facing the household in terms of wage labor (L) is

$$L = T - L^h - l \tag{4}$$

The T represents the total time endowment of the household, which is allocated among wage labor (L), time to children including time for preparing food (L^h) and leisure (l). By combining equations 3 and 4, the full-income (F) constraint is

$$pC + p'I^h = w(T - L^h - l) + M = F \qquad (5)$$

Maximizing the household utility function (1) subject to the full-income constraint (5) and the health production function (2), the reduced-form equation for the health outcome of the ith child can be obtained as

$$H_i = h(p, p', w, Ch, T, M, \phi, \theta, \psi) \qquad (6)$$

Various empirical studies on child health have considered reduced-form equations for the estimation (such as Rosenzweig and Schultz 1983; Senauer and Garcia 1991; Glewwe 1999), since the estimation of the health production function using equation (1) demands many health inputs, which are generally not available in the data.

The NDHS survey data does not provide data on prices and wages. It is plausible to assume that the prices of goods and services and health inputs and also wage rates are unvarying within the community but differ across communities. The unobserved heterogeneity parameter at the community level in part is expected to capture the influence of those factors missing in the models.

The expected relationship between the variables of interest and the stunting status of child is as follows. An increase in education level of the mother is expected to decrease the stunting outcome of a child because of nurturing effects. Similarly, controlling the other factors, the maternal community-level education is expected to have a negative spillover effect on the stunting outcome of children. Mother's height is expected to be negatively related with children's stunting outcomes.

1.6 ESTIMATION ISSUES

Given that stunting status of child is dichotomously measured, a discrete choice model such as logistic regression or probit is the frequently used statistical method, assuming that stunting outcomes of children in the sample are independent. But the assumption of independence becomes invalid if there exists a clustering structure in child nutritional outcome, such as children being nested within household and households within community. Such clustering induces non-independence between children, hence violating the independence assumption. In the existence of clustering of child nutritional outcomes, the use of approaches such as logistic regression yield estimates that are less efficient than the generalized least squares estimates that are based on the true structure of the residual covariance matrix. Additionally, these approaches do not allow an avenue for exploring clustering structure (Goldstein 1991).

To take into account the clustering effects or intra-cluster correlation, a robust variance-covariance matrix is required (Wooldridge 2002). Two approaches are suggested: fixed effects and random effects to take into account the unobserved factors (heterogeneity). These models are distinguished by the assumption on the relationship between observable covariates and heterogeneity; the fixed effects model assumes that covariates and heterogeneity (unobserved variables) are not orthogonal (independent) whereas the random effects model assumes that they are orthogonal. In the case of discrete choice models, the fixed effects estimators are likely to suffer from the incidental parameters problem (Wooldridge 2002). This may occur because fixed effects estimators rely on estimation of constants based on cluster observations, which are fixed and may be quite small. This leads to inconsistent estimates of constants as well as parameters. The estimator is also biased if cluster observations are small. On the other hand, in the random effects models (also known by various names including multi-level models, generalized linear mixed models, hierarchical generalized linear models, random intercept models and mixed-effects models) the expected value of cluster heterogeneity, the idiosyncratic error term and covariance between cluster heterogeneity and idiosyncratic error are assumed to be zero. In the random effects models, the random parameters are estimated in addition to the fixed parameters.

Empirical studies of child health that have considered continuous measures of long-term child nutritional outcome, i.e., height-for-age z score (HAZ) have used fixed effects modeling approaches to account for unobserved heterogeneity (such as Desai and Alva 1998; Glewwe 1999; Senauer and Garcia 1991; Strauss 1990). The multi-level modeling is also considered to be an appropriate statistical technique to estimate the net effect of explanatory variables and uncover unobserved random effects (Goldstein 1991, 2003; Madise *et al.* 1999; Raudenbush and Bryk 2002). Recently, this technique has been used to gain insights into various population issues including childhood mortality (Sastry 1997; Kravdal 2004), fertility (Kravdal 2002), contraception (McNay *et al.* 2003) and child health (Madise *et al.* 1999; Pongou *et al.* 2006).

In this study, as the number of cluster observations is small and the response variable is dichotomous, a three-level multi-level modeling approach with a random intercept specification, i.e., a random-intercept logistic regression model is adopted. Clustering of children's stunting status within the household can be expected because of characteristics common to them such as health inputs, quality of parental care and household pubic goods such as space, which can be expected to differ between households but be the same within the household. Similarly, households may be clustered within the community because of their shared characteristics, such as access to health innovations, exposure to infection, market and climatic conditions, which are common to households within a community but differ across communities. This shows that the child stunting outcome is likely to vary simultaneously at individual, household and community levels.

1.7 EMPIRICAL MODEL AND ESTIMATION

Following Raudenbush and Bryk (2002), the three-level random intercept logistic regression model takes the form discussed below.

Level-I Model (Child-Level)

$$\log\left(\frac{\pi_{ijk}}{1-\pi_{ijk}}\right) = \beta_{0jk} + \sum_{p}^{P} \beta_{pjk} C_{ijk} + \varepsilon_{ijk} \tag{7}$$

where the left-hand side of the equation represents the log odds of being stunted, π_{ijk} represents the probability of the i^{th} child in the j^{th} household and k^{th} community being stunted. The β_{0jk} is the intercept for household j in community k. The C_{ijk} represents p=1,…,P child-level characteristics that predict stunting outcome, and the β_{pjk} represents the corresponding Level-I coefficients that indicate the direction and strength of association between each child-level characteristic and stunting outcome in household *j* in community *k*. Further, the ε_{ijk} represents the Level-I disturbance term (random effect), which is ~N(0, σ^2_c). Although this model seems to resemble a simple logit model, the parameters may not be fixed for reasons explained before.

Level-II Model (Household-Level)

Because children are nested within households, the variation in the parameters in the Level-I model can be modeled as a function of Level-II characteristics. The parameters, $\beta_{0jk,}$ in the Level-I model may vary randomly across households within communities due to household-level characteristics. Therefore, the intercept in the Level-I model can be decomposed as

$$\beta_{0jk} = \beta_{00k} + \sum_{q=1}^{Q_p} \beta_{0qk} H_{qjk} + \gamma_{0jk} \qquad (8)$$

where β_{00k} is the intercept for household *j* in modeling the community effect. The H_{qjk} represents the q=1,…,Q_p household-level characteristics predicting the household effect. The β_{0qk} is the corresponding coefficient representing the direction and strength of the association between household-level characteristics and child-level average effect. The γ_{0jk} is a Level-II random effect that represents the deviation of household effect from its predicted value, based on the household-level model.

Level-III Model (Community-Level)

As children in a household are nested within community, the variation in the parameters, such as β_{00k} in the Level-II model can be modeled as a function of the Level-III characteristics. That is,

$$\beta_{00k} = \beta_{000} + \sum_{s=1}^{S_{pq}} \beta_{p0s} V_{sk} + \mu_{00k} \tag{9}$$

where β_{000} is the intercept for the community-level model for $\beta_{00k.}$ The V_{sk} represents $s=1,\ldots,S_{pq}$ community-level characteristics used as predictors for the community effect, β_{00k}. The β_{p0s} is the corresponding Level-III coefficients that represent the direction and strength of association between community-level characteristics, $V_{sk,}$ and the community effect, β_{00k}. And the u_{00k} is a Level-III random effect that represents the deviation of community k's coefficient, β_{00k}, from its predicted value based on the community-level model.

Combining the equations in Level-I through Level-III, the three-level random-intercept logistic regression model for estimation is as follows

$$\log\left(\frac{\pi_{ijk}}{1-\pi_{ijk}}\right) = \beta_{000} + \sum_{p}^{P} \beta_{pjk} C_{ijk} + \sum_{q=1}^{Q_p} \beta_{0qk} H_{qjk} + \sum_{s=1}^{S_{pq}} \beta_{p0s} V_{sk} + \gamma_{0jk} + \mu_{00k} + \varepsilon_{ijk} \tag{10}$$

where the log odds of the i^{th} child in the j^{th} household and k^{th} community being stunted is the sum of the fixed and random effects components. Thus, the total variation in the likelihood of a child being stunted can be decomposed into the contribution of the fixed effects components that include fixed predictors at different levels such as (C_{ijk}), (H_{qjk}) and (V_{sk}) and the random effects components explaining the variation between children within households (ε_{ijk}), that between households within communities (γ_{0jk}) and that between communities (μ_{00k}).

Random variables are assumed to be distributed normally with mean zero and variance as follows and are also assumed to be independent across levels (Goldstein 1991, 2003). That is,

$$\varepsilon_{ijk} \sim N(0, \sigma^2_c) \qquad \gamma_{0jk} \sim N(0, \sigma^2_h) \qquad \mu_{00k} \sim N(0, \sigma^2_v) \tag{11}$$

The three-level model specified above is no longer a standard logit model because it contains three random variables rather than a single residual term. The variances specified above are unknown and the aim of the proposed multi-level modeling is to estimate those variances or unobserved heterogeneity.

Estimation Approach

This study follows the recently developed adaptive quadrature approach to maximum likelihood estimation of discrete dependent variable with nested random effects (Rabe-Hesketh *et al.* 2005). As opposed to the commonly used Gauss-Hermite quadrature approach, which is biased for large cluster sizes and intra-class correlation, the adaptive quadrature approach provides unbiased estimates of random components with data of different cluster sizes (Rabe-Hesketh *et al.* 2005). The merit of the adaptive quadrature method over the ordinary quadrature method is also described in Goldstein (2003). This study uses the Generalized Linear Latent and Mixed Model (GLLAMM), which is freely downloadable (www.gllamm.org) software that can be run in STATA and provides the necessary commands to run three-level random-intercept models using the adaptive quadrature algorithm (Rabe-Hesketh and Skrondal 2005).

Based on the results of random components, intra-class correlations that measure the strength of correlation between children at household and community levels have been calculated (Rabe-Hesketh and Skrondal 2005). For the children of same community *k* but different households, the residual intra-community correlation for the childhood stunting outcome is defined as the proportion of the total variance due to the community to which an individual child belongs. That is,

$$\rho\,(\text{Community}) = \rho_v = \frac{\sigma^2 v}{\sigma^2 h + \sigma^2 v + \sigma^2 c}, \text{ where } \sigma^2 c = \pi^2/3 = 3.29. \tag{12}$$

For the children also having the same household, the residual intra-household correlation in a community is defined as the proportion of the total variance due to the household in the community to which an individual child belongs, as

$$\rho\,(\text{Household, Community}) = \rho_{hc} = \frac{\sigma^2 h + \sigma^2 v}{\sigma^2 h + \sigma^2 v + \sigma^2 c} \tag{13}$$

Similarly, for the children of same household, the residual intra-household correlation of childhood stunting is defined as the proportion of total variance due to the household to which an individual child belongs. That is,

$$\rho\,(\text{Household}) = \rho_h = \frac{\sigma^2 h}{\sigma^2 h + \sigma^2 v + \sigma^2 c} \tag{14}$$

The post-estimation predicted probability that the i^{th} child in the j^{th} household in the k^{th} community is stunted (Y_{ijk}=1) is estimated for expanded model (Model-IV) of the whole sample model from the parameter estimates and observed response for clusters such as household and community. Similarly, for the same model, predicted household- and community-level random intercepts are estimated as in Rabe-Hesketh and Skrondal (2005).

A series of models are estimated to gain better insights into the effects of maternal human capital variables on childhood stunting. The first set of models are the pooled models (Overall Models) which include rural and urban as well as educated and uneducated mothers in the sample. To ascertain if the community-externality of maternal education is also relevant to the children of uneducated mothers, an additional set of models are estimated (Uneducated Mother Models), based on a restricted sample that includes only the children of uneducated mothers. Lastly, to explore whether or not the effects of maternal human capital variables on childhood stunting vary by urbanization of place of residence, two sets of models are estimated separately for rural community (Rural Models) and urban community (Urban Models). In each of the above models, nested models (Model-I through Model-IV) are estimated to explore whether or not the coefficients for maternal human capital variables are robust when additional variables are incorporated into the model. The modeling steps proceed as follows. Model-I includes only the independent variables, to measure their gross effects. In Model-II, additional child-specific variables are included. Similarly, in Model-III and Model-IV additional household and community variables are incorporated, respectively.

Data and Variables

The analysis is based on the 2001 Nepal Demographic and Health Survey (NDHS) data The NDHS is a nationally-representative comprehensive survey of demographic and health indicators including maternal and child health (MOH/N *et al*. 2002). The sampling procedure consists of a two-stage stratified random sample of households. In the first stage, a systematic sampling with probability proportional to size was used to select 257 primary sampling units (PSUs) -- 42 in urban areas and 215 in rural areas. In the second stage, an average 34 households from each PSU were selected by using a systematic sampling procedure on the complete list of households within each PSU. Each PSU is comprised of a ward and sub-ward. Ward is the smallest political unit. In this study, PSU is used to represent community or cluster. The survey also collected geo-reference data for PSUs using the Global Positioning System (GPS), which provides an avenue for spatial analysis by integrating demographic and health information at the cluster and higher levels such as geographical domains.

A total of 8,602 households were interviewed for household information. From these households, a total of 8,726 ever-married women and 2,261 men (one every third household) in the age range 15-59 years inclusive were successfully interviewed, yielding response rates of 98% and 96% of eligible women and men, respectively. Anthropometric data on weight and height were collected from children (aged less than 5 years) and mothers (aged 15-49 years inclusive).

For the purpose of this study, a total useable sample of 6,125 children aged below five years (1 month to 59 months) nested in 4,250 households and 248 communities is used. An average household has 1.5 children, ranging from 1 to 6 children. At the community-level, the average number of children is 26, ranging from 2 to 34. Slightly more than half (52%) of households have only one eligible child. As almost half of households have at least two eligible children and the number of households in the sample is fairly large, this study uses three-level multi-level models. The variables used in the study are presented below.

Dependent Variable: Stunting status of child is the dependent variable. It is dichotomously measured as '1' if child's height-for-age is less than negative two standard deviations from the median height-for-age (-2 z score) of the National Center for Health Statistics (NCHS)/World Health organization (WHO) reference population, and '0' otherwise.

Independent Variables*:* Three endowments of maternal human capital including mother's education, the community means of mother's education and mother's health are variables of Central interest. Based on years of schooling, mother's education is categorized into three categories: no education, primary level (<=grade 6) and higher than primary level (primary +). Children of mothers with no education are treated as the reference category, with two categories of dummy variables being created. The community mean education is measured as the mean level of education of mothers in the community they belong to, as measured in Kravdal (2004). Height of the mother, measured in centimeters, is specified as a continuous variable.

Controls: Selected child-specific, household-specific and community-specific variables used in other studies have been controlled in the estimated models to net out the effects of the independent variables of interest. The child-specific variables included in the models are age, age-squared, birth order, size at birth, and sex of child. The age of the child measured in months and birth order are specified as continuous variables. Child's size at birth is specified dichotomously as '1' if mother's response to child size at birth was 'average or greater than average' and '0' if otherwise. It is often argued that the measured birth size may be highly correlated with nutritional outcomes such as stunting. The child size at birth variable is based on a subjective response and it is not clear whether the response represent the length or weight of the newly born child. Further, the Pearson correlation coefficient between stunting and size at child's birth is -0.11. Therefore, this variable is specified in the model and is expected to capture in part genetic endowments of parents and prenatal health. The sex of child is also specified as a dichotomous variable as '1' if child is girl or '0' if boy. Breastfeeding is often considered as important child-specific variable (e.g., Madise *et al.* 1999). However, this variable is not used in the models for two important reasons. First, breast feeding in Nepal is almost universal; only 0.3% of children in the sample were reported as not being breast-fed by mothers. Further, while it could be argued that duration of time breast feeding since birth will influence stunting outcomes, child age is strongly correlated with breast feeding duration. The median age for breast feeding is 17 months, with the mean duration being 21 months.

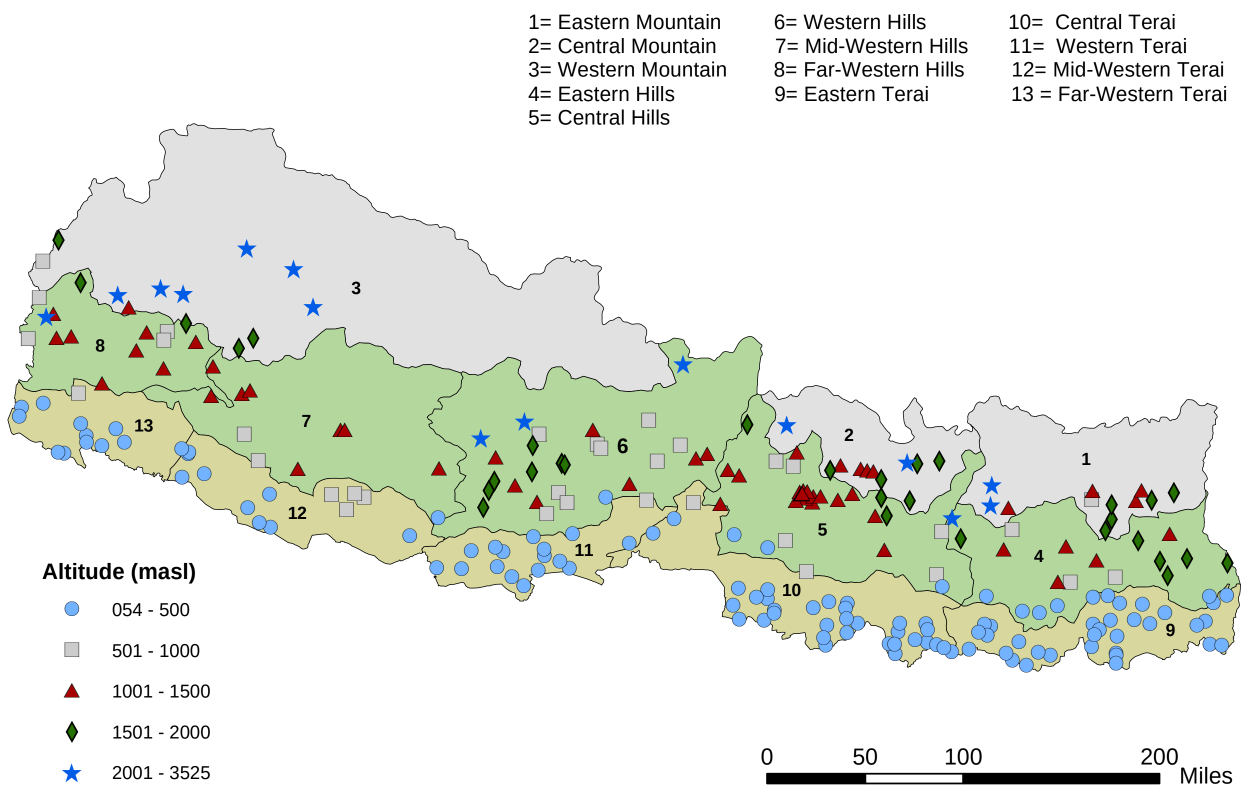
Age of child (and age-squared) is controlled in the models, with age likely accounting for breast-feeding duration in its effect. This important relationship needs to be recognized. The household-level covariates controlled in the models include education of father, age of mother, a household wealth index and ethnicity. The education of father is based on the survey response from the child's mother. Father's education is classified into four categories: no education, primary level, secondary and higher level, and 'do not know'. As in the case of mother's education, the category of fathers with no education is treated as the reference category and dummy variables are created for the other categories of father's education. Age of mother is specified as a continuous variable. The NDHS data set provides a household wealth index variable; the index is calculated using household assets and amenities including water source, toilet facilities. In some studies, the water source and toilet facilities are specified as separate variables. The household wealth index serves as a proxy for household income. Inclusion of income is considered to create a serious endogeneity problem, while household wealth index is considered to be far less problematic (Smith *et al.* 2004). Instead of using household wealth index as a continuous variable, household wealth quintiles (five quintiles) are used. The effect of household wealth quintiles are measured as opposed to a reference category, i.e., Quintile-I.

Nepal hosts more than 60 ethnic groups. Ethnic groups are categorized into five caste/ethnic groups: High-caste-Hindu, Low-caste-Hindu, Hill-Tibeto-Burmese, Terai-Tibeto-Burmese, and 'other' ethnic group. In general, High-caste-Hindus are socio-economically better off compared with other caste/ethnic groups. High-caste-Hindu children are used as the reference category. Household's experience of child mortality is often used to reflect the vulnerability of households in raising healthy child (e.g., Madise *et al.* 1999) and also to control for sample selectivity bias, as child health studies only include those currently living. The household experience of child mortality in the last five years is not included in the models estimated here because it is not clear whether or not child death was nutrition-related. We expect that vulnerability of household in raising healthy children to some extent to be captured by household characteristics and unobserved heterogeneity.

One of the key community-level variables included in the models is altitude. Altitude data are generated for clusters (community) as the distance above mean sea level in meters according to GPS unit measurements. Altitude is preferred over the commonly-used three ecological zones (Mountain, Hills and Terai) as it better reflects the micro-climatic environment than the ecological zones. As shown in Figure 1.2, the distribution sample communities by altitude is not in line with ecological regions. For instance, in the Western hills, communities represent all altitude band categories. Therefore, ecological region fails to capture the variation in micro-environmental condition of sample communities.

Other community-level variables include access to health services, extent of urbanization and developmental regions. The NDHS data do not provide a good variable for access to health services for children in the community. The survey asks a question in the mother's questionnaire whether distance to health services to receive medical help for her a large problem, a small problem or no problem. The response was recoded dichotomously as '1' if response is a large problem and '0' otherwise. A variable for community-level access

Figure 1.2 Distributions of Sample Communities of 2001 NDHS by Altitude



to health services is created as the proportion of households in the community reporting the distance to health services to access medical help as a large problem.

Access to health services for mother's own health and child health may not be the same; however, it is plausible that these aspects are close. To control the extent of urbanization, an urban variable is created and coded '1' if community is designated as urban and '0' if community is rural. Developmental regions are also included to capture variation in the extent of development, treating the Eastern region as reference and other regions such as the Central, Western, Mid-Western and Far-Western regions as dummy variables.

One of the concerns about estimating the effect of community-level maternal education is that this variable may also proxy the effect of community-level economic conditions and community-level environmental sanitary conditions. Therefore, to estimate the net effect of community-maternal education, a community economic status variable was created as community-level median value of the households' wealth index. Given that the wealth index is highly skewed, the median value was considered instead of the mean value. Similarly, a community-level sanitation deprivation index was created using principal component analysis of proportion of households in the community having poor toilet facilities, poor drinking water sources, use of traditional cooking fuels such as wood and cow dung, and traditional unfinished floor materials such as earth, mud and dung.
A series of preliminary logistic regression models were estimated including these community-level variables. However, the results were not satisfactory, likely due to fairly high correlations between community-health access, community sanitary index and

community wealth index, as might be expected. Therefore, instead of using all of these variables, only the community health access variable is used in the estimated models. The estimated coefficient of community health access variable, in part, may capture the influence of community wealth condition and also community sanitary condition.

1.8 RESULTS

Descriptive Results

Table 1.1 provides descriptive statistics for variables included in the models: for the whole sample, for children whose mothers are uneducated, and for the rural/urban residential models. The table also reports one-way analysis of variance (ANOVA) results comparing the variable means between the rural and urban sub-samples. Only the summary statistics of dependent and key independent variables are briefly described here (for control variables refer to Table 1.1). Slightly more than half of preschool-age children in Nepal are found to be afflicted with long-term nutritional deprivation. Significant variation in the prevalence of stunting between rural and urban children is observed, with the average prevalence being higher in rural communities (52%) than in urban locations (38%). Among children of uneducated mothers, prevalence of stunting is higher (55%) than overall prevalence regardless of maternal education and place of residence, indicating that childhood stunting outcome is attributed to mother's education attainment.

Table 1.1 Summary Statistics for Whole Sample, Children from Uneducated Mothers and for Rural/Urban Residence Models

Variable	Whole (n=6,152)		Uneducated Mothers (n=4,636)		Rural (n=5,571)		Urban (n=581)		F-Ratio[1]
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	
Dependent Variable									
Stunting	0.508	0.500	0.549	0.498	0.521	0.500	0.379	0.485	***43.21
Independent Variables									
Mother's Education:									
Primary	0.122	0.328			0.118	0.322	0.165	0.372	***11.07
Higher than primary	0.124	0.330			0.097	0.296	0.386	0.487	***431.03
Community mean	1.441	1.686	0.941	1.149	1.185	1.426	3.895	1.991	***1744.78
Mother's height (cms)	150.382	5.335	150.127	5.370	150.347	5.345	150.714	5.228	2.48
Controls									
Level-I (Child-Level)									
Age	29.604	17.127	29.992	17.118	29.457	17.117	31.015	17.177	*4.36
Age-squared (*100)	11.697	10.520	11.925	10.550	11.606	10.487	12.565	10.805	*4.37
Birth order	3.240	2.143	3.604	2.225	3.303	2.150	2.639	1.971	***50.95
Size at birth >= average	0.775	0.418	0.760	0.427	0.774	0.418	0.780	0.415	0.09
Sex (girl =1)	0.504	0.500	0.495	0.500	0.504	0.500	0.497	0.500	0.1
Level-II (Household-Level)									
Father's Education:									
Primary	0.255	0.436	0.284	0.451	0.260	0.438	0.215	0.411	*5.46
Higher than primary	0.386	0.487	0.263	0.440	0.361	0.480	0.630	0.483	***164.79
Don't know	0.019	0.137	0.023	0.150	0.020	0.139	0.014	0.117	0.95
Mother's age	27.746	6.361	28.685	6.505	27.905	6.424	26.222	5.503	***37.05
Household size	7.184	3.379	7.261	3.369	7.220	3.416	6.849	2.983	*6.35
Wealth Index Quintiles									
Quintile-I	0.259	0.438	0.295	0.456	0.282	0.450	0.036	0.187	***170.51
Quintile-II	0.208	0.406	0.245	0.430	0.224	0.417	0.059	0.235	***88.3
Quintile-III	0.190	0.392	0.203	0.403	0.203	0.402	0.065	0.247	***65.14
Quintile-IV	0.190	0.392	0.187	0.390	0.196	0.397	0.126	0.332	***17.09
Quintile-V	0.154	0.361	0.070	0.255	0.095	0.294	0.714	0.452	***2069.7
Caste/Ethnicity									
Low-caste Hindu	0.147	0.354	0.166	0.372	0.145	0.352	0.169	0.375	2.42
Hill-Tibeto-Burmese	0.252	0.434	0.234	0.423	0.255	0.436	0.222	0.416	2.98
Terai-Tibeto-Burmese	0.119	0.324	0.143	0.350	0.125	0.331	0.067	0.250	***16.75
Other ethnic group	0.098	0.297	0.121	0.326	0.099	0.299	0.083	0.276	1.69
Level-III (Community-Level)									
Altitude (500 masl)	1.614	1.450	1.630	1.494	1.671	1.476	1.074	1.021	***90.52
Health access difficult	0.534	0.288	0.574	0.279	.564	.279	0.239	0.179	***756.34
Urban (yes=1)	0.094	0.292	0.056	0.231					
Developmental Regions:									
Central	0.275	0.446	0.284	0.451	0.267	0.442	0.353	0.478	***19.63
Western	0.165	0.372	0.142	0.349	0.173	0.378	0.098	0.298	***21.15
Mid-Western	0.139	0.346	0.152	0.359	0.143	0.351	0.102	0.302	**7.69
Far-Western	0.191	0.393	0.214	0.410	0.186	0.389	0.243	0.429	***11.11

*=P<0.05 **= P<0.01 ***=P<0.001 1=One-Way ANOVA for means by residence

About one-fourth of mothers of eligible children have formal schooling, and about half of these have attained higher than primary-level schooling. Also observed is significant variation in the breadth (percent of mothers educated) and the depth (average number of years of schooling) of maternal education by residence. In urban communities, more than half (55%) of mothers have some level of schooling as compared to one-fifth (21%) of mothers in rural communities. At the community-level, the mean level of education among mothers of preschool-age children in 2001 is 1.4 years. Again, there is a statistically significant difference in the community-level mean level of schooling between rural and urban mothers. The average height of a mother in the full sample is 150 cm, which does not vary by place of residence.

Unobserved Heterogeneity in Childhood Stunting

To determine the relevance of the random-intercept logistic regression, the null (unconditional) models were initially estimated. Except for the urban model, in all other models, the estimated coefficients for the household- and community-level variances were highly significant, indicating the existence of unobserved heterogeneity in child stunting at higher levels. Hence, except for the urban model (logistic regression), for all other models the random-intercept logistic regression models were estimated, controlling child, household- and community-level characteristics. The random effects results for the overall, uneducated mother and residence models are reported in Tables 1.2 through 1.5. Given that the random-intercept logistic and logistic regression models are quite different types, the usual likelihood ratio test cannot be performed to ascertain which model better performs. However, highly significant coefficients of random variables together with the larger log likelihood values suggest that the random-intercept logistic regression model out-performs the logistic regression model except for the urban model. The coefficients of both household- and community-level variances are statistically significant in all models.

The results provide evidence that the variance in child stunting in Nepal can be attributed to unobserved heterogeneity at the household and community levels. Tables 1.2 through 1.5 also present the intra-class correlations at the household and community levels. At the household-level, correlations range from 0.18 to 0.19 and at the community-level the coefficients are almost the same, i.e., 0.03, implying that the share of household-level heterogeneity in the total variance of child stunting ranges from 18% to 19%, while that of community-level heterogeneity is 3%. The correlation coefficient value reflects the degree of inequality in stunting between similar children at the household and community levels. The extent of inequality between similar children is six times greater among households than that among communities. The results suggest that children of some households in the community have a higher risk of being stunted than children in other households.

Influence of Maternal Own Education

For the overall model, the initial model shows that the coefficient of maternal own-education is negative and statistically highly significant, showing that an increase in maternal education decreases the long-term nutritional deprivation of children (Model-I, Table 1.2). Compared to children with uneducated mothers, those of mothers with primary-level or higher than primary-level education are 22% and 41% less likely to be stunted, respectively. However, the statistical significance for mother’s primary-level

Table 1.2 Maximum Likelihood Estimates for Three-Level Random-Intercept Logistic Regression Models for Childhood Stunting [Overall Model], Nepal, 2001

Parameters	Model-I			Model-II			Model-III			Model-IV		
	Odds	Sig	z-stat	Odds	Sig	z-stat	Odds	Sig	z-stat	Odds	Sig	z-stat
Fixed Effects												
Mother's Education:												
Primary	0.78	**	-2.85	0.846		-1.57	0.892		-0.97	0.885		-1.04
Higher than primary	0.591	***	-4.96	0.679	**	-2.99	0.77		-1.87	0.765		-1.92
Community mean	0.862	***	-5.96	0.806	***	-7.04	0.852	***	-4.86	0.874	***	-3.73
Mother's height (cms)	0.933	***	-11.89	0.917	***	-12.07	0.916	***	-12.01	0.917	***	-11.9
Age of child (months)				1.197	***	18.46	1.196	***	18.01	1.196	***	18.03
Age-squared				0.997	***	-15.23	0.998	***	-14.77	0.998	***	-14.78
Birth order				1.029		1.69	1.076	*	2.5	1.082	**	2.7
Size at birth >= average				0.512	***	-7.99	0.522	***	-7.65	0.531	***	-7.43
Sex (girl =1)				1.075		1.09	1.087		1.25	1.093		1.33
Father's Education:												
Primary							1.099		0.99	1.087		0.88
Higher than primary							0.864		-1.46	0.868		-1.41
Don't know							1.356		1.13	1.454		1.4
Mother's age							0.98	*	-2.04	0.977	*	-2.36
Household size							1.015		1.24	1.017		1.43
Wealth Index												
Quintile-II							0.656	***	-3.94	0.683	***	-3.58
Quintile-III							0.603	***	-4.32	0.644	***	-3.74

Quintile-IV							0.623	***	-4.03	0.655	***	-3.58
Quintile-V							0.516	***	-4.32	0.575	***	-3.47
Caste/Ethnicity:												
Low-caste Hindu							1.195		1.5	1.21		1.61
Hill-Tibeto-Burmese							0.794	*	-2.2	0.693	***	-3.3
Terai-Tibeto-Burmese							0.686	**	-2.64	0.826		-1.33
Other ethnic group							1.033		0.21	1.268		1.51
Altitude (500 masl)										1.203	***	4.95
Health access difficult										1.18		0.85
Urban (yes=1)										0.949		-0.3
Developmental Regions:												
Central										1.302	*	2.17
Western										1.394	*	2.36
Mid-Western										1.063		0.39
Far-Western										1.019		0.12
Random Effects												
Variance												
Household-level (σ^2_h)	0.241		(0.108)	0.814		(0.186)	0.827		(0.190)	0.814		(0.189)
Community-level (σ^2_v)	0.140		(0.031)	0.224		(0.048)	0.19		(0.047)	0.128		(0.039)
Intra-Class Correlation												
Household-level (ρ_h)	0.066			0.188			0.192			0.192		
Community-level (ρ_v)	0.04			0.055			0.046			0.031		
Log Likelihood	-4019.45			-3633.88			-3549.12			-3529.08		

*=p<0.05 **=p<0.01 ***=p<0.001 Note: Figures in parentheses are standard errors

Table 1.3 Maximum Likelihood Estimates for Three-Level Random-Intercept Logistic Regression Models for Childhood Stunting [Children of Uneducated Mother Model], Nepal, 2001

Parameters	Model-I			Model-II			Model-III			Model-IV		
	Odds	Sig	z-stat	Odds	Sig	z-stat	Odds	Sig	z-stat	Odds	Sig	z-stat
Fixed Effects												
Mother's Education												
Community mean	0.847	***	-4.830	0.790	***	-5.520	0.846	***	-3.740	0.880	**	-2.600
Mother's height (cms)	0.931	***	-10.630	0.915	***	-10.650	0.916	***	-10.520	0.918	***	-10.380
Age of child (months)				1.204	***	16.250	1.204	***	16.170	1.203	***	16.150
Age-squared				0.997	***	-13.660	0.998	***	-13.530	0.998	***	-13.510
Birth order				1.031		1.720	1.057		1.730	1.062		1.890
Size at birth >=average				0.503	***	-7.090	0.518	***	-6.800	0.527	***	-6.610
Sex (girl =1)				1.124		1.520	1.130		1.590	1.138		1.690
Father's Education												
Primary							1.081		0.770	1.063		0.610
Higher than primary							0.906		-0.900	0.908		-0.880
Don't know							1.437		1.280	1.543		1.540
Mother's age							0.984		-1.420	0.981		-1.700
Household size							1.012		0.880	1.015		1.100
Wealth Index												
Quintile-II							0.648	***	-3.780	0.678	***	-3.400
Quintile-III							0.579	***	-4.220	0.625	***	-3.610
Quintile-IV							0.552	***	-4.490	0.582	***	-4.070
Quintile-V							0.525	***	-3.260	0.561	**	-2.820

Caste/Ethnicity:												
Low-caste Hindu							1.177		1.240	1.194		1.350
Hill-Tibeto-Burmese							0.822		-1.540	0.707	*	-2.520
Terai-Tibeto-Burmese							0.635	**	-2.910	0.785		-1.530
Other ethnic group							0.972		-0.170	1.231		1.220
Altitude (500 masl)										1.230	***	4.750
Health access is difficult										1.103		0.430
Urban (yes=1)										0.952		-0.210
Developmental Regions												
Central										1.268		1.660
Western										1.326		1.650
Mid-Western										1.137		0.710
Far-Western										0.993		-0.040
Random Effects												
Variance												
Household-level (σ^2_h)	0.189		(0.121)	0.801		(0.215)	0.782		(0.213)	0.765		(0.212)
Community-level (σ^2_v)	0.167		(0.039)	0.279		(0.063)	0.215		(0.058)	0.150		0.048
Intra-Class Correlation												
Household-level (ρ_h)	0.052			0.183			0.182			0.182		
Community-level (ρ_v)	0.046			0.064			0.050			0.036		
Log Likelihood	-3072.03			-2717.52			-2689.02			-2672.51		

*=p<0.05 **=p<0.01 ***=p<0.001 Note: Figures in parentheses are standard errors

Table 1.4 Maximum Likelihood Estimates for Three-Level Random-Intercept Logistic Regression Models for Childhood Stunting [Rural Model], Nepal, 2001

Parameters	Model-I			Model-II			Model-III			Model-IV		
	Odds	Sig	z-stat	Odds	Sig	z-stat	Odds	Sig	z-stat	Odds	Sig	z-stat
Fixed Effects												
Mother's Education:												
Primary	0.708	***	-3.460	0.783	*	-2.010	0.799		-1.790	0.794		-1.850
Higher than primary	0.627	***	-3.910	0.740	*	-2.070	0.832		-1.170	0.825		-1.230
Community mean	0.871	***	-4.420	0.822	***	-5.150	0.874	***	-3.500	0.891	**	-2.790
Mother's height (cms)	0.930	***	-11.640	0.914	***	-11.710	0.915	***	-11.500	0.917	***	-11.350
Age of child (months)				1.196	***	17.310	1.197	***	17.270	1.196	***	17.250
Age-squared				0.997	***	-14.250	0.998	***	-14.140	0.998	***	-14.110
Birth order				1.034		1.880	1.071	*	2.240	1.074	*	2.330
Size at birth >= average				0.487	***	-7.980	0.503	***	-7.630	0.510	***	-7.480
Sex (girl =1)				1.119		1.600	1.127		1.690	1.133		1.770
Father's Education:												
Primary							1.095		0.920	1.085		0.830
Higher than primary							0.818	*	-1.920	0.822		-1.870
Don't know							1.348		1.070	1.437		1.310
Mother's age							0.979	*	-1.980	0.977	*	-2.180
Household size							1.014		1.090	1.017		1.330
Wealth Index												
Quintile-II							0.656	***	-3.900	0.679	***	-3.590
Quintile-III							0.598	***	-4.310	0.633	***	-3.820

Quintile-IV							0.624	***	-3.910	0.647	***	-3.610
Quintile-V							0.520	***	-3.790	0.563	***	-3.340
Caste/Ethnicity:												
Low-caste Hindu							1.238		1.680	1.226		1.620
Hill-Tibeto-Burmese							0.778	*	-2.240	0.675	**	-3.290
Terai-Tibeto-Burmese							0.645	**	-2.940	0.778		-1.680
Other ethnic group							0.882		-0.770	1.082		0.470
Altitude (500 masl)										1.208	***	4.820
Health access difficult										1.193		0.850
Developmental Regions:												
Central										1.372	*	2.380
Western										1.450	*	2.500
Mid-Western										1.065		0.380
Far-Western										0.952		-0.300
Random Effects												
Variance												
Household-level (σ^2_h)	0.252		(0.116)	0.833		(0.200)	0.814		(0.198)	0.794		(0.197)
Community-level (σ^2_v)	0.168		(0.037)	0.267		(0.057)	0.213		(0.053)	0.142		(0.043)
Intra-Class Correlation												
Household-level (ρ_h)	0.068			0.190			0.189			0.188		
Community-level (ρ_v)	0.045			0.061			0.049			0.034		
Log Likelihood	-3669			-3247.21			-3211.92			-3192.77		

*=p<0.05 **=p<0.01 ***=p<0.001 Note: Figures in parentheses are standard errors

Table 1.5 Logistic Regression Models for Childhood Stunting [Urban Model], Nepal, 2001

Parameters	**Model-I**			**Model-II**			**Model-III**			**Model-IV**		
	Odds	Sig	z-stat	Odds	Sig	z-stat	Odds	Sig	z-stat	Odds	Sig	z-stat
Fixed Effects												
Mother's Education:												
Primary	1.415		1.360	1.626		1.750	1.726		1.790	1.686		1.700
Higher than primary	0.560	*	-2.580	0.731		-1.250	0.758		-0.970	0.752		-0.990
Community mean	0.828	**	-3.450	0.791	***	-4.020	0.791	***	-3.470	0.787	**	-3.110
Mother's height (cms)	0.934	***	-3.810	0.929	***	-3.860	0.924	***	-3.870	0.922	***	-3.920
Age of child (months)				1.160	***	5.470	1.175	***	5.690	1.179	***	5.780
Age-squared				0.998	***	-4.470	0.998	***	-4.640	0.998	***	-4.700
Birth order				1.090		1.680	1.105		1.120	1.129		1.350
Size at birth >= average				0.712		-1.470	0.726		-1.340	0.742		-1.230
Sex (girl =1)				0.797		-1.180	0.771		-1.300	0.776		-1.250
Father's Education:												
Primary							1.242		0.640	1.201		0.540
Higher than primary							1.550		1.270	1.560		1.270
Don't know							2.398		0.980	2.469		0.990
Mother's age							0.981		-0.630	0.975		-0.820
Household size							1.045		1.250	1.041		1.110
Wealth Index												
Quintile-II							0.721		-0.520	0.769		-0.410
Quintile-III							1.057		0.090	1.207		0.290
Quintile-IV							0.522		-1.090	0.584		-0.890

Quintile-V							0.548		-1.070	0.693		-0.630
Caste/Ethnicity:												
Low-caste Hindu							0.909		-0.300	0.909		-0.280
Hill-Tibeto-Burmese							0.943		-0.220	0.802		-0.750
Terai-Tibeto-Burmese							1.365		0.730	1.336		0.640
Other ethnic group							3.974	**	3.350	4.655	***	3.590
Altitude (500 masl)										1.084		0.470
Access is difficult										1.996		1.020
Developmental Regions:												
Central										1.167		0.380
Western										0.848		-0.370
Mid-Western										0.799		-0.520
Far-Western										1.274		0.630
Log Likelihood	-356.74			-326.42			-315.69936			-313.40324		
LR Chi^2	57.4	***		118	***		139.48	***		144.07	***	

*=p<0.05 **=p<0.01 ***=p<0.001

education disappears when child-specific variables are included (Model-II, Table 1.2). Further incorporation of household- and community-level variables still keeps the coefficient of mother's primary level education statistically insignificant, but the coefficient of higher than primary-level education retains to be statistically significant at 10% level of significance (Model-III and -IV, Table 1.2). As opposed to children from uneducated mothers those from mothers with higher than primary-level education attainment have 24% lower odds of being stunted. The decline in the effect of maternal own education in the expanded models (Model-III and Model-IV) may have been attributed to household and community contextual factors. To determine which particular variables have moderated the effect of maternal education, logistic regression models were estimated with different combinations of both household- and community-level variables. The household wealth and urban variable stand out as being strong confounding factors. Further analysis with a full set of variables except community-level mother's education shows that the significance of mother's education is retained even controlling for wealth and urban variables. This suggests that the effect of mother's own education become less pronounce when the community-mean education of mothers is incorporated in the model.

Many studies, however, have concluded that maternal education is a significant predictor of child long-term nutritional status. Most of those studies have failed to account for many important variables including household- and community-level heterogeneity and community context variables including community-level maternal education. Our results show that failure to account for those factors yields overestimated effects of maternal own education especially at lower level of schooling. Maternal education also plausibly serves as a proxy for access to health services. Generally, it assumed that demand for health of children of better-educated mothers is greater and they tend to have greater access to health services. As a result, the effect of education is overestimated. Therefore, in addition to incorporation of the household's health access variable, an additional interaction term between mother's education and access was used to measure the complementary or supplementary relationship between education and health access. However, results show that the interaction term is not significant (results not reported here); therefore, this variable is dropped in subsequent analyses.

Figure 1.3 compares the extent to which predicted probabilities that the i^{th} child in the j^{th} household in the k^{th} community is stunted (Y_{ijk}=1) vary by mother's education level and residence. In both rural and urban communities, probabilities of a child being stunted decrease with increase in the level of mother's education. However, the mean predicted response for children from rural mothers is considerably higher than for those from urban mothers for all education levels, showing the rural-urban disparity in the response of mother's education for reducing child stunting. The box plot in Figure 1.4 illustrates the extent to which predicted household- and community-level random-intercepts vary by the level of maternal education attainment. It should be noted that the predicted random-intercept for children within the household is the same but different between households. Similarly, the community-level predicted random-intercept is the same for children and households within the community, but different between communities. The variation in the predicted intercept for both household- and community-level by mother's education is trivial.

Figure 1.3 Predicted Probability of Child Stunting by Mother's Education and Residence

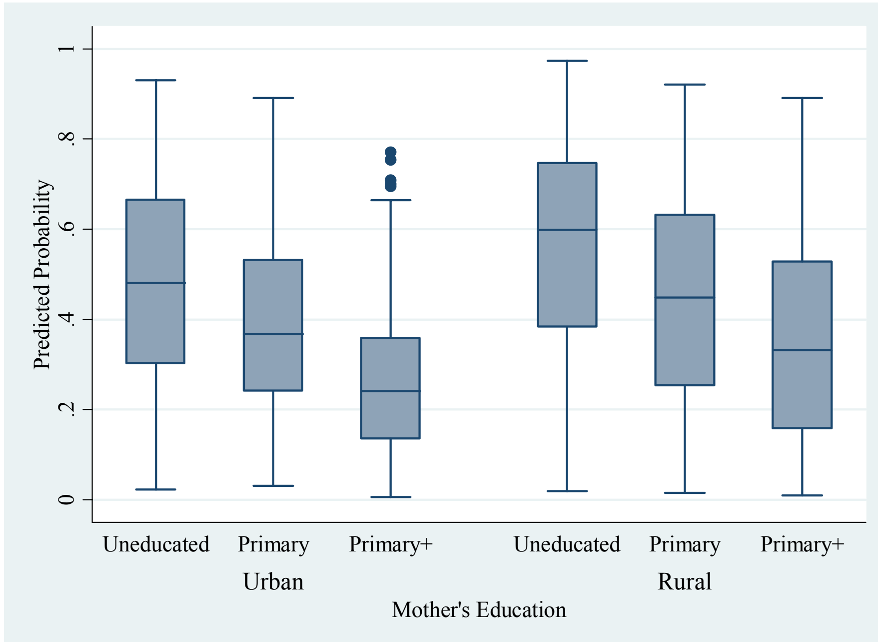
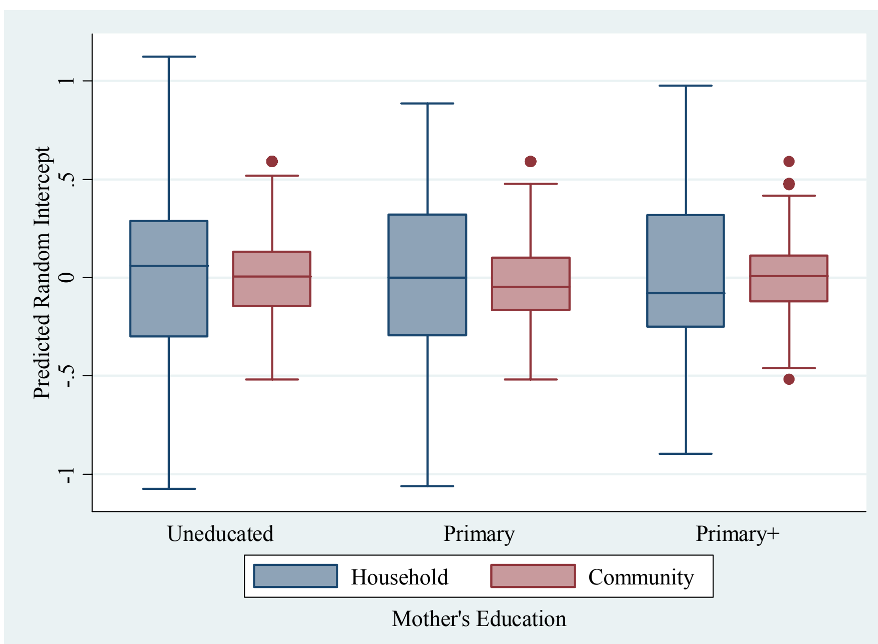


Figure 1.4 Predicted Random-Intercept for Child Stunting by Mother's Education



The observed rural-urban disparity in the effect of maternal education on childhood stunting in part may have been attributed to breadth and depth of maternal education, which are poor in rural communities of Nepal. Mean comparisons of various variables between rural and urban places in the descriptive analyses also indicate that residence of children serves as a proxy for various factors including access, micro-environmental conditions, variation in exposure to infections, and many other aspects that affect child health. In addition, the residence distinction such as rural and urban allows for an examination of the effect of breadth and depth of maternal education on child health. Of the total eligible mothers in the rural-urban sub-samples, those with education level less than grade 10 account for 97% of the rural sub-sample, with an average level of 1.19 years (SD=2.65). In urban areas, this accounts for 87% with an average level of 3.89 years (SD=4.21). Therefore, models were estimated separately for the rural and urban sub-samples. Without the residential models, we would not only be able to examine the effect of fixed effect covariates but also household-level and community-level heterogeneity, which may differ between these two models. The motivation for rural and urban models is also due to that fact that the coefficient for the urban variable which was negative and highly significant in the simple model with only urban variable as independent variable later turned out to be statistically not significant in the full model.

The results obtained from the residential models are interesting (Tables 1.4 and 1.5), showing quite different effects of maternal education on child nutrition in rural and urban communities. In the rural model, the coefficients for mother's primary-level and higher than primary-level education are less than one and significant in initial models (Model-I and –II Table 1.4). For instance, according to Model-II, children with mothers who have primary level education have 22% lower odds of being stunted compared with those from uneducated mothers. Similarly, for mothers who have higher than primary-level education, the odds of children being underweight is 26% less than that of children with uneducated mothers. The inclusion of household- and community-level variables still retains the significance (at 10% level) of the coefficient for mother's primary education with a slight reduction in the value of the coefficient (odds ratio = 0.79) but the coefficient for mother's higher than primary-level education becomes insignificant. In the urban model, the coefficient for mother's higher than primary--level education is insignificant (Table 1.5). But in contrast, the coefficient for mother's primary-level education exceeds one and is significant at 10% level. The results show that even mothers' lower levels of education are important in rural communities but this is not the case in urban communities. The lack of significance of coefficient for mother's secondary and higher than primary-level education may have been due to the mediating effect of community education of mother as well as other household-level factors such as wealth.

Community-Level Externality of Maternal Education

In the whole sample model (Table 1.2), the coefficient for community-level maternal education is negative and statistically highly significant in all four model specifications. According to the expanded model (Model-IV), every unit increase in community-level maternal education reduces the likelihood of being stunted of children in the community by 13%. This result provides evidence of a strong positive externality (spillover) of community-level maternal education on long-term nutritional health of children, even after controlling child-, household- and other community-level factors including community access to health services. This signifies that, in the context of Nepal where the literacy rate among women is very low, proximity of educated others in the community is beneficial to child nutritional health. The positive effect of community-level education of mother on long-term nutritional health of children is consistent with the findings of recent studies on individual fertility and mortality in India (Kravdal 2002, 2004).

An additional model was estimated to ascertain if children of uneducated mothers also benefit from other's education in the community through spillover effects. The results are reported in Table 1.3. Interestingly, results show that even children from uneducated mothers positively benefit from the community externality of maternal education, suggesting that improved nutritional technology and practices are 'spilled over' to uneducated mother through social interaction or/and social influence. The children from uneducated mothers are 12% less likely to be stunted for each unit increase in the community-level education of mothers.

Further, the residential models also show that children in both urban and rural places benefit nutritionally from community-level education of mothers (Tables 1.4 and 1.5). However, the benefits vary in their extent. In both rural and urban models, the coefficients are negative and significant at 1% with odds ratio of 0.89 and 0.79, respectively (Model-IV, Tables 1.4 and 1.5). Rural children from uneducated mothers have 11% lower odds of being stunted for every unit increase in community-level maternal education, controlling all other factors. It is almost twice as high if children are from uneducated mothers in urban communities. This may have been due to higher level of community-level maternal education in urban communities as compared to that in rural communities.

The result of spillover effect of community maternal education on stunting outcome of children from uneducated mothers is consistent with findings of the study on contraceptive use in India (McNay *et al.* 2003). For uneducated mothers, the educated mothers in the community could be an important reference group and source of knowledge including improved nutritional health technology. This is widespread especially in rural areas where access to communication and health infrastructures are poor and the main source of health innovation and practices are innovators in the community. This result confirms the application of diffusion theory on child nutrition in which nutritional technologies are transmitted from better-educated to uneducated mothers through social interaction or/and social influence.

Based on the results from children of uneducated mother model, one might argue that the these results do not support the universal education proposed in Millennium Development Goals as there seems that it is not necessity to educate every mother in the society. This argument may not be valid for number of reasons. First, results provide a clear evidence that maternal own education is crucial for reducing childhood stunting in Nepal. Next, even the educated mothers seem to benefit from community-level maternal education as shown by whole model and residence models. Further, as shown by rural and urban model results, the negative spillover effect of community-level maternal education on childhood stunting seems to be stronger if community-level maternal education is higher. Lastly, from the holistic perspective results provide further evidence that children of educated children are far better off than those from uneducated mothers.

Figure 1.5 shows the predicted probability of the i^{th} child being stunted by community-mean education of mother. The fitted value and the 95% confidence interval presented in the graph are based on the quadratic prediction (refer to Rabe-Hesketh and Skrondal 2005). The predicted probability of children being stunted declines almost linearly with the increase in the community mean of mother's education. The relatively steeper slope of the curve indicates a stronger positive externality of community-level education of mother in reducing child stunting. Figure 1.6 is based on the quadratic prediction of predicted random intercepts. The household-level prediction of intercept appears concave but very modest across the community-mean education of mother. The community-level prediction, on the other hand, varies substantially with the level of education. The predicted community-level random-intercept seems to follow a clear curvilinear pattern with community mean education of mother. The predicted community intercepts decrease with the increase in community-mean education until it reaches to level three and then it increases substantially.

Figure 1.5 Predicted Probability and 95% Confidence Interval of Child Stunting by Community-Mean Education of Mother

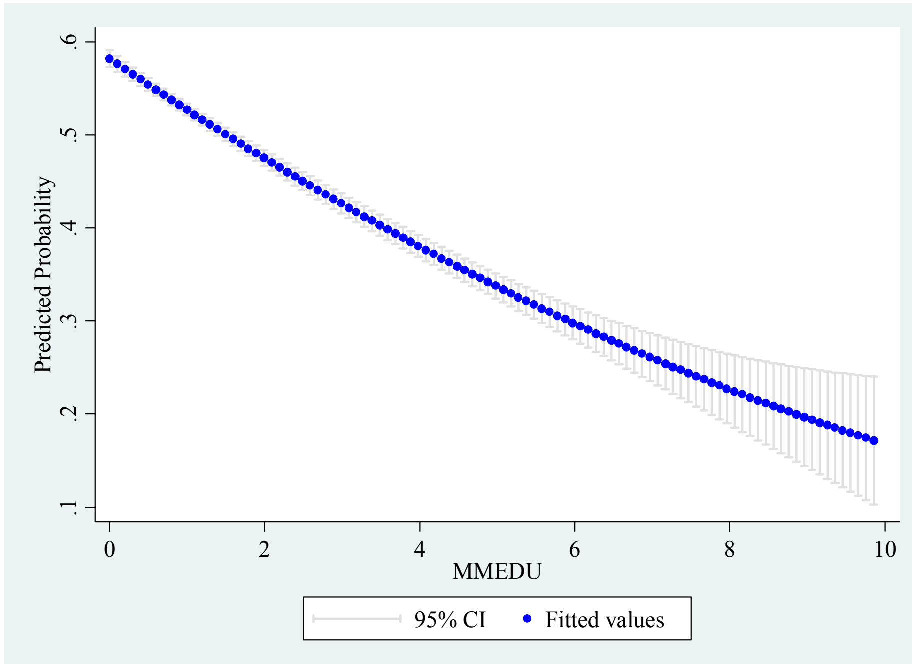
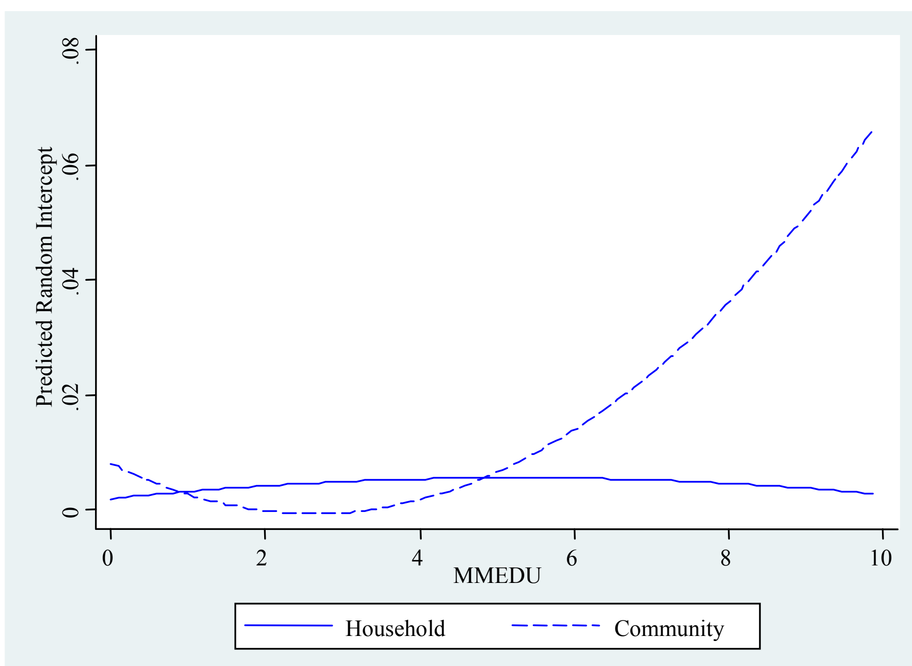


Figure 1.6 Predicted Random-Intercept for Child Stunting by Community-Mean Education of Mother



Intergenerational Transmission of Health

The results from the whole sample model show that the coefficients of mother's height are statistically highly significant across four specifications and are robust (Model-I through Model IV, Table 1.2). Adjusting the effects of all other factors, every centimeter increase in height of mother decreases the odds of children being stunted by 8%. The same level of effects (round up) is also evident even if the mothers are uneducated at all (Table 1.3) or the places they live (Table 1.4 and 1.5). This result provide a strong evidence that the intergenerational transfer of mother's height to long term nutritional status of child is robust regardless of mother's education and the extent of urbanization of place of residence. This illustrates that the effect of mother's height on stunning of child to the greater extent captures the genetic transformation than the current health environment. This result further validates the findings of other studies in Brazil (Kassouf and Senauer 1996), five Sub-Saharan African counties (Madise *et al.* 1999), in Russia (Fedorov and Sahn 2005), in Vietnam (Haughton and Haughton 1997) and in South Africa (Glick and Sahn 1998). However, different from other studies this study also control for variables like altitude, community access to health services, community-level maternal education and unobserved factors.

The predicted probability of child being stunted declines almost linearly with the increase in the height of mother (Figure 1.7). While the predicted household heterogeneity shows a U-shaped relationship with mother's height, the predicted community heterogeneity with respect to mother's height at community level shows a negative relationship but not perfectly linear (Figure 1.8). These post-estimation results indicate the coefficient for mother's height may vary both between households and between communities.

Figure 1.7 Predicted Probability of Child Stunting by Mother's Height

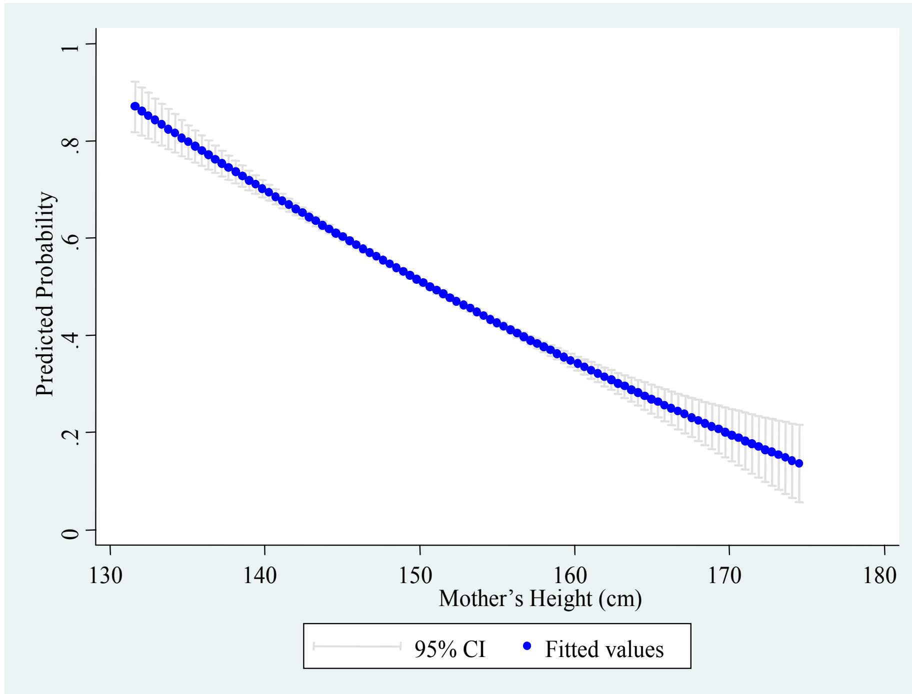
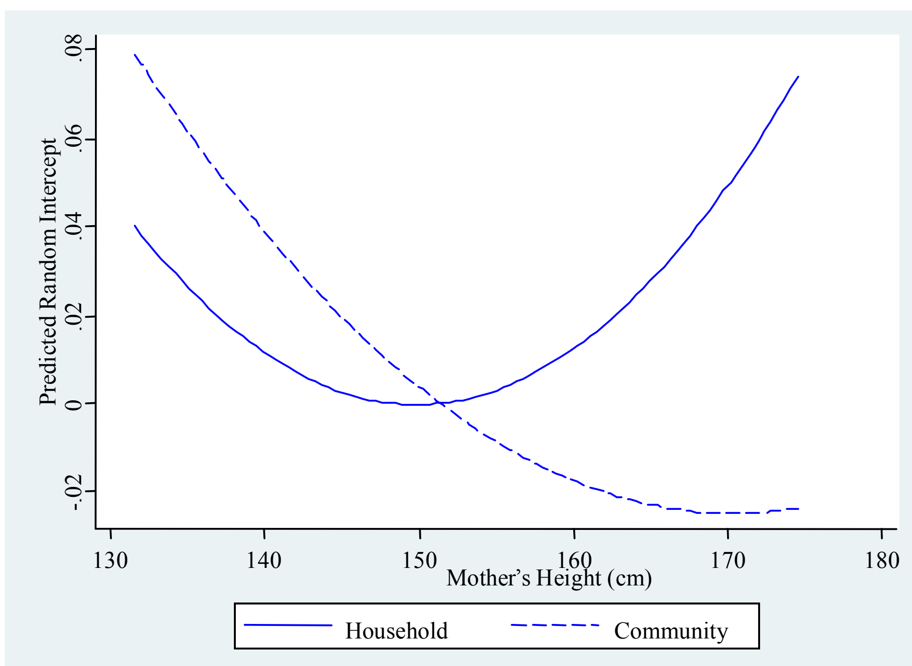


Figure 1.8 Predicted Random-Intercept for Child Stunting by Mother's Height



Influence of Other Factors

Child-Specific Factors: As reported in other studies, child age appears to be a strong determinant of child stunting in all models. The highly significant positive and negative signs of coefficients for the age and age-squared variables show that child age has a concave relationship with stunting outcome. The effect of child age may have also captured some influence of breast feeding practices which varies by age of the child. Birth order appears to be another significant determinant of child stunting except in the urban model. The odds of being stunted increases with birth order. The coefficient for size at birth is highly significant and robust, except in urban model. A child with size at birth perceived as equal or more than average in the community is 47-49% less likely to be stunted. It is not clear whether subjective response of size at birth measure the length or weight of the child; however it seems that the size at birth that reflects the genetic endowments of parents and also fetus health during pregnancy is very important factor shaping the child health in later life. Statistically, while there appears to be no sex differential in childhood stunting in overall and urban models, it appears to be case in rural communities and among children from uneducated mothers. In rural communities and among children from uneducated mothers, girls have higher odds of being stunted than boys.

Household-Specific Factors: Although both breadth and depth of education of father's is higher than the mother's, it is interesting that the father's education has no significant influence on child stunting (Table 1.2). This appears to be true even if their spouses (mothers) are uneducated (Table 1.3). In the rural model, however, the effect of father's higher than primary-level education is negative and significant at 10% level (Table 1.4), but is not significant in the urban model (Table 1.5). Mother's age is found to have a significant negative relationship with child stunting in both the whole sample model and the rural model. The household wealth index quintiles stand out as another significant factor negatively shaping child stunting, except in urban model. As compared to household wealth Quintile-I, an increase in household wealth quintile lowers the odds of children being stunted. The ethnic background of children appears to be another important determinant of child stunting. Despite the fact that High-caste-Hindus are socio-economically better off than any other ethnic group, the Hill-Tibeto-Burmese ethnic group children have lower odds of being stunted as compared to children from High-caste-Hindu children, except in urban areas. Similarly, in rural locations, children of the Terai-Tibeto-Burmese ethnic group appear to be less likely to be stunted than those of High-caste-Hindu. Besides social and economic factors, culturally-influenced food practices and genetic factors may have played an important role.

Community-Specific Factors: The coefficient for community access to health, measured as proportion of households reporting that access to health facilities is difficult when they are ill, is not statistically significant. Altitude of current place of residence appears to be important factors shaping childhood stunting in Nepal, except in urban communities. Every unit (500 masl) increase in altitude is likely to increase childhood stunting by 20%-23%. The coefficient of the urban variable is not statistically significant. Child stunting is observed to vary by development region. As opposed to children from the Eastern region, children in the rural areas and overall (whole sample) in the Central and Western regions of Nepal have higher odds of being stunted (Tables 1.2 and 1.4). The coefficients for the mid- and Far-Western regions are not statistically significant. Similarly, there appears to be no regional variation among urban children (Table 1.5).

1.9 CONCLUSIONS

This study offers additional insights into our understanding of the key determinants of long-term child nutritional deprivation. Net of household-level and community-level factors, the variation in child stunting is significantly attributed to household-level and community-level heterogeneity. As can be expected, the share of household-level heterogeneity is substantially greater than that of community-level heterogeneity. The multi-level modeling approach adopted in this study is found to be an improvement over the simple logistic regression approach, as children are nested within households and households within communities, because of characteristics common to children at higher levels.

Maternal education is one of the key variables of interest. Maternal own-education appears to be an important predictor negatively shaping the long-term childhood nutritional deprivation in Nepal. Overall, the statistical significance of influence of the lower levels of maternal education disappears when child, household-level and community-level factors including community maternal education and unobserved factors are controlled. For higher levels of maternal education, the influence of maternal own education remains statistically significant. Results from the residential models, on the other hand, provide an opposite story. Even when household-level and community-level factors are controlled, the negative influence of community-level maternal education stands out to be robust in explaining long-term child nutritional deprivation. This result is consistent regardless of urbanization of community, but varies in extent. Most interestingly, even children whose mothers are uneducated are found to benefit from education of other children's mothers in the community, providing evidence of negative externality (spillover effect) of community-level maternal education in shaping childhood stunting in Nepal.

Intergenerational transmission of mother's health is also of concern here. The height of mother is found to be negatively related to childhood stunting regardless of mother's education and urbanization of community where child is raised, even when size at birth and other child-, household- and community-level variables are controlled. The notion that a taller mother tends to have a taller child relative to his/her age provides evidence of the intergenerational transmission of genetic endowment and in part the effect of post-natal environmental effects. It should be noted that the estimated coefficient for mother's height can be biased in the absence of father's height. The father's height was not included because this variable is not recorded by the survey for the fathers of all children.

Among other factors, child age and size at birth are important child-specific factors. Similarly, among the household-specific variables, wealth status and ethnic background are strong predictors of long-term childhood stunting. Regional variation such as development region represents the key community variable showing significant variation in long-term child nutritional deprivation, within the Eastern region being better off than other regions especially Central and Western.

Several important policy implications can be drawn from the findings, to help alleviate long-term nutritional deprivation among preschool-age children in Nepal. Firstly, given the negative influence of mother's own-education and negative community-externality of mother's education, long-term nutritional deprivation among children can be alleviated to a great extent through promotion of education of mothers and women. The negative community spillover effect of maternal education to childhood stunting and the residential variation in the extent of their effects suggest that policy should further emphasize women's education, particularly where women are educationally disadvantaged. Secondly, the strong relationship between mother's height and child stunting suggest that policy should focus not only on child nutrition but also on mothers' long-term nutritional health. The findings from the residential models suggest the existence of geographical disparity -- by region and by residence -- in the prevalence of childhood stunting. These factors are also linked with the education level of mothers. This suggests that to achieve the Millennium Development Goals set forth by the Nepalese government, the policy focusing on education and health of mothers should equally take into account geographical inequality in problems of stunting by reallocating resources to the Central and Western regions of Nepal and to the higher altitude places of Nepal, especially where access to developmental and health infrastructure is poor. Although not the focus of this study, the alleviation of poverty at the household level should not be considered in isolation of the health policy of alleviation of childhood nutritional deprivation in Nepal.

Since this study is based on a single year of data, it is not possible here to examine the dynamics of childhood stunting in response to changes in key determinants. Analysis of multiple-year data, even if panel data are not available, would provide better insights into the relationships being measured. In light of spillover effects of maternal education, it is worth assessing if similar relationships exist in other health aspects of children. The contextual variables such as extent of urbanization, access to health facilities, community environmental deprivation, altitude and developmental regions seem to interact each other. In practice, these variables are typically specified as separate variables as has also been done in this study. Constructing a local contextual composite variable, may not only help better estimate the models but also help better target communities that need special policy actions to alleviate the significant problem of child nutritional deprivation in Nepal.

1.10 ENDNOTES

[1] In practice, the terms malnutrition and undernutrition are often used interchangeably. Shetty (2002) distinguishes malnutrition as the deviation from adequate nutrition, including undernutrition or overnutrition (obesity). Undernutrition reflects inadequate dietary intake and also infections and poor care. UNICEF (2006) defines undernutrition as the outcome of insufficient food intake and repeated infectious diseases. It includes underweight, stunting and wasting and deficiencies in vitamins and minerals.

[2] Stunting is measured using a widely-used nutritional anthropometry measure which measures the variation in physical dimensions and gross composition of human body at different ages and degree of nutrition (Jelliffe 1966, as cited in Shetty 2002). A child is classified as stunted if the height-for-age falls below minus 2 standard deviations from the median height-for-age (-2 z score) of the National Center for Health Statistics (NCHS)/(World Health organization (WHO) reference population. Stunting reflects the long-term growth faltering or long-term cumulative effects resulting from inadequate nutrition and/or recurrent illness (Shetty 2002, de Onis *et al.* 2000). Alternately, long-term nutritional deprivation is measured as a continuous measure as the standardized score (z score) of height-for-age (HAZ). While the continuous measure does not reflect the severity of nutritional status such as being *stunted,* the latter does not capture the detailed information in the data. Given the severity of child stunting in Nepal, this study uses the discrete measure of child nutritional outcome.

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2. COMMUNITY ENVIRONMENTAL CONTEXTS AND CHILDHOOD UNDERWEIGHT STATUS IN NEPAL: A MULTI-LEVEL MODELING APPROACH

2.1 ABSTRACT

This essay examines the determinants of childhood underweight status, a short-term nutritional deprivation, among preschool-age children in Nepal. In specific, this study utilizes a multi-level modeling approach applied to 2001 Nepal Demographic and Health Survey data to investigate the extent to which childhood underweight is influenced by two community environmental contexts: season and altitude of current place of residence. Seasonal effect on childhood underweight status is robust; much higher odds of children being underweight exist during the unfavorable season than during the favorable season. The impact of household wealth on the influence of unfavorable season is negative and significant especially in rural communities, indicating that wealthier households have better coped with environmental stresses associated with this season. Results of the influence of altitude on childhood underweight status are mixed. While in the urban communities the odds of children being underweight decrease with altitude, in the overall model the influence becomes less strong when caste/ethnic background of children are taken into consideration. Results also show that underweight status of children is not independent at the household and community levels, justifying the random-intercept logistic regression models adopted here over the logistic regression, except in the urban model.

Findings strongly suggest that public health policies aimed at achieving the Millennium Development Goals of alleviating childhood underweight prevalence in Nepal should emphasize addressing the seasonally-attributed factors that trigger the prevalence of underweight. Public child health policy should also go hand-in-hand with the policy of poverty alleviation. Further, the policy should emphasize maternal health, maternal education, and access to health services and consider geographical disparity in childhood underweight status in the Western rural communities and lower-altitude urban communities.

2.2 INTRODUCTION

UNICEF (2006) estimates that 146 million children worldwide in the preschool-age cohort (age below five years) as underweight[1]. As reported by the United Nations (2002), half of the childhood mortality in the world is attributed to children being underweight. Because of the widespread prevalence and dire negative consequences associated with underweight status, the alleviation of childhood underweight status has become a global concern. At the global level, the Millennium Summit 2000-- as part of Millennium Development Goal (MDG) 1: *Eradicate Extreme Hunger and Poverty* --set the target of reducing the prevalence of underweight by half between 1990 and 2015 (United Nations 2002). Similarly, at the national level, in accordance with the MDGs, the Nepal government set the target of reducing the prevalence of child underweight from 57% in 1990 to 29% by 2015 (United Nations Country Team of Nepal 2002). Yet, the prevalence of underweight in Nepal is still high at 48% (MOH/N *et al.* 2002), which substantially exceeds the cut-off of 40% for a serious public health problem (WHO 1995). The depressing fact is that Nepal is the only country in South Asia reported to have made no progress toward meeting the MDGs (UNICEF 2006). A critical understanding of why disproportionate proportions of children in Nepal are still underweight becomes crucial.

Previous studies on child underweight have primarily focused on child-specific and household-specific factors (for instance, Madise *et al*. 1999) and some community-level factors (e.g., Pongou *et al.* 2006). Recently, increasing recognition has been given to community contexts as an important determinant of undernutrition (Sastry 1997; Desai and Alva 1998; Pongou *et al.* 2006). However, surprisingly, many past studies have considered only limited community context such as degree of urbanization of place and regions (for instance, Kassouf and Senauer 1996; Madise *et al.* 1999). In specific, the significance of community environmental contexts such as season and altitude that reflect the short-term and long-term micro-climatic environmental contexts of place of residence is entirely disregarded, with a few exceptions of studies on the effect of season (e.g., Bairagi 1986; Frank *et al.* 1996; Panter-Brick 1997; Wright *et al.* 2000). Two of the above studies (Frank *et al.* 1996; Wright *et al.* 2000) are based on clinical records and do not control for many confounding variables. Similarly, the study by Bairagi (1986) and Panter-Black (1997) are limited in geographical coverage and also in accounting for unobserved heterogeneity and other factors. In the context of physio-climatically diverse Nepal, food security and the incidence of diseases and infections, to a greater extent, are likely to be closely associated with season (Panter-Brick 1997) and altitudes of place of residence. Therefore, studies ignoring these factors may yield biased estimates. Further, except for a few exceptions (e.g., Madise *et al.* 1999; Pongou *et al.* 2006), previous studies have relied on the assumption that the underweight outcome among children is independent, and have disregarded the existence of unobserved heterogeneity at higher levels, such as household and community. Failure to account for such heterogeneity, if it exists, yields inefficient parameter estimates (Goldstein 1991, 2003).

This study, while accounting for household- and community-level heterogeneity and other relevant factors, examines the extent to which the community environmental contexts of season and altitude shape the prevalence of underweight status among preschool-age children in Nepal. This study also explores the wealth effect on the childhood underweight impact of season.

2.3 PAST STUDIES

Community Environmental Contexts and Childhood Underweight Status

Among others, two important environmental contexts that are potentially relevant to childhood underweight outcome are season and altitude of place. Literature shows a dearth of studies on the seasonality of underweight prevalence, with a few exceptions (e.g., Bairagi 1986; Frank *et al.* 1996; Panter-Brick 1997; Wright *et al.* 2000). On the seasonal variation in child mortality, there are few studies in the Asian context (Becker 1981a; Muhuri 1996). Season can affect child nutritional health in the short-run in various ways. First, it is closely associated with incidence of infections and illness. For instance, the incidence and transmission of bacterial diarrhea, dysentery, one of the leading causes of underweight, are highest during the rainy season (Henry and Rahim 1990; WHO 1992; Panter-Brick 1997). Second, in agrarian societies, food security is season specific (Bairagi 1986). Generally, access to food is higher during post-harvest months but low during pre-harvest. Third, underweight status of children may also be associated with seasonal work distress and, hence, parent's inability to give time to take care of them (Wandel *et al.* 1992; Wright *et al.* 2000). Heavy work pressure among parents during the rainy reason may result in poor food handling and less time available for children (Muhuri 1996). Further, access to food during the pre-harvest months is aggravated by the higher price of food grains. This could have a significant impact on poor households as higher prices of food grains likely result in more spending on staple foods than other nutrient-rich foods. The demand for income for purchasing grains may further reduce mother's time for children (Wright *et al.* 2000).

These factors in combination may have much more detrimental health impacts on children during the pre-harvest months relative to post-harvest. Given that the Nepal Demographic and Health Survey (NDHS) data were collected not in a single month but for six months, the months of interview can have strong association with underweight status of children. It is reasonable to assume that children whose anthropometric data (height, weight and age) were recorded during the rainy season or the food deficit months have greater risks of being underweight than those whose anthropometric data were recorded during spring or the food-sufficient months. If seasonal variation in underweight status due to month of interview exists, the failure to account for season when modeling childhood underweight status results in omitted variable problems.

Bairagi (1986) examined the net influence of famine and also season on the weight-for-age measure of children aged 1-4 years in rural Bangladesh. He found that when comparing the famine to the non-famine period, the weight-for-age of children was positively related. Similarly, he found that when comparing the unfavorable season (unfavorable months in terms of food availability) to the favorable season (favorable months in terms of food availability), the weight-for-age of children was also positively related. It should be noted that the Bairagi study was limited to rural communities and did not cover the wider geographical area that would include urban communities. Based on data from a small village predominated by the Tamang ethnic group in Nepal, Panter-Brick (1997) examine monthly growth of children aged between 0 and 49 months with relation to seasonal environment. The author found that the progression of months from winter to monsoon seasons had contributed to substantial loss in weight of children. Similarly, based on monthly data from a clinic-based growth monitoring program in Zimbabwe, Wright *et al.* (2000) provide evidence of seasonal variation in child nutritional stress at the national level. Their results show that higher prevalence of underweight was recorded during pre-harvest months (January-March) for all years (1988-1995) except in 1992. In 1992, the absence of seasonal effect on underweight was attributed to severe drought. They also found that in the majority of districts studied there was no seasonal variation in child underweight status. Further they find no variation in underweight prevalence between predominantly subsistence agriculture and the more commercial agriculture districts. Another study based on children (age 6-24 months) visiting the Boston City Hospital Pediatric Emergency Department in the U.S. between July 1989 and June 1992 found that the prevalence of weight-for-age below the fifth percentile was higher during winter and early spring than during the remaining months of the year (Frank *et al.* 1996). They suspect that this could be associated with cold stress and infections. Finally, although not directly related to child nutrition, Muhuri (1996) also provides evidence of seasonal variation in child mortality in Bangladesh; the net effect on child mortality being lower in the post-harvest season than in the dry-season.

Altitude is another community environmental context of interest. Although there are few studies on the impact of altitude on the growth or stunting outcome of children (e.g., Clegg *et al.* 1972; Pawson *et al.* 2001; Kebede 2005), studies looking at the effect of altitude on childhood underweight are nonexistent, to our best knowledge. This could be, in part, due to the unavailability of altitude data. Altitude of the place of residence that captures long-term environmental contexts can influence child nutritional health in the short-term in four major ways. First, relative to lower altitude places, high altitude places are hypoxic (deficiency of oxygen), higher in solar radiation, cold and less humid, all of which may have differential impacts on health of child and mother (Pawson *et al.* 2001; Kebede 2005). Second, altitude is associated with differential exposure to infections. For instance, lower altitude places are humid and pose a greater risk of infections relative to higher altitude places. Third, altitude also reflects the extent of physical access and access to health institutional infrastructure. However, this may be dependent on the degree to which a country is developed. If a country has well-developed transportation infrastructure, altitude may not be a problem, but it can be a large problem in developing countries with poor transportation infrastructure. In Nepal, where more than 80% of land is hills and mountains, altitude of place is expected to matter. Fourth, altitude also captures the diversity in the availability of food and types of foods, which may have impacts on child health particularly in places where market links are poor. For instance, in high altitude places in Nepal, livestock is the main source of food, whereas in the plains, grains and in the hills, fruits and grains are main sources of food and income. With regard to underweight, higher altitude places seem to be disadvantaged in terms of oxygen availability, physical access and access to food, but those effects may be offset by the relatively lower incidence of infections. The net effect of altitude on childhood underweight is therefore not clear.

There exist few studies that assess the influence of altitude on childhood stunting. A study by Pawson *et al.* (2001) conducted in Peru did not find a strong effect of altitude on childhood stunting. But two studies conducted in Ethiopia found conflicting effects of altitude. Clegg *et al.* (1972) found a positive association between altitude and child growth, but a recent study by Kebede (2005) showed that altitude measured in terms of log of meter above mean sea level had negative effects on height-for-age z-score. Kebede (2005) argues that his study reflects the net effect of altitude better than the study of Clegg *et al.* (1972) in that the latter did not control for other confounding variables including individual-level, household-level and community-level heterogeneity.

Other Determinants of Child Underweight Status

Child-specific Factors: Among child-specific factors, age, size at birth, sex of child, and birth order are important child-specific leading determinants of child anthropometric status. Vella *et al.* (1992) report that undernutrition progresses with age, but there is a limit. Breastfeeding practice is another child-specific variable often controlled in child health studies (e.g., Vella et al. 1992; Madise *et al.* 1999). The relevance of this variable, however, is dependent on the countries and regions under study. In a country where breast feeding to children is almost universal and the duration of breast feeding is long, the use of this variable may not add much to the model, given that child age is included in the model. The age and square term of age are likely to proxy the duration of breast feeding that varies by age. Size at birth of the child is also likely to be associated with underweight status. It is reported that small size at birth is negatively associated with weight-for-age (Madise *et al*. 1999).

Sex of the child is another variable widely used to measure the sex differential in nutritional status, which may arise from differential access to food and health care; however, the empirical evidence is mixed (DeRose 2000). Studies carried out in six Sub-Saharan African countries, namely Ghana, Malawi, Nigeria, Tanzania, Zambia and Zimbabwe, show that female children are better nourished than male children (Madise *et al.* 1999). On the other hand, studies conducted in Jamaica (Melville *et al.* 1988) and studies conducted in rural Bangladesh (Bairagi 1986) found that boys were nutritionally better off than girls. A study conducted in rural Côte d'Ivoire, however, did not show sex-differentials in undenutrition (Strauss 1990). Haddad *et al.* (1996) cited in Marcoux (2002) state that evidence on male biased nutrition is not widespread and is mainly concentrated in South-East Asia, with some geographical variation. Marcoux (2002) agrees that nutritional deprivation among girls is less pervasive, however, he recognizes that results based on limited number of samples may not provide indicator of the global extent of sex-differentials in child undernutrition. The sex-differentials in underweight status could differ between countries and also due to the extent of geographical coverage of the sample. In Nepal, boys are, in general, valued more than girls because of the widespread feeling of their greater contribution to old-age security, their right to inherit parental property, and better prospects for making income. Human capital investment in girls is perceived to be of less worth as the returns from investment are shifted to other families after marriage.

Birth order is often used as a variable in empirical studies. As the number of children increases parents find less time to take care of them and an additional child also spread household budgets. This could result in younger children being relatively disadvantaged in terms of care and nutrition. Therefore, it is likely that children with higher in birth order are more likely to be undernourished than children in lower birth order. Madise *et al.* (1999) report a negative and statistically significant effect of birth order on weight-for-age z-score in Zimbabwe, but a statistically insignificant effect on weight-for-age in other five counties that were studied.

The recent experience of diarrhea among children is another variable often controlled in the model (e.g., Madise *et al*. 1999). However, it is likely that the causation between underweight status and incidence of diarrhea is not one-way. Incidence of diarrhea may be positively related with underweight status of children, but the risk of incidence of diarrhea may be higher among children who are already underweight relative to those who are nutritionally better off.

Parent/Household-Specific Factors: Parent's education, health, mother's age, household wealth, and ethnicity are also expected to be important factors affecting child nutrition. The maternal age is likely to influence child undernutrition, as health and vitality of the mother changes with age (Casterline *et al.* 1989). Parental education, especially education of mothers, is expected to affect child underweight status in various ways. The mechanisms through which maternal education influences child health have been widely studied by economists, demographers and other social scientists (Caldwell 1979; Kassouf and Senauer 1996; Grossman and Kaestner 1997; Handa 1999; Variyam *et al.* 1999; Pongou *et al.* 2006). Those mechanisms are described in essay one. Comparing women with a secondary level of education to those with no education, Madise *et al.* (1999) find that maternal education has a positive effect on the weight-for-age z-score of children in Ghana, Nigeria and Tanzania. .

Genetic endowment represents another parent-specific factor. The nutrition spillover from mother to child can occur in part through sharing genetic endowment and in part through behavioral effects (Haughton and Haughton 1997; Ganz 2001; Kebebe 2005). Since the underweight status is a short-run anthropometric indicator of childhood nutritional deprivation, the behavioral effect may be more relevant than the genetic. Therefore, instead of the mother's height, the weight of the mother should better capture the nutritional spillover from mother to a child. The Body Mass Index (BMI) of mother (calculated as weight over height squared) provides another indicator used to measure the nutritional status of adults (Marcoux 2002; Smith *et al.* 2004). The BMI measure differs from the height measure in that the latter does not change once women reach adulthood and is therefore is less sensitive to exposure to health environmental factors, but the former fluctuates largely due to health environment and dietary intake and is recognized as an important predictor of overall health (HMG/N 2000). Controlling the size at birth, which is more likely to proxy genetic characteristics of parents and also prenatal health, the estimated effect of mother's BMI is likely to capture more of the behavioral effect than the genetic. If mothers are altruistic to children, then healthier mothers should have healthier children. Many studies have shown that if the mother is undernourished her child is also likely to be undernourished (Madise *et al.* 1999; Ramakrishna *et al.* 1999 cited in Smith and Haddad 2000).

The household wealth that reflects the household's economic status is a commonly-used to control the households' ability to purchase food, invest in child health and care of child (e.g., Burgard 2002). It is assumed that children from households with higher wealth index are less likely to be underweight. Ethnic background may influence child underweight because of variation in the intrinsic attitudes towards child health, health seeking-behavior and food practices. In the context of Nepal, caste/ethnicity background of households is believed to capture socio-cultural background including choices of food and meat. Because of socio-cultural restrictions on the food choices, even the children from socio-culturally conservative but well-off families may suffer from being underweight compared with children from liberal caste/ethnic groups.

Community-Specific Factors: The extents of urbanization as well as regions are commonly used community factors. Recently, the community-level externality of maternal education has been used to predict mortality and fertility in developing countries (e.g., Kravdal 2002, 2004). Essay one of this dissertation examined the influence of community-level maternal education on childhood stunting. Results provide evidence of a negative spillover effect of community-level maternal education on childhood stunting in Nepal. A similar effect can be expected on underweight.

2.4 CONCEPTUAL FRAMEWORK

The conceptual framework used here corresponds to that used in the first essay, except for the dependent variable and several covariates. The conceptual framework is based on the household economic model (Becker 1981; Behrman and Deolalikar 1988). A household is assumed to maximize the following joint utility function:

$$U_j = U(H, C, l) \qquad (1)$$

where U_j is the joint utility function of the j^{th} household with mother and father. The utility parents derive is dependent on the nutritional health status of a child (*H*), the consumption of goods and services from the market (*C*) and amount of leisure time (*l*). The household maximizes the joint utility function subject to the full-income constraint that includes budget and time constraints and the i^{th} child's health production function (H_i). The health of child is considered as a household-produced good. The health production function of an individual child is specified as:

$$H_i = H(I_i, G_i, Ch_i; \phi, \theta, \psi_h, \psi_c) \qquad (2)$$

where H_i represents the health outcome of the i^{th} child. The I_i is the child health input including dietary intake, child care time by parents, and the medical care provided when the child is sick; G_i is the child's health endowment, which is unobservable but is proxied by parents' health; Ch_i is the child's observable characteristics including age, birth order, size at birth, and sex; ϕ represents observable household characteristics including maternal education, mother's BMI and age, household wealth, ethnicity and household size; θ *is* community characteristics including community access to health services, market price of consumption goods and services, micro-environmental conditions such as season and altitude, geographical location such as regions and community-level education of mothers; ψ_h is the unobserved household attributes such as quality of parenting, household public goods such as floor space and level of sanitation. These attributes are common to children within the household, whereas ψ_c represents unobserved community attributes such as sanitation condition, exposure to infection, and community location, which are common to children in households within the same community. In the child health production function (eq. 2), the quality and quantity of health input is influenced by the parent's health investment decision such as investment in dietary supplies and in medical care when a child is ill and time devoted to care of child. However, the investment in child health may be dependent on the household's economic status.

Equation 3 provides the budget constraint faced by the household, that is

$$pC + p'I^h = wL + M \tag{3}$$

where p is the vector of prices of market goods and services and p' is the price of health inputs. The I^h represents investment in health, M represents the household's non-wage income, w is the wage rates of parents, and L represents labor time allocated to wage work. The time constraint faced by household in terms of L is:

$$T - L^h - l \tag{4}$$

where the T represents the total time endowment of the household, which is apportioned among wage labor (L), time to children (L^h) and leisure (l). By combining equations 3 and 4, the full-income (F) constraint is

$$pC + p'I^h = w_i(T - L^h - l) + M = F \tag{5}$$

Maximizing the household utility function (1) subject to the full-income constraint (5) and the health production function (2), the reduced-form equation for the health outcome of the ith child can be obtained

$$H_i = h(p, p', w, Ch, T, M, \phi, \theta, \psi) \qquad (6)$$

As others have done (e.g., Rosenzweig and Schultz 1983; Senauer and Garcia 1991; Glewwe 1999), and as in essay one of this dissertation, this study also uses the reduced-form approach for the estimation of the child health production function. The price and wages variables are not available in the data used for this study. It is assumed that prices of goods and services and health inputs and also wage rates are unvarying within the community but differ across communities. The unobserved heterogeneity parameter at the community level in part is expected to capture the influence of those factors missing in the models.

It is expected that controlling other factors, in the unfavorable season children are more likely to be underweight because of limited access to food and a relatively higher incidence of infections. Similarly, it is expected that an additional unit increase in altitude of place of residence will increase the likelihood of children being underweight.

2.5 ESTIMATION ISSUES

Again the estimation issues discussed here correspond to that discussed in essay one. A discrete choice model such as logistic regression is commonly used to estimate the underweight outcome. One of the important assumptions of logistic regression is that child underweight outcomes are independent. But this assumption is unlikely if there exists a clustering structure in child nutritional outcomes, such as children being nested within households and households within communities. That is, the underweight outcomes of children within the household may be similar because of the common characteristics children share within the household. Such clustering induces non-independence between child underweight outcomes, hence violating the independence assumption of logistic regression. In the existence of clustering of child nutritional outcomes, the use of approaches such as logistic regression yield estimates that are less efficient than the generalized least square estimates that are based on the true structure of residual covariance matrix. Additionally, these approaches do not provide an avenue for exploring clustering structure (Goldstein 1991).

To take into account clustering effects or intra-cluster correlation, a robust variance-covariance matrix is required (Wooldridge 2002). Two approaches are suggested: fixed effects and random effects models to take into account the unobserved factors (heterogeneity). These models are distinguished by the assumption on the relationship between observable covariates and heterogeneity; the fixed effects model assumes that covariates and heterogeneity (unobserved variables) are not orthogonal (independent) whereas the random effects model assumes that they are orthogonal. In the case of discrete choice models, the fixed effect estimators are likely to suffer from the incidental parameters problem (Wooldridge 2002) as the estimators rely on estimation of constants based on cluster observations, which is fixed and may be quite small. This leads to inconsistent estimates of constants as well as parameters. The estimator is also biased if cluster observations are small. On the other hand, in the random effects models (also known as multi-level models, generalized linear mixed models, hierarchical generalized linear models, random-intercept models and mixed-effects models) the expected value of cluster heterogeneity, the idiosyncratic error term and covariance between cluster heterogeneity and idiosyncratic error are assumed to be zero. In the random effects models, the random parameters are estimated in addition to the fixed parameters. Recently, the multi-level modeling is increasingly used to estimate the net effect of explanatory variables and uncover unobserved random-effects (Goldstein 1991, 2003; Madise *et al.* 1999; Raudenbush and Bryk 2002).

As mentioned in essay one, clustering of children within the household is likely because of characteristics such as health inputs, quality of parental care and household pubic goods such as space, which can be expected to differ between households but be the same within the household. Similarly, households may be clustered within the community because of their shared characteristics, such as access to health innovations, community sanitation, and market, which are common to households within a community but differ across communities. Therefore, the childhood underweight outcome is likely to vary simultaneously at individual, household and community levels.

2.6 EMPIRICAL MODEL AND ESTIMATION

The structure of the empirical model corresponds to that discussed in essay one, except for the dependent variable and several covariates. Following Raudenbush and Bryk (2002), the three-level random intercept logistic regression model takes the form discussed below.

Level-I Model (Child-Level)

$$\log(\frac{\pi_{ijk}}{1-\pi_{ijk}}) = \beta_{0jk} + \sum_{p}^{P} \beta_{pjk} C_{ijk} + \varepsilon_{ijk} \qquad (7)$$

where the left-hand side of the equation represents the log odds of being underweight, π_{ijk} represents the probability of the i^{th} child in the j^{th} household and k^{th} community being underweight. The β_{0jk} is the intercept for household j in community k. The C_{ijk} represents p=1,…,P child-level characteristics that predict an underweight outcome, and the β_{pjk} represents the corresponding Level-I coefficients that indicate the direction and strength of association between each child-level characteristic and the underweight outcome in household j in community k. The ε_{ijk} represents the Level-I disturbance term, which is ~N(0, σ^2_c). Parameters in equation (7) may not be fixed for reasons explained before.

Level -II Model (Household-Level)

Assuming that children are nested within households, the variation in the parameters in the Level-I model can be modeled as a function of the Level-II characteristics. The parameters, $\beta_{0jk,}$ in the Level-I model may vary randomly across households within communities due to household-level characteristics. Therefore, the intercept in the Level-I model can be decomposed as

$$\beta_{0jk} = \beta_{00k} + \sum_{q=1}^{Q_p} \beta_{0qk} H_{qjk} + \gamma_{0jk} \qquad (8)$$

where β_{00k} is the intercept for household j in modeling the community effect. The H_{qjk} represents the q=1,…,Q_p household-level characteristics predicting the household effect. The β_{0qk} is the corresponding coefficient representing the direction and strength of the association between household-level characteristics and child-level average effect. The γ_{0jk} is a Level-II random effect that represents the deviation of household effect from its predicted value, based on the household-level model.

Level-III Model (Community-Level)

Assuming that children in a household are further nested within community, the variation in the parameters, such as β_{00k} in the Level-II model can be modeled as a function of the Level-III characteristics. That is,

$$\beta_{00k} = \beta_{000} + \sum_{s=1}^{S_{pq}} \beta_{p0s} V_{sk} + \mu_{00k} \quad (9)$$

where β_{000} is the intercept for the community-level model for $\beta_{00k.}$ The V_{sk} represents $s=1,\ldots,S_{pq}$ community-level characteristics used as predictors for the community effect, β_{00k}. The β_{p0s} is the corresponding Level-III coefficients that represent the direction and strength of association between community-level characteristics, V_{sk} and the community effect, β_{00k}. And the u_{00k} is a Level-III random effect that represents the deviation of community k's coefficient, β_{00k}, from its predicted value based on the community-level model.

Combining the equations in Level-I through Level-III, the three-level random-intercept logistic regression model for estimation is as follows

$$\log\left(\frac{\pi_{ijk}}{1-\pi_{ijk}}\right) = \beta_{000} + \sum_{p}^{P} \beta_{pjk} C_{ijk} + \sum_{q=1}^{Q_p} \beta_{0qk} H_{qjk} + \sum_{s=1}^{S_{pq}} \beta_{p0s} V_{sk} + \gamma_{0jk} + \mu_{00k} + \varepsilon_{ijk} \quad (10)$$

where the log odds of the i^{th} child in the j^{th} household and k^{th} community being underweight is the sum of the fixed and random effects components. The total variation in the likelihood of a child being underweight can be decomposed into the contribution of the fixed effects components that include fixed predictors at different levels such as C_{ijk}, H_{qjk} and V_{sk} and the random effects components explaining the variation between children within households (ε_{ijk}), that between households within communities (γ_{0jk}) and that between communities (μ_{00k}).

Random variables are assumed to be distributed normally with mean zero and variance as follows and are also assumed to be independent across levels (Goldstein 1991, 2003). That is,

$$\varepsilon_{ijk} \sim N(0, \sigma^2_c) \qquad \gamma_{0jk} \sim N(0, \sigma^2_h) \qquad \mu_{00k} \sim N(0, \sigma^2_v) \tag{11}$$

The three-level model specified above is no longer a standard logit model because it contains three random variables rather than a single residual term. The variances specified above are unknown and the aim of the proposed multi-level analysis is to estimate those variances or unobserved heterogeneity.

Estimation Method

As in essay one, this study also follows the recently-developed adaptive quadrature approach to maximum likelihood estimation of discrete dependent variable with nested random effects (Rabe-Hesketh *et al.* 2005). As opposed to the commonly used Gauss-Hermite quadrature approach, which is biased for large cluster sizes and intra-class correlation, the adaptive quadrature approach provides unbiased estimates of random components with data of different cluster sizes (Rabe-Hesketh *et al.* 2005). The merit of the adaptive quadrature method over the ordinary quadrature method is also described in Goldstein (2003). This study uses the Generalized Linear Latent and Mixed Model (GLLAMM) routine in STATA (Rabe-Hesketh and Skrondal 2005).

Intra-class correlations that measure the strength of correlation between children at the household and community levels are calculated based on the coefficients of the random components. Further, the post-estimation predicted probability that the i^{th} child in the j^{th} household in the k^{th} community is underweight (Y_{ijk}=1) is estimated from the parameter estimates and observed responses for clusters such as household and community. Similarly, predicted household- and community-level random intercepts are estimated as in Rabe-Hesketh and Skrondal (2005).

A series of models are estimated to gain better insights into the effects of community environmental context variables on childhood underweight. The first set of models is the pooled models (Overall Model) which include rural and urban sub-samples. Next, to explore whether or not the effects of community environmental context on childhood underweight vary by the urbanization of place of residence, two sets of models are estimated separately for rural sub-sample (Rural Models) and urban sub-sample (Urban Models). In each of the above sets, nested models are estimated to explore whether or not the coefficients for season and altitude are robust when additional variables are incorporated into the model. The first model (Model I) includes only the independent variables, to measure their gross effects. In Model II, additional variables except the ethnicity and interaction terms are included. Similarly, in Model III, ethnicity variables are added. In the last model (Model IV), interaction terms between season and household wealth indicator, season and urban residence, and season and altitude are incorporated to explore if the wealth effect offsets the effect of bad season on childhood underweight and if seasonal effects are moderated by extent of urbanization and altitude, respectively.

Data and Variables

The data used in this essay are the same as used in essay one. This study uses data from the 2001 Nepal Demographic and Health Survey (NDHS). The NDHS is a nationally-representative comprehensive survey of demographic and health indicators including maternal and child health (MOH/N *et al.* 2002). The sampling procedure consists of a two-stage stratified random sample of households. In the first stage, a systematic sampling with probability proportional to population size was used to select 257 primary sampling units (PSUs) - 42 in urban areas and 215 in rural areas. In the second stage, an average 34 households from each PSU were selected by using a systematic sampling procedure on the complete list of households within each PSU. Each PSU is comprised of a ward and sub-ward. Ward is the smallest political unit. In this study, PSU is used to represent community or cluster. The survey also collected geo-reference data for PSUs using the Global Positioning System (GPS), which provides an avenue for spatial analysis by integrating demographic and health information at the cluster and higher levels such as geographical domains. A total of 8,602 households were interviewed for household information. From these households, a total of 8,726 ever-married women and 2,261 men (one every third household) in the age range 15-59 years inclusive were successfully interviewed, yielding response rates of 98% and 96% of eligible women and men, respectively. Anthropometric data on weight and height were collected from children (aged less than 5 years) and mothers (aged 15-49 years inclusive).

For the purpose of this study, a total useable sample of 6,125 children aged below five years nested in 4,250 households and 248 communities is used. An average household has 1.5 children, ranging from 1 to 6 children. At the community level, the average number of children is 26, ranging from 2 to 34. Slightly more than half (52%) of households have only one eligible child. As almost half of households have at least two eligible children and the number of households in the sample is fairly large, this study uses three-level multi-level models. The variables used in the study are presented below.

Dependent Variables

The underweight status of a child is the dependent variable, which is measured dichotomously as '1' if weight-for-age falls below negative 2 standard deviations from the median weight-for-age of the NCHS/WHO reference population and '0' otherwise.

Independent Variables

***Season*:** Nepal has four climatic seasons: Spring (March – May) – is warm in the low lands while moderate at higher altitudes; Summer (June – August) - is also the monsoon season, the weather is wet and hot; Autumn (September – November) - is nice; and Winter (December – February) - is cold with occasional snowfalls at higher elevations. Waterborne diseases and infection are more prevalent during the summer than during winter. Rice and maize are key staple foods in Nepal. Rice is harvested in November/December; maize is harvested in July/August. In terms of food security, the post-harvest months are relatively more favorable than the pre-harvest months. The NDHS survey was conducted over a period of 6 months starting from Nepali month *Magh* (mid-January, 2001) through *Asar* (end of June, 2001). Considering climatic factors and relative access to food, the months of interview can be divided into two groups: "Favorable Season (first three months) and "Unfavorable Season (later three months). During the first three months, access to food is relatively higher and the prevalence of infections is relatively lower than during the later three months. A dummy variable is created as '1' if the unfavorable season and '0' if otherwise. It is plausible to expect that as compared to children measured for anthropometric data during the favorable season, those measured during the unfavorable season are more likely to be underweight.

***Altitude*:** Ecologically, the country is divided into three regions: Mountain, Hills and Terai. In practice, researchers use ecological regions to proxy climatic and access factors. However, the ecological zone may not necessarily reflect the inherent variability within a specific zone. This also depends on the communities selected in the sample. For instance, in the hilly regions, there are many communities in the sample located in the valley that may not represent a typical characteristic of the Hills. On the other hand, altitude of communities avoids this problem (refer to Figure 1.2). Therefore, as altitude reflects access to food as well as risks of infections, it should better represent the local environmental context than ecological region. The NDHS has collected altitude data for community/cluster, measured as altitude mean above sea level (masl) using global positioning (GPS) units. Communities at higher altitudes have relatively poorer access to food and health infrastructure, and are more likely to be hypoxic than communities in lower altitude places, but the high altitude places also have a lower risk of children being infected with diseases. Therefore, the net effect of altitude on child underweight is not clear.

Controls

Child-specific covariates included in the underweight status model are age in months, age squared, birth order, size at birth (specified dichotomously as '1' if parent's response to child birth weight was 'average and greater than average' and '0' if otherwise), and sex of child (girl=1).

Parent/household-level covariates include age of the mother; her education level (no education (reference), primary-level (<=grade 6), and higher than primary-level); community mean of maternal education to capture the community externality of maternal education; Body Mass Index (MBI) of mother; father's education as reported by mother (no education as reference, primary-level, higher than primary-level, and do not know); caste/ethnicity grouped into five categories as High-caste-Hindu (reference), Low-caste-Hindu, Hill-Tibeto-Burmese, Terai-Tibeto-Burmese and other ethnic groups; number of household members; and household wealth index constructed using household assets and amenities including water source, toilet facilities. As in essay one, instead of using a raw household wealth index, the household's position in quintiles of the wealth index is considered. The bottom quintile of household wealth index (i.e., Quintile-I) is treated as the reference category. The use of household wealth quintiles instead of a raw wealth index also allows us to measure the interactive effect of wealth on the relationships between other variables such as season and underweight status of children.

In addition to altitude of place of residence and season as independent variables, community-level covariates controlled in the models include community access to health services. As used in the first essay, this variable is measured as the proportion of households in the community reporting that access to health services is difficult when mothers are ill. Other community variables controlled in the models include the extent of urbanization of the place of residence (urban=1) and developmental regions, treating the Eastern region as the reference region.

2.6 RESULTS

Descriptive Results

The descriptive statistics (mean and standard deviation) of the variables included in the models are given in Table 2.1. The table also statistically compares the means of the variables between rural and urban sub-samples. In 2001, almost half of preschool-age children in Nepal were suffered from short-term nutritional deprivation. A significant residential difference in the mean prevalence of childhood underweight is observed, with prevalence higher in rural (49%) than in urban communities (36%). The share of children measured for anthropometric data is fairly balanced by season in rural areas but not in urban areas. Of the total children measured for anthropometric data, 45% were measured

Table 2.1 Summary Statistics for Whole Sample and for Rural/Urban Residence Models

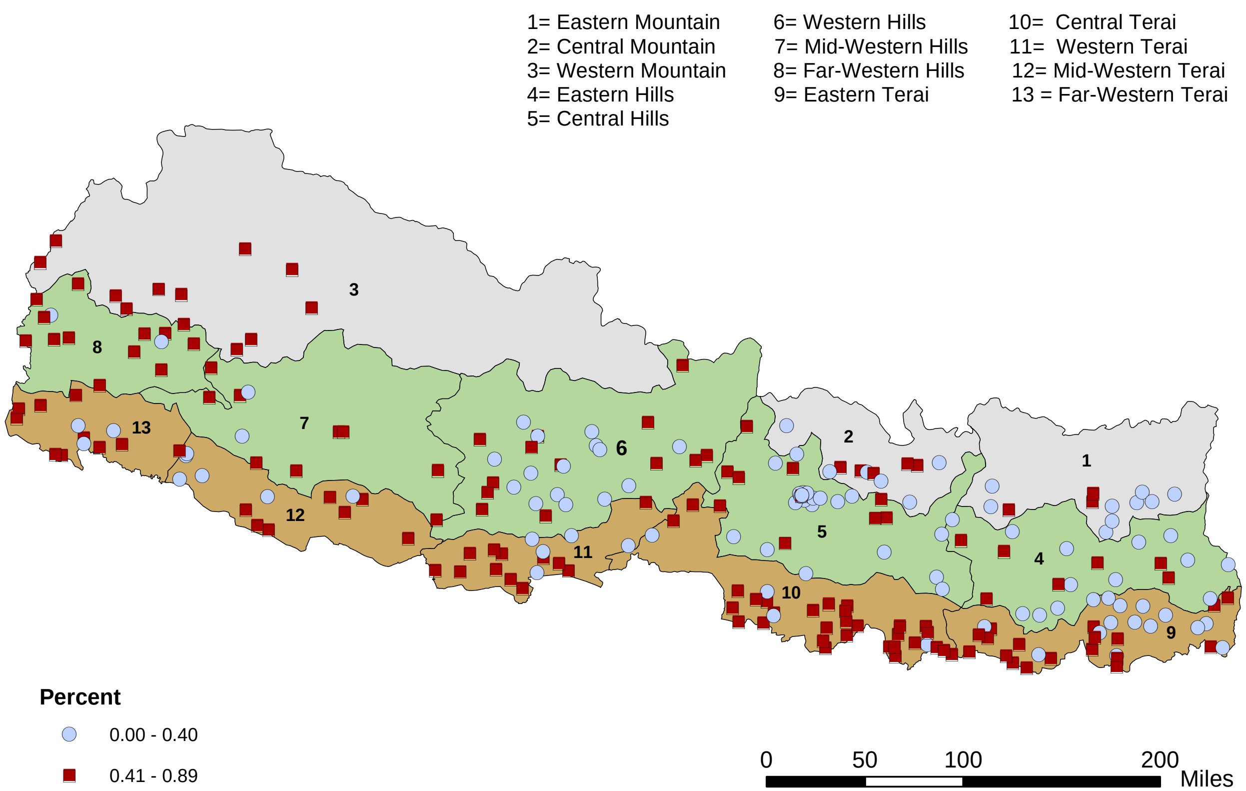
Variable	Whole (n=6,152)		Rural (n=5,571)		Urban (n=581)		F-Ratio[1]
	Mean	SD	Mean	SD	Mean	SD	
Dependent Variable							
Underweight (yes=1)	0.480	0.500	0.492	0.500	0.356	0.480	***39.28
Independent Variables							
Altitude (500 masl)	1.614	1.450	1.671	1.470	1.074	1.020	***90.52
Season (unfavorable=1)	0.455	0.490	0.471	0.500	0.299	0.460	***63.57
Season_Wealth	1.124	1.540	1.109	1.480	1.265	2.050	*5.37
Season_Urban	0.028	0.160					
Altitude_Urban	0.101	0.440					
Controls							
Level-I (Child-Level)							
Age	29.604	17.130	29.457	17.120	31.015	17.180	*4.36
Age-squared (*100)	11.697	10.520	11.606	10.480	12.565	10.800	*4.37
Birth order	3.240	2.140	3.303	2.150	2.639	1.970	***50.95
Size at birth >= average	0.775	0.420	0.774	0.420	0.780	0.410	0.090
Sex (girl =1)	0.504	0.500	0.504	0.500	0.497	0.500	0.100
Level-II (Household-Level)							
Mother's age	27.746	6.360	27.905	6.420	26.222	5.500	***37.05
Mother's BMI	20.256	2.440	20.177	2.330	21.006	3.220	***61.080
Mother's Education:							
Primary	0.122	0.330	0.118	0.320	0.165	0.370	***11.07
Higher than primary	0.124	0.330	0.097	0.290	0.386	0.480	***431.03
Community mean	1.441	1.680	1.185	1.420	3.895	1.990	***1744.78
Father's Education:							
Primary	0.255	0.430	0.260	0.440	0.215	0.410	*5.46
Higher than primary	0.386	0.480	0.361	0.480	0.630	0.480	***164.79
Don't know	0.019	0.130	0.020	0.140	0.014	0.180	0.950
Household size (numbers)	7.184	3.380	7.220	3.420	6.849	2.980	*6.35
Wealth Index Quintiles							
Quintile-I (reference)	0.259	0.438	0.282	0.450	0.036	0.187	***170.51
Quintile-II	0.208	0.406	0.224	0.417	0.059	0.235	***88.3
Quintile-III	0.190	0.392	0.203	0.402	0.065	0.247	***65.14
Quintile-IV	0.190	0.392	0.196	0.397	0.126	0.332	***17.09
Quintile-V	0.154	0.361	0.095	0.294	0.714	0.452	***2069.7
Caste/Ethnicity							
Low-caste Hindu	0.147	0.350	0.145	0.350	0.169	0.370	2.420
Hill-Tibeto-Burmese	0.252	0.430	0.255	0.430	0.222	0.420	2.980
Terai-Tibeto-Burmese	0.119	0.320	0.125	0.330	0.067	0.250	***16.75
Other ethnic group	0.098	0.300	0.099	0.300	0.083	0.270	1.690
Level-III (Community-Level)							
Health access difficult	0.773	0.420	0.800	0.400	0.516	0.500	***251.27
Urban (yes=1)	0.094	0.290					
Developmental Regions							
Central	0.275	0.440	0.267	0.440	0.353	0.490	***19.63
Western	0.165	0.370	0.173	0.380	0.098	0.300	***21.15
Mid-Western	0.139	0.340	0.143	0.350	0.102	0.300	**7.69
Far-Western	0.191	0.390	0.186	0.390	0.243	0.430	***11.11

*=p<0.05 **=p<0.01 ***=p<0.001

and recorded during unfavorable season and the remaining 55% during the favorable season. In rural areas, the share of children enumerated in unfavorable season accounts for 47% and in urban areas, it accounts for only 30% of eligible children. The average altitude of the current place of residence is 807 meters above mean sea level (masl), ranging from 54 masl to as high as 3525 masl. Significant variation in altitude is also observed between rural and urban communities; the average altitude of rural and urban communities is 836 masl and 537 masl, respectively.

Figure 2.1 illustrates the community-level prevalence of underweight among preschool-age children in Nepal for 2001. Communities with solid red squares are those having a serious public health problem as the underweight prevalence rate exceeds the cut-off at 40% (WHO 1995). There are communities where the prevalence is as high as 89%. Communities with solid blue circles are those below the cut-off, with few communities having no underweight children of preschool-age. The prevalence of underweight among children varies across developmental and ecological regions; children from communities in the Eastern regions appear relatively better-off than those from communities in Western regions. While the high prevalence of underweight is concentrated in communities located in the Central terai and Far-Western regions, the low prevalence of underweight is concentrated in mid-hills of Eastern, Central and Western regions, where the Hill-Tibeto-Burmese ethnic groups are the predominant inhabitants.

Figure 2.1 Community-Level Prevalence of Underweight among Children, Nepal, 2001



Influence of Altitude

Altitude of place of current residence is one of the key factors of interest. Table 2.2 reports the results from the whole random-intercept logistic regression model predicting childhood underweight in Nepal. Controlling for season, the altitude of the place of current residence is negatively related to short-term childhood nutritional deprivation (Model I, Table 2.2). The results show that an additional unit increase in altitude (500 masl) is likely to decrease underweight prevalence among preschool-age children by 8%. Further, to determine whether the relationship between altitude and the underweight outcome is non-linear, the squared term of altitude was introduced. The coefficient of the squared term which appeared marginally significant in the logistic regression model is statistically insignificant when household and community-level heterogeneity are controlled. The squared term is not included in the final models. It appears that although higher altitude is assumed to proxy factors contributing to underweight such as hypoxic conditions, relatively poor access to food and infrastructure including health service institutions, the influence of these factors seems to be offset by the relatively lower likelihood infections. This result contrasts with the results Kebebe (2005) reports for Ethiopia for stunting.

The effect of altitude may be contextual and therefore may differ between countries. In the context of Nepal, altitude may also proxy the influence of other factors such as caste/ethnicity background of households. This is highly likely because the geographical distribution of caste/ethnicity is associated with altitude. While higher altitude places are predominantly inhabited by Hill-Tibeto-Burmese ethnic groups, lower altitude places are

Table 2.2 Maximum Likelihood Estimates for Three-Level Random-Intercept Logistic Models for Childhood Underweight Status [Overall Model], Nepal, 2001

Parameters	Model-I			Model-II			Model-III			Model-IV		
	Odds	Sig	z-stat	Odds	Sig	z-stat	Odds	Sig	z-stat	Odds	Sig	z-stat
Fixed Effects:												
Altitude (500 masl)	0.916	*	-2.330	0.912	*	-2.380	0.981		-0.500	1.014		0.340
Season (unfavorable=1)	1.760	***	5.220	1.696	***	5.170	1.621	***	4.930	2.142	***	4.180
Season_Wealth										0.870	*	-2.390
Season_Urban										1.790		1.810
Altitude_Urban										0.628	**	-3.120
Age of the child (months)				1.178	***	17.960	1.177	***	17.940	1.176	***	17.880
Age_squared (*100)				0.998	***	-16.320	0.998	***	-16.300	0.998	***	-16.220
Birth order				1.035		1.230	1.031		1.110	1.029		1.040
Birth size >= average				0.441	***	-9.850	0.446	***	-9.780	0.446	***	-9.800
Sex (girl =1)				1.190	**	2.690	1.197	**	2.800	1.202	**	2.860
Mother's age				0.986		-1.430	0.990		-1.050	0.991		-0.980
Mother's BMI				0.830	***	-11.370	0.849	***	-10.070	0.847	***	-10.200
Mother's Education:												
Primary				0.925		-0.690	0.932		-0.620	0.936		-0.580
Higher than primary				0.654	**	-3.130	0.632	***	-3.360	0.632	***	-3.360
Community mean				0.907	**	-2.590	0.920	*	-2.270	0.927	*	-2.090
Father's Education:												
Primary				0.976		-0.260	1.012		0.130	1.012		0.140
Higher than primary				0.852		-1.690	0.884		-1.290	0.877		-1.380
Don't know				1.280		0.970	1.243		0.860	1.249		0.880
Household size				1.006		0.560	1.009		0.850	1.009		0.770
Wealth Index:												
Quintile-II				0.750	**	-2.850	0.732	**	-3.110	0.808	*	-2.000
Quintile-III				0.795	*	-2.040	0.777	*	-2.260	0.911		-0.740
Quintile-IV				0.705	**	-3.080	0.699	***	-3.190	0.871		-0.960
Quintile-IV				0.623	**	-3.010	0.633	**	-2.940	0.810		-1.160

Caste/Ethnicity												
Low-Caste Hindu							1.177		1.450	1.166		1.370
Hill-Tibeto-Burmese							0.495	***	-6.210	0.501	***	-6.180
Terai-Tibeto-Burmese							1.004		0.030	0.993		-0.050
Other ethnic group							1.099		0.620	1.103		0.650
Health access difficult				1.306		1.290	1.380		1.630	1.415		1.810
Urban (yes=1)				0.956		-0.240	0.983		-0.100	1.349		1.160
Developmental Regions:												
Central				1.389	*	2.530	1.345	*	2.390	1.484	***	3.210
Western				1.434	*	2.430	1.261		1.620	1.336	*	2.090
Mid-Western				1.527	**	2.630	1.163		0.950	1.200		1.190
Far-Western				1.288		1.650	0.958		-0.280	0.950		-0.350
Random Effects:												
Variance												
Household-level (σ^2_h)	0.467		(0.130)	0.647		(0.164)	0.601		(0.161)	0.592		(0.160)
Community-level (σ^2_v)	0.388		(0.060)	0.210		(0.047)	0.164		(0.042)	0.135		(0.038)
Intra-Class Correlation												
Household-level (ρ_h)	0.113			0.156			0.148			0.147		
Community-level (ρ_v)	0.094			0.051			0.040			0.034		
Log Likelihood	-4126.6			-3657.4			-3630.9			-3622.3		

*=p<0.05 **=p<0.01 ***=p<0.001 Note: Figures in parentheses are standard errors

Table 2.3 Maximum Likelihood Estimates for Three-Level Random-Intercept Logistic Models for Childhood Underweight Status [Rural Model] Nepal, 2001

Parameters	Model-I			Model-II			Model-III			Model-IV		
	Odds	Sig	z-stat	Odds	Sig	z-stat	Odds	Sig	z-stat	Odds	Sig	z-stat
Fixed Effects:												
Altitude (500 masl)	0.934		-1.760	0.941		-1.520	1.007		0.170	1.003		0.080
Season (unfavorable=1)	1.543	***	3.810	1.546	***	4.060	1.488	***	3.850	2.184	**	4.140
Season_Wealth										0.864	*	-2.430
Age of the child (months)				1.178	***	17.250	1.177	***	17.230	1.177	***	17.220
Age_squared (*100)				0.998	***	-15.650	0.998	***	-15.630	0.998	***	-15.610
Birth order				1.035		1.180	1.033		1.130	1.035		1.180
Size at birth >= average				0.445	***	-9.290	0.447	***	-9.300	0.446	***	-9.320
Sex (girl =1)				1.217	**	2.910	1.224	**	3.010	1.227	**	3.040
Mother's age				0.987		-1.300	0.990		-0.970	0.990		-0.990
Mother's BMI				0.830	***	-10.570	0.850	***	-9.230	0.850	***	-9.260
Mother's Education:												
Primary				0.885		-1.020	0.893		-0.950	0.898		-0.900
Higher than primary				0.702	*	-2.350	0.672	**	-2.620	0.674	**	-2.600
Community mean				0.904	*	-2.420	0.919	*	-2.080	0.921	*	-2.020
Father's Education:												
Primary				0.994		-0.060	1.031		0.340	1.035		0.370
Higher than primary				0.846		-1.710	0.873		-1.380	0.870		-1.410
Don't know				1.308		1.030	1.276		0.940	1.278		0.950
Household size				1.002		0.170	1.006		0.500	1.005		0.410
Wealth Index:												
Quintile-II				0.751	**	-2.810	0.733	**	-3.080	0.808	*	-1.970
Quintile-III				0.773	*	-2.270	0.755	*	-2.500	0.883		-0.960
Quintile-IV				0.701	**	-3.080	0.693	***	-3.210	0.874		-0.910
Quintile-IV				0.617	**	-2.860	0.629	**	-2.770	0.804		-1.120

Caste/Ethnicity												
Low-Caste Hindu							1.203		1.550	1.210		1.600
Hill-Tibeto-Burmese							0.475	***	-6.250	0.481	***	-6.170
Terai-Tibeto-Burmese							0.997		-0.020	0.983		-0.120
Other ethnic group							0.998		-0.010	0.998		-0.010
Health access difficult				1.348		1.410	1.426		1.740	1.448		1.830
Developmental Regions:												
Central				1.505	**	2.990	1.427	**	2.710	1.439	**	2.800
Western				1.554	**	2.900	1.328		1.930	1.357	*	2.090
Mid-Western				1.573	**	2.740	1.157		0.890	1.165		0.940
Far-Western				1.326		1.770	0.927		-0.470	0.906		-0.610
Random Effects												
Variance												
Household-level (σ^2_h)	0.439		(0.134)	0.632		(0.169)	0.581		(0.165)	0.584		(0.165)
Community-level (σ^2_v)	0.356		(0.063)	0.193		(0.048)	0.116		(0.043)	0.148		(0.042)
Intra-Class Correlation												
Household-level (ρ_h)	0.108			0.154			0.146			0.145		
Community-level (ρ_v)	0.087			0.047			0.029			0.037		
Log Likelihood	-3756.5			-33392.8			-3312.6			-3309.6		

*=p<0.05 **=p<0.01 ***=p<0.001 Note: Figures in parentheses are standard errors

Table 2.4 Logistic Regression Models for Childhood Underweight Status [Urban Model], Nepal, 2001

Parameters	Model-I			Model-II			Model-III			Model-IV		
	Odds	Sig	z-stat	Odds	Sig	z-stat	Odds	Sig	z-stat	Odds	Sig	z-stat
Altitude (500 masl)	0.657	***	-4.290	0.643	**	-2.600	0.707	*	-1.960	0.707	*	-1.970
Season (unfavorable=1)	1.872	**	3.280	2.145	**	2.960	2.109	**	2.860	2.845		1.130
Season_Wealth										0.933		-0.340
Age of the child (months)				1.155	***	5.230	1.153	***	5.140	1.153	***	5.130
Age_squared*100				0.998	***	-4.760	0.998	***	-4.670	0.998	***	-4.660
Birth order				1.006		0.060	0.965		-0.380	0.965		-0.380
Birth size >= average				0.437	***	-3.420	0.446	**	-3.280	0.444	***	-3.290
Sex (girl =1)				0.985		-0.080	0.988		-0.060	0.992		-0.040
Mother's age				0.989		-0.340	0.998		-0.070	0.998		-0.060
Mother's BMI				0.834	***	-4.690	0.834	***	-4.540	0.834	***	-4.520
Mother's Education:												
Primary				1.225		0.650	1.223		0.630	1.225		0.640
Higher than primary				0.588		-1.840	0.553	*	-1.990	0.554	*	-1.980
Community mean				0.929		-0.890	0.921		-0.990	0.919		-1.010
Father's Education:												
Primary				0.780		-0.720	0.797		-0.650	0.780		-0.700
Higher than primary				0.837		-0.520	0.910		-0.270	0.891		-0.320
Don't know				1.093		0.080	1.056		0.050	1.081		0.070
Household size				1.057		1.560	1.062		1.660	1.062		1.630
Wealth Index:												
Quintile-II				1.228		0.320	1.129		0.190	1.237		0.300
Quintile-III				3.816	*	2.030	3.688		1.940	4.111		1.880
Quintile-IV				1.344		0.500	1.142		0.210	1.305		0.360
Quintile-IV				1.256		0.390	1.197		0.290	1.404		0.430
Caste/Ethnicity												
Low-caste Hindu							0.823		-0.580	0.813		-0.620
Hill-Tibeto-Burmese							0.721		-0.990	0.711		-1.030
Terai-Tibeto-Burmese							0.682		-0.850	0.686		-0.840
Other ethnic group							2.097		1.770	2.068		1.730

Health access difficult			0.525		-0.920	0.546		-0.850	0.524		-0.900
Developmental Regions:											
Central			1.489		1.010	1.445		0.920	1.424		0.880
Western			0.769		-0.580	0.815		-0.450	0.819		-0.430
Mid-Western			1.110		0.250	1.003		0.010	0.996		-0.010
Far-Western			1.068		0.180	1.301		0.660	1.292		0.640
LR Chi_Squared	38.34	***	150.84	***		157.290	***		157.410	***	
Log likelihood	-359.20		-302.95			-299.73			-299.67		

*=p<0.05 **=p<0.01 ***=p<0.001

predominantly inhabited by the Terai-Tibeto-Burmese ethnic groups and other ethnic/caste groups. Hill-Tibeto-Burmese people are distinctly different from the High-caste-Hindu (reference group) in terms of food habits and cultural restrictions on certain foods, especially meats; the former group is relatively more liberal than the latter group. To ascertain whether there exists the influence of caste/ethnicity on the effect of altitude, a series of models were estimated.

The effect of altitude remains statistically significant even after the incorporation of child-, household-(except caste/ethnicity) and community-level variables, including community access to health services (Model II, Table 2.2). However, the statistical significance disappears when the caste/ethnicity variable (Model III, Table 2.2) is introduced; and the coefficient of Hill-Tibeto-Burmese variable is negative and highly significant, suggesting that distribution of caste/ethnicity is altitude bound. Hence, the influence of altitude becomes less important. By residence, while altitude is not a significant factor in the rural model (Table 2.3), it is in the urban model (Table 2.4). In the urban model, a 500 masl increase in altitude decreases the odds of being underweight by 29% (Model IV, Table 2.4).

The results of post-estimation assessment of the predicted probability of a child being underweight, based on the final overall model (Model IV, Table 2.2), are presented in Figure 2.2. The predicted probability of a child being underweight appears to show a convex relationship with altitude. The risk of a child being underweight decreases at a

Figure 2.2 Predicted Probability and 95% Confidence Interval of Childhood Underweight Status by Altitude (500 masl)

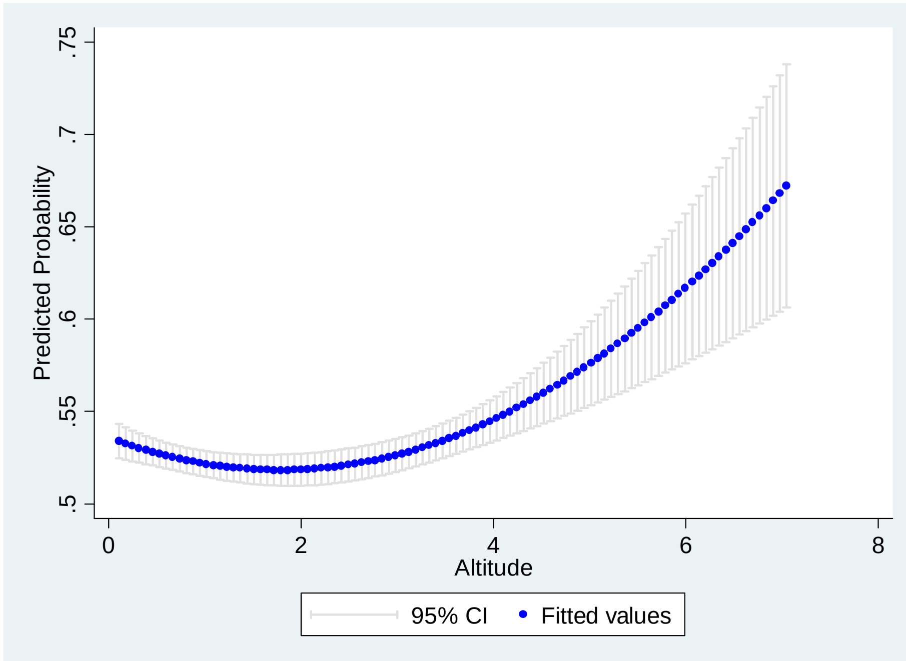
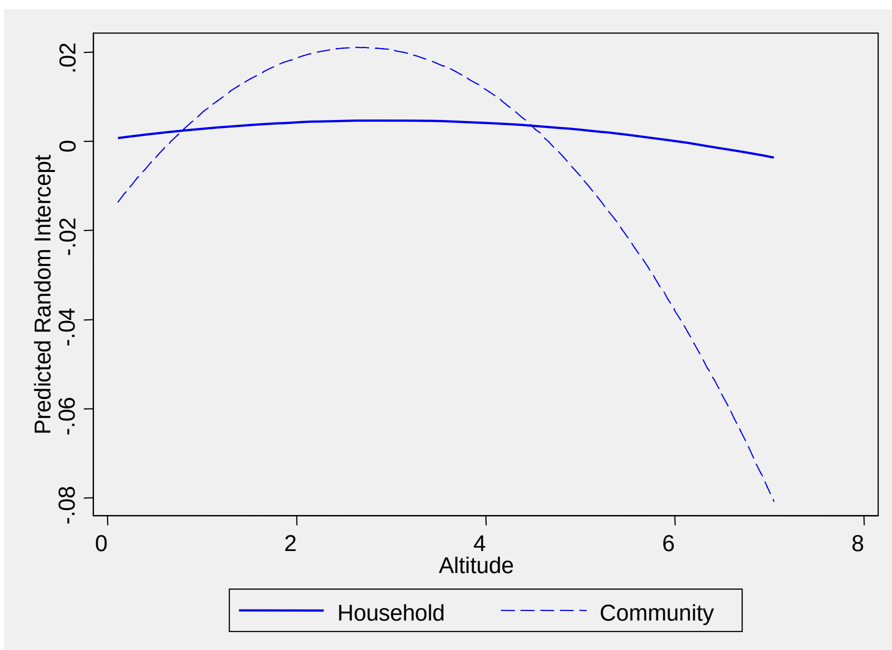


Figure 2.3 Predicted Random-Intercept for Childhood Underweight Status by Altitude (500 masl)



slow rate with altitude until the altitude reaches about 1000 meters above mean sea level and then it ascends relatively at the faster rate. Figure 2.3 presents the predicted random intercepts with respect to altitude. The contribution of altitude to predicted heterogeneity at household level is small, but it is considerable at the community level, which is as expected.

Interaction Effects on the Influence of Altitude

The effect of altitude on childhood underweight may vary by the extent of urbanization of the communities where children are brought up. An interaction term between altitude and urban was introduced to explore if the effect of altitude is consistent between urban and communities. Compared to rural communities, in urban communities the odds of children being underweight is reduced by 37% for each additional unit increase in altitude (500 masl) (Model IV, Table 2.2). Interestingly, although the odds ratios for both altitude and urban variables are greater than 1 (but not significant), the influence of altitude in urban areas is less than 1 and is statistically significant. This may occur because most urban communities at higher altitudes are large cities such as Kathmandu and Pokhara, where access to health infrastructure is far better than in other urban communities in Terai. The high-altitude large cities are also climatically less favorable for infections.

Influence of Season

Season measured in terms of months in which children were enumerated for anthropometric data is assumed to capture differences in the extent of food security and incidence of infections and diseases that determine nutritional status of children. Controlling the influence of altitude, the odds of being underweight for children surveyed in the unfavorable season are as high as 76% compared with those enumerated in favorable season (Model I, Table 2.2). When child factors, household factors (except ethnicity) and community factors, including community access to health services are controlled (Model II, Table 2.2), the coefficient of season retains its significance but its magnitude declines to 70% and it further declines to 62% when ethnicity is added into the model (Model III). Model IV in Table 2.2 further controls the interaction terms such as influence of season associated with wealth status of household and urban residence. Additionally, controlling these interaction terms, the odds of children enumerated in the unfavorable season being underweight relative to these enumerated in the favorable season substantially increases. This indicates that the risk of children being underweight during the unfavorable season is much higher if children are from relatively poor households and living in rural communities as opposed to those from relatively wealthier households in urban communities. This result provides strong evidence of seasonal variation in underweight prevalence and further influence of urbanization of place of residence and households' economic condition. The relatively poor access to food and also the relatively higher incidence of infections and diseases in the unfavorable season may have triggered the prevalence of underweight during the unfavorable season.

Residential models with respect to seasonal effect provide interesting results. In the rural communities, compared to children surveyed in favorable season those enumerated in the unfavorable season have a 54% higher odds of being underweight when only altitude is controlled (Model I, Table 2.3) and have 118% higher odds of being underweight when all other factors including the interaction terms with wealth are controlled (Model IV,

Figure 2.4 Predicted Probability and 95% Confidence Interval of Childhood Underweight Status by Season

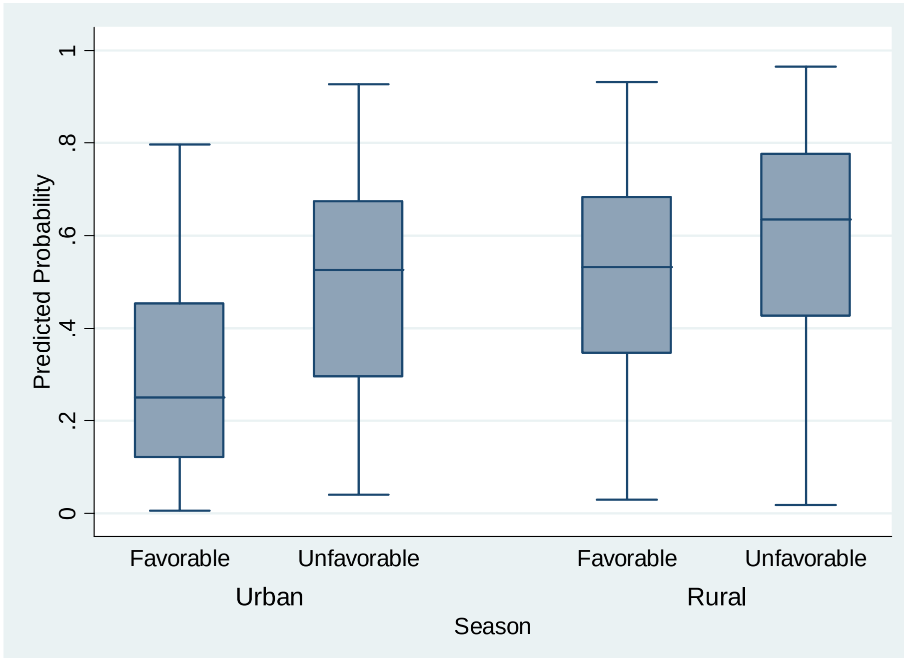


Figure 2.5 Predicted Random-Intercept for Childhood Underweight Status by Season

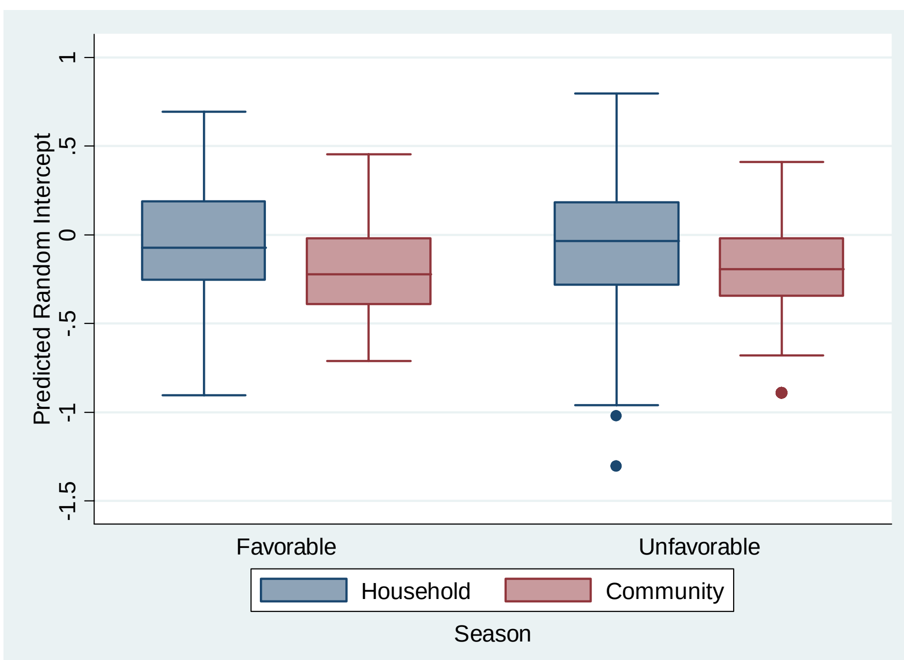


Table 2.3). In the urban model, the odds of children being underweight are higher by 87% in the initial model (Model I, Table 2.4) and by 111% when all other factors except the interaction term are controlled (Model III, Table 2.4). Interestingly, when an interaction term with household wealth is incorporated in the urban model the statistical significance disappears (Model IV, Table 2.4). However, coefficient of the interaction term is not statistically significant.

Figure 2.4 compares the predicted probability of the i^{th} child in the j^{th} household in the k^{th} community being underweight ($Y_{ijk}=1$) by season and residence. In both the rural and urban community models, the probability of a child being underweight is higher in the unfavorable season than in the favorable season. Although the mean predicted probabilities of a child being underweight are consistently higher in rural areas by season, the differences in the seasonal impact is higher in urban communities, showing the rural-urban disparity in the influence of season on underweight prevalence. Compared to the favorable season, in the unfavorable season the risk of a child being underweight is substantially higher in urban communities than in rural communities, which is also evident from the regression results (Tables 2.3 and 2.4). Figure 2.5 shows the extent to which the predicted household- and community-level random intercepts are associated with season. Although there appears to be considerable inter-level (between household and community) variation in the predicted intercepts in both seasons, the intra-level variation is not observed.

Interaction Effects on the Influence of Season

Although season itself does not discriminate among children of any class and residence, variation in seasonal impact can be expected because of households' differential ability to cope with environmental stresses during the unfavorable season. To explore whether the effect of season varies due to household economic status (e.g., household wealth) and community context (e.g., the extent of urbanization measured as rural *vs* urban), additional models with interaction terms were estimated (Model IV, Tables 2.2 and 2.3). Generally, it is anticipated that poorer households are less capable of addressing the seasonal impact on the nutritional health of their children than wealthier households. The interaction term, the product of season (unfavorable=1) and wealth index quintiles as a continuous variable, was introduced. The random-intercept logistic regression results for the overall model as well as the rural model show that, after controlling for all other factors including altitude, community access to health services, other interaction terms and random variables, the coefficient of this interaction term is negative and statistically significant (Tables 2.2 and 2.3). Although in the unfavorable season, more children are likely to be underweight, children from relatively wealthier households are less likely to be underweight than those from poorer households. An additional unit increase in household status as measured by wealth quintiles decreases the likelihood of children being underweight by 13% in the overall model and by 14% in the rural communities. (Model IV, Tables 2.2 and 2.3). This shows that, overall in Nepal and specifically in rural communities, parents from relatively wealthier households seem to have better coped with the unfavorable seasonal effects on their child's health than parents from poorer households. In urban communities, the influence of the unfavorable season on underweight status is statistically not related to the wealth status of households (Model IV, Table 2.4).

The coefficient of the interaction term between urban and season is significant at the 10% level. Compared to the favorable season, in the unfavorable season the odds of children being underweight in urban communities is 79% as high (Model IV, Table 2.2)

Influence of Unobserved Heterogeneity

The random effect components in Table 2.2 present the results for unobserved heterogeneity at the household- and community-levels for the overall model. Both the coefficients of the household- and community-level variances are highly significant across the models (Model I through IV, Table 2.2). Almost one-sixth (15%) of the variance in child underweight is attributed to household-level unobserved factors and 3% to community-level unobserved factors (Model IV), confirming that underweight outcomes of children in Nepal are not independent, but are related within the households and communities because of shared characteristics. Residential models of underweight status show that the random coefficients are significant only for the rural model. The amount of variance in childhood underweight outcome explained by unobserved heterogeneity in the rural model is comparable with the overall model (Model IV, Table 2.3). In both rural communities and overall in Nepal, inequality in underweight status between similar children among households is about four times larger compared to inequality in underweight status of similar children among communities.

Influence of Other Factors

***Childhood-Specific Factors*:** Age of the child, size at birth, and sex appear to be significant child-specific factors contributing to underweight. In all models (overall, rural and urban), age of the child is positively related to underweight but there is a limit as shown by a concave relationship. This relationship may also capture the duration of breast feeding practice and vulnerability of child to infections. Size at birth is another important factor influencing childhood underweight status. Children of those mothers who reported the size at birth of child was average or above have a 55% lower odds of being underweight as compared to children whose parents reported their children were below average birth weight, even after controlling for the maternal health indicator (BMI). The effect of size at birth in part may proxy the genetic characteristics of parents that are not captured by the maternal health indicator. An example includes father's genetic traits. The relationship between size at birth and underweight status later in life indicates that in addition to genetic endowments, prenatal health during pregnancy is important for a healthy childhood. Sex differential in underweight status appears to be prevalent, especially in rural communities. Girls have 21% (overall model) to 23% (rural model) higher odds of being underweight than boys.

Household-Specific Factors: Among parents' characteristics, the Body Mass Index of the mother and mother's education level including community mean maternal education appear as significant factors influencing childhood underweight. Surprisingly, despite the fact that both the breadth and depth of maternal education are lower than the father's education, only maternal education stands out to be negatively related to childhood underweight status. As compared to children of uneducated mothers, those of mothers with higher than primary-level education have a 37% lower odds of being underweight in the overall model 33% lower odds in rural communities, and 45% lower odds in urban communities. Maternal lower-level education (primary) seems to have no influence on reducing childhood underweight, relative to no education. However, there appears to be a negative spillover effect of community maternal education on childhood underweight. An additional mean year of maternal education at the community-level lowers childhood underweight incidence by 7% in overall model and 8% in rural communities. But in the urban communities, the negative spillover effect of community maternal education on childhood underweight is not statistically significant.

Household wealth status and ethnicity are important factors influencing the underweight problem. In both the overall and rural models, as compared to children from the lowest wealth quintile households, those from higher wealth quintile households have significantly lower odds of being underweight (Models I through III, Table 2.2). The estimated coefficients indicate that the relationship between underweight status and household wealth status is not linear. Compared to wealth Quintile-I household the odds of a child being underweight first declines and later increases with an increase in household wealth. However, when the interaction terms with other variables are introduced into the model (Model IV, Tables 2.2 and 2.3), only the coefficient of wealth Quintile-II is statistically significant. In the case of the urban model, none of the wealth quintile variables is significant. The caste/ethnic background of households appears to be another important determinant of childhood underweight. As compared to High-caste-

Hindu children, the Hill-Tibeto-Burmese children have lower odds of being underweight (50% in the overall model and 52% in the rural model). The caste/ethnic backgrounds of the households appear to be not a statistically significant predictor of childhood underweight in the urban model.

Community-Specific Factors: Among the community-level factors, the community access to health services and development region variables appear to be important predictors of childhood underweight status in Nepal. Controlling all other factors including interaction terms, an increase in proportion of households in the community experiencing difficulty in access to health services is likely to increase the odds of a child being underweight, which is much higher in urban than in rural communities. It should be noted that this variable is statistically significant (at 10% level) only in the fully expanded model, i.e., Model-IV. Results show that in the overall model the extent of urbanization is not related to underweight status of children. As compared to children from the Eastern region, those from the Central and Western regions of Nepal have higher odds of being underweight in both in the overall and rural models, documenting the significant regional disparity in the childhood underweight problem, especially in rural communities. Statistically, there appears to be no regional variation in childhood underweight across urban communities.

2.8 CONCLUSIONS

This study focuses on two community environmental contexts: season and altitude of place of residence as potential determinants of short-term childhood nutritional deprivation in Nepal. Season stands out as a very strong factor contributing to short-term nutritional deprivation of children in Nepal. As opposed to the favorable season, the risks of children being underweight in the unfavorable season are exceedingly high regardless of place of residence. This result is consistent with the Bairagi (1986) findings for Bangladesh. Compared to that study, the geographical coverage and the model specifications in this study are more comprehensive. Despite the fact that season does not discriminate among children of any class, in the unfavorable season, children of wealthier household are much better-off relative to those from relatively poorer households, particularly in rural communities.

Although altitude reflects the long-term community environmental context, it is also related to short-term nutritional deprivation of children in Nepal. Generally, it is anticipated that children at the higher altitudes are more likely to be underweight as these places are hypoxic, and have less access to health infrastructure and food. Our results for risk of childhood underweight are in contrast. In the overall model, the odds of children being underweight significantly decrease with altitude, but later it appears that caste/ethnicity background of households moderate this effect. However, in the urban model the odds of children being underweight with altitude continue to be substantially lower. Rural-urban differences in the effect of altitude may have been attributed to variation in the mean altitude of urban and rural communities, household economic well-being which is highly skewed in urban communities, access to health services and also to the micro-climatic environment itself. For instance, the urban communities found at lower altitudes especially in the terai are highly humid and therefore pose a greater risk of disease infections to children. The urban communities in higher altitudes are mainly large cities (e.g., Kathmandu and Pokhara). These places are climatically pleasant and access to health infrastructure is far better.

Methodologically, the multi-level modeling approach (random-intercept logistic models) adopted in this study out-perform the logistic regression modeling approach, except in the case of urban model. That is, childhood underweight status of children is not independent at the household level because of shared characteristics such as household public goods and maternal care and at the community-level because of common factors such as community sanitation level and exposure to infections. Net of child-, household- and other community-specific factors, both household-level and community-level unobserved factors explain variation in childhood underweight prevalence, especially in rural communities. The share of household-level heterogeneity is four times as high as the share of community-level heterogeneity in explaining the variance in childhood underweight incidence. The contribution of household- and community-level unobserved factors are, however, not statistically significant in the urban models.

Child age, size at birth, and sex are strong child-specific factors. Among the household-specific factors, maternal education, wealth and ethnicity are strong predictors of short-term nutritional deprivation in Nepal. Among the community-level factors, community-level maternal education, the extent of community access to health services and the regional variables are stronger in effect. Results provide evidence of geographical disparities in the short-term nutritional deprivation of children in Nepal; the Eastern region is better-off than other regions especially the Central and Western regions. Further, children in Nepal seem to be nutritionally deprived in part because of poor access to health services. However, an increase in level of community-level education of mothers is beneficial to short-term childhood nutritional health.

Policy implications that can be drawn from the findings of the study towards alleviating the long-standing high prevalence of underweight and achieving the Millennium Development Goals are as follows. Firstly, health policies toward alleviating underweight status should focus on seasonal variations in childhood underweight, especially emphasizing the unfavorable season during which the incidence of diseases and infections is high and access to food is poor. In light of the wealth effect on the influence of season, the alleviation of poverty should be integral part of overall child health policy. Secondly, altitudinal variation in underweight prevalence suggests that the health intervention should emphasize communities, especially lower altitude urban communities that are climatically vulnerable for incidence of diseases and infections that trigger underweight prevalence. Although not the main focus of this study, findings suggest that public policies emphasizing on maternal education, maternal health, access to public health services and geographically-disadvantaged communities are immensely important in order to achieve the Millennium Development Goals.

The season variable specified here does not include the entire months in a year due to survey coverage, including peak monsoon months such as July/August, during which risks of incidence of diseases and infections are much higher. Further, during this period it is likely that parental time and care to children is constrained by increased labor demand for farming. Therefore, the estimates obtained for season should not be generalized for the entire post-harvest or pre-harvest months. It is plausible that the severity of underweight could be much higher if we include the peak monsoon months. A study including all months and the availability of panel data would provide much better insights into seasonality of childhood underweight.

2.9 ENDNOTES

[1] Underweight reflects mainly the short-term nutritional status of a child (FAO 1998). It is measured using widely-used anthropometric measures, i.e., weight-for-age. To determine the nutritional status of a child, the weight-for-age parameter is compared with internationally-accepted reference standards such as those from the National Center for Health Statistics (NCHS)/WHO (HMG/N 2000). In empirical studies, two approaches are commonly used to measure the short-term nutritional status of a child. The first approach uses a continuous measure, i.e., the standardized score (z score) of weight-for-age (WAZ). The second approach uses a categorical measure, such as underweight. A child is classified as underweight if weight-for-age falls below minus 2 standard deviations from the median weight-for-age (-2 z score) of the NCHS/WHO reference population. In this study the categorical measure is used, considering the severity of underweight prevalence.

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3. GOVERNMENT FARM PAYMENTS AND OFF-FARM LABOR RESPONSE OF PRINCIPAL FARM OPERATORS: A SPATIAL ANALYSIS OF U.S. COUNTY-LEVEL DATA

3.1 ABSTRACT

Using county-level data from the 2002 U.S. Census of Agriculture, this study examines *participation* and *scale* effects of government farm payments on off-farm responses of principal farm operators, taking into consideration spatial autocorrelation bias and endogenous government payments. This study in part contributes to the literature on off-farm employment through its use of a recently-developed technique –the Feasible Generalized Spatial Two-Stage Least Squares (FGS2SLS) estimator -- to deal with a system of equations with spatial lagged dependent variables and spatial dependency in error structure as well as endogenous explanatory variables. The empirical results provide evidence of spatial dependency of off-farm employment of principal farm operators in the U.S. Both *participation* and *scale* of government farm payments negatively shape the off-farm response of principal farm operators. However, the extent of the effects varies substantially depending on how the payment variables are specified and also by payment type and the magnitude of income transfer. While the effects of participation in Commodity Credit Corporation Loan (CCCL) and Other Federal Farm Program (OFFP) payments on off-farm employment are negative and statistically significant, participation in Conservation Reserve and Wetland Reserve (CRWRP) payments appears statistically insignificant. The CCCL payment effect is three times stronger than that of the OFFP payment. Interestingly, in terms of scale effect, payment types exhibit the opposite

pattern: the effect of CRWRP payment per farm is almost twice as large as the OFFP payment per farm and almost five times as large as the CCCL payment per farm. Given that the off-farm employment impact of income transfer is associated with the magnitude of transfers, a strong cap on payments seems relevant for policy consideration.

3.2 INTRODUCTION

Government farm payments to the U.S. agricultural sector represent a significant income transfer. In 1996, payments totaled over $7.3 billion in real terms (year 2000=100) and increased to 22.9 billion dollars in 2000 (USDA/ERS 2003). In 2002, because of phasing out of emergency payments, farm payments declined to $11.2 billion but payments again totaled $23 billion in 2005. During 1996-2005, the annual growth rate of farm payments was 35% in real terms. We expect these payments to lower the propensity for off-farm work by farm operators (OECD 2001; Burfisher and Hopkins 2003; Ahearn *et al.* 2006). However, both the hours and proportion of operators involved in off-farm work as well as numbers quitting farming is not decreasing but increasing (Goetz and Debertin 2001; El-Osta *et al.* 2004; Shrestha *et al*. 2006; USDA/ERS 2006[2]), even as government payments have increased substantially (USDA/ERS 2003, 2006; Ahearn *et al.* 2004a; Key and Roberts 2003). According to USDA/ ERS statistics (USDA/ERS 2006), in 1974 about 47% of principal farm operators participated in off-farm employment for salary and wages, and this increased to 55% by 2002. Even off-farm employment of principal farm operators for 200 days or more annually increased, from 28% in 1974 to 39% in 2002, with an annual increment of 0.4%. The extent to which government farm payments shape off-farm employment, therefore, is an important policy concern.

The concern over the growing share of farm operators employed off-farm is often linked to its close association with the survival of farms. Some scholars consider off-farm work as more of a *lifestyle choice* -- as a second job and means for securing retirement and health benefits -- instead of a transition out of agriculture (Mishra *et al.* 2002). Others

[2] www.ers.usda.gov/Briefing/ FarmIncome/Data/Constant-dollar-table.XLS

argue that it is a way out of farming (e.g., Goetz and Debertin 2001). Several studies have examined the relationship between government farm payments and off-farm employment directly or indirectly using farm-level data (e.g., El-Osta *et al.* 2004; Ahearn *et al.* 2006) and a few studies have used aggregate county-level data on selected geographical areas (e.g., Huffman 1980; Goodwin and Bruer 2003). Past studies show that the relationship between government farm payments and off-farm employment of farm operators is mixed, suggesting a need for further comprehensive studies. Additionally, past studies have ignored possible *spatial dependency* of principal farm operators' off-farm work decisions and potential *endogeneity* of government payments, with few exceptions (such as El-Osta *et al.* 2004). The key concern is that failure to account for spatial dependency and endogeneity, if they exist, results in biased and inefficient parameter estimates (Anselin 1998).

Using county-level data, this paper examines the relationships between the off-farm employment decision of principal farm operators and government farm payments in the U.S., focusing on 1) whether the spatial dimension (space) is important in modeling principal farm operators' off-farm employment decisions and 2) the effect of government farm payments on principal farm operators' off-farm labor response. The effect of government farm payments is examined in terms of *participation* in government payment programs (County-level share of farms receiving government payments) and *scale* of government payments (County-level government payments average per farm), irrespective of type of payment (hereafter referred to as TOTAL) and by payment type

(Conservation Reserve Program and Wetland Reserve Program (CRWRP), Commodity Credit Corporation Loans (CCCL), and Other Federal Farm Programs (OFFP).

3.3 GOVERNMENT FARM PAYMENTS IN THE US

Since 1933, the U.S. government has supported the farm sector in different forms on the grounds that farm income is subject to price shocks, business cycles and macroeconomic policies that are beyond the farmer's control. In addition, farm households are often considered to be economically disadvantaged relative to non-farm households. Recently, this argument has received less support in the U.S., in part because of the ever-increasing share of off-farm income in farm household income and its large contribution to farm household income. Off-farm income not only has reduced the income gap between farm- and non-farm households, but also has reduced the disparity in income among farm households (Findeis and Reddy 1987; Ahearn *et al*. 2006). Mishra *et al.* (2002) state that in contrast to conventional thinking, farm households are not necessarily financially worse-off compared to non-farm households.

In the last two decades, U.S. agriculture has witnessed a considerable shift in farm support policies. Until 1996, the main focus of farm policy was on acreage limits and commodity storage programs (Westcott *et al.* 2002). Direct payments to farmers were through the deficiency payments. The main intention of deficiency payments was to provide farm income support, to protect farm households from volatility in market prices. The deficiency payments would include price spread between the target price and commodity market price or price support loan rate whichever was higher (Abler and Blandford 2006).

In 1996, the Federal Agricultural Improvement Reform (FAIR) Act marked a major change in farm programs and policies, argued to be more market-based (USDA/ERS 1997). The major changes in policies and programs included elimination of set-aside requirements, mandatory crop insurance, freeing farmers from production restrictions and also ending the deficiency payments based on differences between market price and target price. Instead, the legislation authorized 'decoupled' payments, which involved a predetermined annual lump-sum income transfer to operators for the duration of the legislation (1996-2002). The lump-sum income transfer was based on historical criteria, such as past participation in commodity programs but was not dependent on current production choices, input use and market prices (El-Osta *et al.* 2004; Abler and Blandford 2006). To be eligible for such payments, farmers were required to comply with the Conservation Reserve Programs and Wetland Reserve Programs (CRWRP).

In 2002, the Farm Security and Rural Investment Act, called the 2002 Farm Act, extended agricultural programs through 2007 and brought about another shift in U.S. farm programs and policies. Under this new policy scenario, government payments included decoupled payments now called 'direct payments', counter-cyclical payments (CCP), and marketing loans and payments for conservation reserve programs (Burfisher and Hopkins 2003; Westcott *et al.* 2002). The 2002 Farm Act provided income support for commodities such as wheat, feed grains, rice, upland cotton, oil seeds, soybeans, and peanuts. The direct payments under the 2002 act are similar to production flexibility contracts (PFC) under 1996 FAIR Act but instead of setting payment rates annually, an annual fixed payment rate is fixed on a per unit basis for the entire period 2002-2007

(Westcott *et al.* 2002). Additionally, the CCP is a new program under the 2002 Farm Act. This includes price-dependent benefits for covered commodities. The CCP payment rate is equivalent to the difference between the effective price for the commodity in question and the target price. Under the 2002 Farm Act, the commodity loan program was continued with marketing loan provisions. Marketing loan provisions included loan deficiency payments and marketing loan gains when the market price of loan commodities is low. So its function is to reduce the revenue risks associated with price volatility. The 2002 Farm Act further expands the environmental quality and incentives programs. Under this program, farmers are provided cost-shares, rental payments[3], and other direct payments in return for adopting environmentally-friendly farming practices or setting aside environmentally-sensitive private land from farming.

Guided by different objectives, various types of government farm payments are in place to support farm families in the U.S. The 2002 U.S. Census of Agriculture divides government payments into three major components. 1) Conservation Reserve Program and Wetland Reserve Program (CRWRP). The CRWRP payments include cost sharing, rental payments and direct payments in return for using environmentally-friendly agricultural practices or a set aside. It also includes voluntary programs to restore and protect wetlands on private property. 2) Commodity Credit Corporation Loans (CCCL). The CCCL includes annual lump-sum payments for applicable crops such as barley, canola and other rapeseeds, corn, cotton, flaxseed, oats, mustard seed, rice, sunflowers, soybeans, sorghum, sunflower seeds and wheat; counter-cyclical payments; and

[3] Annual rental payments based on rental value of agricultural land specified for the CRP acres and maintained for conservation purposes but not for harvesting.

marketing loans. Although the Commodity Credit Corporation loan programs have provisions to purchase milk products at a specified floor price, the available data does not include the benefits to the dairy sector. Similarly, the government transfers to peanuts and sugar producers are not included. 3) Other Federal Farm Program (OFFP). Other Federal Farm Program payments include loan deficiency payments for applicable crops such as wheat, rice, corn, grain, sorghum, barley, oats, cotton, wool and lentils.

3.4 PAST STUDIES

One of the potential responses to changing farm incentives resulting from farm payments is adjustment in the allocation of time to on-farm work, off-farm work and leisure (Findeis 1998; Abler and Blandford 2006). If government farm payments are fully-decoupled, transfers are expected to have no effect on production incentives but on the principal operator's time allocation to off-farm work and leisure because of an income or wealth effect (Singh *et al*. 1986; Findeis 1998; OECD 2002; Burfisher and Hopkins 2003; Ahearn *et al.* 2006). That is, government transfer payments are likely to make, like other consumption goods, leisure more affordable as the value of leisure relative to the marginal value of additional wage earning increases. The hours allocated to farming and/or off-farm work could decline. Conversely, if income transfers are not fully-decoupled, the transfer is likely to decrease relative prices of agricultural inputs and increase the profitability of farming. Farm operators, therefore, are likely to alter production (Abler and Blandford 2006; Ahearn *et al.* 2006). Income transfers may also ease borrowing constraints and may increase investment in farms, such as size increase in crop acreage (Goodwin and Mishra 2004). Findeis (2002) argues that when taken across the farm household, the income effect may result in a decline in on-farm work time rather than a decline in off-farm work, depending on the 'order of work' – i.e., whether work time is first allocated to farm work or to off-farm employment. Therefore, it becomes an empirical issue whether government income transfers to farm communities have stronger income or substitution effects.

Various scholars have examined the effect of government farm payments on off-farm employment of farm operators and spouses, and in some cases of farm men and women. Using farm-level data from the U.S. for 1996, and 1999, Ahearn *et al.* (2006) found that the likelihood of farm operators working off-farm declined significantly with higher government payments. Ahearn *et al.* (2006) also report that the impacts of total government payments vary by year; the negative impacts of government payments were higher in 1996 than in 1999. The difference in the extent of effect between these two years was identified as due to the magnitude of payment difference, instead of a change in policy. The income transfer was significantly greater in 1999 than in 1996. Similarly, Serra *et al*. (2003), using a sample of farms from Kansas observed from 1993 through 2000, estimated the effect of household wealth on off-farm labor decisions. Strong evidence of a negative effect of wealth on off-farm labor supply was observed. The study results also showed that the effect of government payments was negative but not statistically significant for the first period (1993-1995), but negative and significant in the second period (1996-2000). A study by El-Osta *et al.* (2004), examined the impact of PFC payments and other government payments on farm and off-farm labor as well as total labor supply using 2001 farm level data from the Agricultural Resource

Management Survey (ARMS), USDA. They found that the PFC payment increased hours of labor allocation on-farm but decreased off-farm work time. Overall, labor allocation adjustment in response to government payments was shown to be small. They also conclude that the income transfer has served to dampen the trend towards more off-farm work. Goodwin and Mishra (2004) examined the determinants of off-farm labor supply of operators and the relationship between off-farm employment and farming efficiency. Using 2001 data from the ARMS, they found Agricultural Market Transition Act (AMTA) payments to have negative and significant effects on off-farm work hours. They also found that off-farm labor supply negatively influenced farming efficiency. Using state-level data for 1978-96 from the U.S., Ahearn *et al.* (2004a) examined how government payments affect the linkages between off-farm work, productivity, and farm consolidation and also how government payments influence farm exits from agriculture. Results show that government payments have a negative impact on the odds that farm operators work off-farm at least 200 days per year and that the odds of farm exit are positively influenced by the odds of off-farm work. They also showed that size of farms is not endogenous to off-farm employment. However, the odds of off-farm employment were shown to have an endogenous relationship with farm productivity, concentration in farm production and the odds of farm exit.

Past studies show that the effect of government payment on the off-farm employment decision is not always consistent, suggesting a need for further comprehensive studies. Moreover, past studies have failed to account for two important estimation issues: possible existence of spatial dependence of off-farm employments and endogeneity of government farm payments with few exceptions (e.g., El-Osta *et al.* 2004). The farm's location may strongly influence off-farm work decisions because off-farm employment is dependent on the availability of work and transaction costs (Jones 1984; Findeis *et al.* 1991). Arguably, the rationale for spatial analysis for modeling economic behavior is two-fold. Firstly, the data collection process linked with the spatial units such as county may present measurement error (Anselin 1998; LeSage 1999). Second, and more importantly, what occurs in one space may *depend* on what occurs in another adjoining space because the economic behavior of agents in one place may dependent on that of agents in surrounding places due to social interaction effects such as neighborhood effects, peer effects, or spillover effects (Akerlof 1997; Anselin 1998; LeSage 1999; Jaenicke 2004). With regard to off-farm response of principal farm operators, the spatial dependence can be expected to occur because of the fact that off-farm labor markets may not be confined to one county but to multiple counties resulting in *spillover* effects to surrounding counties. Similarly, social interaction among principal operators of surrounding counties can be valuable for sharing experiences about off-farm opportunities, hence, may affect the labor allocation decision of peers.

Secondly, although endogenous relationships of off-farm employment with farm efficiency and productivity are widely reported (Ahearn *et al.* 2004b; Goodwin and Mishra 2004), the possible endogeneity of government payments with off-farm response has been debated but usually ignored in empirical analyses with few exceptions (such as El-Osta *et al.* 2004). The *endogenous* relationship between government payments and off-farm employment of the principal operators may occur for the several reasons (Abler and Blandford 2006). Farms that have received government payments may have owned or rented the land with base acreage being assigned. Such farms may have comparative advantages in the production of program crops depending of the land characteristics such as soils, climate and irrigation and these land characteristics may be correlated with production. Because of this farm-level fixed effect the government payment variables, in part, may serve as proxies for the omitted characteristics if they are not taken into account in the models resulting in overestimation of the effect of government payments variables.

3.5 CONCEPTUAL MODEL

The framework for the off-farm response model is drawn from the time allocation model (Rosenzweig 1980; Sumner 1982; Singh *et al*. 1986; Huffman 1991; El-Osta *et al.* 2004; Goodwin and Mishra 2004). It is assumed that the principal farm operator aims to maximize household utility from his/her leisure time (l^P), the leisure of other family members (l^O), and consumption of goods (C), as follows:

$$U(l^P, l^O, C) \tag{1}$$

The utility function (1) is maximized subject to time and budget constraints, and production technology as specified below:

$$L = L^P + L^O + L^{FP} + L^{FO} + l^P + l^O \tag{2}$$

$$I = W^P L^P + W^O L^O - t(T^P) - t(T^O) + pQ - p_1 X + GP + M + A = C \tag{3}$$

$$Q = f(L^{FP}, L^{FO}, X; \alpha) \tag{4}$$

$$L^P, L^O, GP \geq 0;\ L^{FP}, L^{FO}, l^P, l^O\ X, M > 0 \tag{5}$$

Equation (2) describes the time constraints faced by the farm household, where L is the annual total time endowment of the household, which are allocated between off-farm work, on-farm work, and leisure (home time). The L^P and L^O are, respectively, the labor time allocated to off-farm employment by the principal farm operator *(P)* and others *(O)*. The income earned from off-farm employment are assumed to be spent on consumption or/and farming. L^{FP} and L^{FO} represent the time allocations of the principal farm operator and other farm family members to farm work.

The budget constraint faced by the household is given in equation (3). The household total income is comprised of net income from off-farm employment, net income from farm production, exogenous income, and income from assets. The net income from off-farm employment includes the product of wages earned from off-farm employment and time allocated to off-farm work (resulting in off-farm earnings) of the principal operator (W^pL^p) and other farm household members (W^OL^O) less the transaction cost of off-farm employment for the principal operator $t(T^P)$ and others $t(T^O)$. The transaction cost for the principal farm operator is defined *as* $t(T^P) = T_0 + (L^P)*\tau$, where T_0 represents the fixed transaction cost which includes the cost of job search and logistics and τ is the variable transaction cost, which include the total cost of commuting to and from work each day (Goetz and Debertin 2001). Net farm income consists of the value of farm production (pQ) less input costs (p_1X). In the equation, GP is the decoupled government farm payment (there could be coupling taking place as well), M is exogenous income, A is income from assets, p is the price of agricultural output, p_1 is the vector of input prices, W^P and W^O are, respectively, the wage rates of the principal farm operator and other family members, Q is agricultural output, and α represents the characteristics of the farm and household members. Net household income is used for consumption of goods C, where the price of goods is normalized to one. It should be recognized that while farm payments in the U.S. are argued to be 'effectively decoupled', the payments may not be entirely exogenous, as specified in equations (3). If this is the case, government payments levels will be affected by current labor decisions (and vice versa)--i.e., introducing endogeneity into the model. This results in a different conceptual model, where GP is not exogenous.

The technology for production is defined in equation (4). Since production is part of the income equation, as shown in equation (4), the value of time in farming is determined by the production function. Substituting (4) into (3), we obtain the budget constraint as follows:

$$C= W^P L^P + W^O L^O - t(T^P) - t(T^O) + pf(L^{FP}, L^{FO}, X; \alpha) - p_1 X + GP + M + A \qquad (6)$$

As specified in equation (5), we assume that time allocation to leisure and farm works, and consumption of goods, have internal solutions. However, the allocation of time to off-farm labor may have a corner solution. Hence, for the time allocation to off-farm work we specify the Kuhn-Tucker conditions. Consider λ and η to be the Lagrange multipliers, respectively, for household income and time allocation. These terms reflect the marginal utility of extra dollar of consumption expenditure (i.e., marginal utility of income) and marginal utility from extra labor allocation. Then, the first-order conditions for maximizing the utility function (1) with respect to the constraint set (2-5) are as follows:

$$U'_{L^P} - \eta - \lambda W^p + \tau \le 0, \left(U'_{L^P} - \eta - \lambda W^p + \tau\right)L^p = 0, L^p \ge 0 \quad (7)$$

$$U'_{L^{FP}} - \eta - \lambda p f'_{L^{FP}} = 0 \quad (8)$$

$$U'_{l^P} - \eta = 0 \quad (9)$$

$$U'_C - \lambda = 0 \quad (10)$$

Equations 7 and 8 provide the optimality conditions for off-farm labor and farm labor allocation, respectively. Similarly, equations 9 and 10 are optimality conditions for leisure and consumption, respectively. The *U'* in above equations refers to marginal utility with respect to argument in question and *f'* refers to marginal product with respect to inputs use.

If an interior solution exists for off-farm labor of the principal farm operator, using equations (7) and (8), we can derive the following optimality relationship for the allocation of time between off-farm work and on-farm work:

$$\frac{U'_{L^P}}{U'_{L^{FP}}} = \frac{\lambda W^p + \eta - \tau}{\lambda p f'_{L^{FP}} + \eta}\text{, which can be rewritten as} \quad (11)$$

$$\frac{U'_{L^P}}{W^p *} = \frac{U'_{L^{FP}}}{p f'_{L^{FP}} *} \quad (12)$$

where $W^p * = \lambda W^p + \eta - \tau$ and $p f'_{L^{FP}} * = \lambda p f'_{L^{FP}} + \eta$

Similarly, equations (7) and (9) provide the optimality relationship for the allocation of time between off-farm work and leisure:

$$\frac{U'_{L^P}}{U'_{l^P}} = \frac{\lambda W^p + \eta - \tau}{\eta} \quad (13)$$

Equation (11) represents the optimality condition in which the marginal rate of substitution between off-farm and farm labor allocation is equal to the ratio of the shadow price of labor allocated to off-farm works to the shadow price of labor allocated to farm works. Equation 11 can be expressed as equation (12). This relationship suggests that principal farm operators work off-farm as opposed to working on-farm as long as the marginal utility per dollar from off-farm work exceeds the marginal utility per dollar from farm work at the margin (LHS>RHS). In contrast, if LHS<RHS, an opposite decision is expected and if it is strictly equal then principal operators are indifferent between off-farm and on-farm work (El-Osta *et al.* 2004).

Government farm payments--if not fully-decoupled-- are likely to affect the relationship in equation (12) via altering the marginal utility per dollar from farm and off-farm employment. The net effect of the payments is dependent on the income and substitution effect of the income transfer. For instance, if the income transfers are fully decoupled, leisure will be more attractive resulting in RHS<LHS in equation (13), hence decreasing the labor allocation to off-farm works as the marginal utility per dollar from off-farm work would decrease. Similarly, in equation (12) we expect LHS<RHS, suggesting a lower propensity of principal farm operators to be involved in off-farm employment. If the income transfer is coupled, it would supplement the output prices (p) farms receive, thus increasing the labor allocation to farming as payments are linked with the quantity of applicable crops produced. El-Osta *et al.* (2004) mention that coupled payments could have both wealth and substitution effects. Further, the income transfer may reduce capital (borrowing) constraints and encourage investment in farms including increases in the size of farm operations and adoption of new technologies. Such investment is expected to increase labor allocation to farms as long as the marginal utility per dollar from farm

work exceeds the marginal utility per dollar from off-farm work. Therefore, the net effect is dependent on the nature of the effect of income transfers.

From the spatial perspective, an increase in the share of principal farm operators working off the farm in neighboring counties reflects LHS>RHS in equation (12). This is likely to have positive spillover effects on the off-farm work of principal farm operators in the county, as the labor market faced by principal operators in the region is more likely to be the same. Additionally, the social interactions among farm operators may further motivate each other to work off-the farm as long as LHS>RHS in equation (12).

3.6 DESCRIPTION OF SPATIAL MODELS

This section provides an overview of the spatial econometric process, including information about the detection of spatial dependency, spatial regression models, and selection of appropriate spatial regression models and techniques available to estimate those models.

As opposed to aspatial models, such as the ordinary least squares (OLS) method, spatial econometric models are justified when there exists spatial correlation in error in OLS regression. Spatial autoregressive models appear to be analogous to autoregressive models in time series; however, they differ in that the former represents the multidimensional nature of dependence and latter a single dimension. The properties of OLS, therefore, cannot be applied to a spatially-lagged dependent variable (Anselin 1998). While in time series with a lagged dependent variable, the OLS estimator is consistent as long as the error does not show serial autocorrelation. This is not the case with spatially-lagged dependent variables. OLS estimators in the presence of spatial residual autocorrelation are both biased and inconsistent for autoregressive parameters. For this reason, the two-step generalized least squares procedure that can be applied to deal with serial autocorrelation is not applicable to spatial autoregressive parameters (Anselin 1998).

Detecting Spatial Dependency. Moran's I statistics, that measure correlation between the variable in question and it's spatially weighted variable, are commonly used to detect spatial correlation in OLS residuals. With a row-unstandardized spatial weight matrix (W), Moran's I statistics are defined as (Anselin 1998)

$$I = \frac{N}{S} * \left(\frac{e'We}{e'e} \right) \tag{14}$$

and with a row-standardized spatial weight matrix, it is defined as,

$$I = \frac{e'We}{e'e} \tag{15}$$

where *e* is the vector of OLS residuals, N is the number of observations and S is the sum of all of the spatial weights in the matrix (also called standardization factor). For the significance test of the null hypothesis, i.e., no spatial autocorrelation, the Moran's I statistics are compared with the z scores.

Alternatively, asymptotic tests based on Maximum Likelihood methods such as Wald test, Lagrange Multiplier (LM) test and Likelihood Ratio tests can be used to ascertain the spatial correlation in error terms. These maximum likelihood tests are asymptotically equivalent. The LM test is also commonly used to diagnose the residual spatial dependency in the presence of lagged dependent variables. The LM test can be defined as follows (Anselin 1988).

$$LM = \left(\frac{1}{tr\{W + W')W\}}\right) * \left(\frac{e'We}{\sigma^2}\right)^2 \sim \chi^2(1) \qquad (16)$$

This test is based on the null hypothesis of no autocorrelation.

Spatial Weight Matrix. The spatial weight matrix (*W*) is the key element in the spatial econometric model. The underlying reason for using it is to establish a relationship between observations or associated residuals of spatial units. The *i* and *j* elements of the *n x n* weight matrix, i.e., the w_{ij}, represent the potential spatial dependency between the i^{th} observation or associated error with the j^{th} neighboring observation or associated residuals. If $i=j$, then $w_{ij} = 0$, implying that they are not neighbors or the diagonal element of the matrix is zero. If w_{ij}=1 then i^{th} and j^{th} spatial units, such as counties, are neighbors. The neighbor is specified based on spatial extent of influence. Two basic types of spatial weighting matrix applied in the literature are the contiguity-based spatial weight matrix and the distance-based spatial weight matrix.

Contiguity-Based Spatial Weight Matrix. Descriptions of contiguity-based matrices are discussed in LeSage (1999) and Kelejian and Robinson (1995). The contiguity-based spatial weight matrix establishes the relationship between neighbors based on shared borders or vertices of the lattice. The construction of this type of matrix requires polygon data. Rook and Bishop contiguities are two basic contiguities. Rook contiguity is defined as w_{ij}=1 if one spatial unit shares common sides with neighboring spatial units and 0, if otherwise. Bishop contiguity is defined as w_{ij}=1 if one spatial unit shares common vertices with neighboring spatial units and 0, if otherwise. Queen Contiguity combines the features of both Rook and Bishop contiguities and contiguity is defined as w_{ij}=1 if one spatial unit shares a common side or vertices with its neighboring units and 0, if otherwise.

Distance-Based Spatial Weight Matrix. This matrix uses the distance between the spatial units. Construction of this type of matrix requires the point location of unit or XY coordinates. The distance-based spatial weight matrix is defined as w_{ij}=1 if $d_{ij} \leq m$, where d_{ij} is the distance between the i^{th} and j^{th} units and m is a distance cut-off value, reflecting the neighborhood of influence being specified. The specification of the distance-based weight matrix is dependent on how neighborhood is defined. With respect to spatial interaction theory, it can be expressed as $w_{ij} = \frac{1}{(d_{ij})^{\alpha}}$, where α is the parameter of power of influence. If α =1, the decay effect is linear and higher if it is greater than one, implying that the influence of the neighboring unit declines as we move further away (Anselin and Bera 1998).

One important manipulation in the spatial weight matrix is row standardization, which can be expressed as $w_{ij}^{s} = \frac{d_{ij}}{\sum_i d_{ij}}$. This process normalizes the sum of the weights of each row to be unity. Row standardization ensures that the weight to be between 0 and 1. Further, it makes comparison of spatial parameters between models possible (Anselin and Bera 1998). Row-standardization is commonly used in maximum likelihood estimation;

however, the resulting matrix is likely to be asymmetric even when the original matrix is symmetric (Anselin and Bera 1998).

The spatial weight matrix is used to construct the spatial lag operator as a product of the spatial weight matrix and vector of observations, which could be a vector of the dependent variable or vector of error terms. Depending on the association of the spatial lag with the dependent variable or error term, the specifications are called the spatial lag model and spatial error model, respectively, which are briefly described below (LeSage 1999).

Spatial Lag Model (SLM). Spatial regression model can be specified as

$$Y=\rho W(Y) + X\beta+\varepsilon, \quad \varepsilon \sim N(0, \sigma^2 I_n) \tag{17}$$

where Y is a $n\times 1$ vector of observations on the dependent variable, ρ is the spatial autoregressive parameter, W is the spatial weight matrix of dimension $n\times n$, WY is the spatially-lagged dependent variable, X is a $n\times k$ matrix of observations on the exogenous variables, β is a $k\times 1$ vector of parameters to be estimated, and ε is a $n\times 1$ vector of error terms. One point of caution with this specification is that WY as an explanatory variable behaves similar to the presence of an endogenous variable regardless of correlation structure of the errors (Anselin and Bera 1998). Reformulating the equation (16), we get $Y=(I-\rho W)^{-1}X\beta+(I-\rho W)^{-1}\varepsilon$ and the covariance structure of Y is given by $\sigma^2(I-\rho W)^{-1}(I-\rho W')^{-1}$. *The* $(I-\rho W)^{-1}$ matrix is a full matrix with $\rho\neq 0$. As a consequence, the error terms become globally correlated and correlation decays with order of contiguity. Therefore, OLS estimator for the above specification will not be consistent (Anselin and Bera 1998), suggesting joint estimation of WY along with Y.

Theoretically, spatial dependence in a response variable is likely to exist because agents in one spatial unit may emulate agents in neighboring spatial units through social interactions. Statistically, this may arise because of unobservable latent variables that are spatially correlated (LeSage 1999). In the case of off-farm employment, this model may be justified if we believe that the off-farm employment decisions of principal farm operators in one county are influenced by the off-farm employment decisions of principal farm operators in neighboring counties.

Spatial Error Model (SEM). The spatial error model is relevant when the spatial dependency operates through the error structure. The model is written as

$$Y = X\beta + \mu, \qquad \mu = \lambda W\mu + \varepsilon \qquad \varepsilon \sim N(0, \sigma^2 I_n) \tag{18}$$

where λ is the spatial autoregressive parameter similar to ρ. The other terms are as described in the spatial lag model. Spatial error dependency may capture unobserved variables that 'spill over' across the spatial units and also the measurement errors. Therefore, λ is considered as a nuisance parameter (Anselin and Bera 1998). The error covariance of SEM is non-spherical and, hence, the OLS estimator is unbiased but not consistent. Kelejian and Prucha (1999) have demonstrated that the Generalized Method of Moments (GMM) estimator of λ is consistent and asymptotically normal.

General Spatial Model (GSM). The spatial dependency may also operate through both spatial lag in the dependent variable and error terms. If both the spatial autoregressive parameter (ρ) and spatial error coefficient (λ) are statistically significant, it suggests that the general spatial model that nests both spatial lag and spatial error structures is appropriate (LeSage 1999). The general spatial model with one spatial weight matrix (*W*) takes the following form

$$Y= \rho W(Y) + X\beta + \mu, \quad \mu= \lambda W\mu + \varepsilon \quad \varepsilon \sim N(0, \sigma^2_\varepsilon) \tag{19}$$

Selection between Spatial Regression Models. Selection of an appropriate spatial regression model is critically important. Anselin (2005) proposes the following decision rules based on LM tests and their robust forms: 1) Conduct LM-Lag and LM-Error tests and if one of them is significant and the other is not then select the model corresponding to the test which rejects the null hypothesis of no spatial correlation, 2) If both LM tests are significant, conduct the robust LM tests: Robust LM-Lag and Robust-Error tests. If one of them is significant, then the select the model corresponding to the one which is significant, 3) If both robust forms of LM test are significant, then select the model corresponding to the one which has the larger test statistic. This decision rule suggests for selecting either the SLM or SEM even if both spatial lag and error parameters are significant. However, LeSage (1999) suggests that if spatial lag model is chosen and there exists evidence of spatial dependence in error structure of this model, the GSM is appropriate. In practice, researchers often consider GSM if both spatial lag and spatial error parameters are significant.

Spatial Regression Estimation Techniques. The maximum likelihood (ML) method is commonly used to estimate spatial lag and spatial error models. One of the reasons for its popularity is due to availability of routines such as LeSage's Matlab tool box. The precondition for the use of the ML method includes the assumption of normality of error terms, and the spatial weight matrix is row-standardized. The parameters estimates using the ML method possess the usual asymptotic properties including consistency, normality and efficiency. The appropriate significance test for the spatial error parameter is the likelihood ratio test (Anselin and Bera 1998).

Despite its popularity, the ML method is computationally constrained when the data is large and the weight matrix is not row-standardized. One of the problems with row standardization is that the matrix is not symmetric even when the original matrix is symmetric. Moreover there is no good reason based on economic theory to row standardize (Bell and Bockstael 2000). Alternatively, Kelejian and Prucha (1999) have developed the generalized estimator, which is feasible even for extremely large samples and is consistent even if errors are not normal. However, one caveat with this method is that it does not provide standard errors for the spatial error parameter; hence, does not allow direct testing of hypothesis about estimated parameters, λ. Nevertheless, the estimated β and δ parameters have asymptotic properties of a feasible GLS estimator (Kelejian and Prucha 1999).

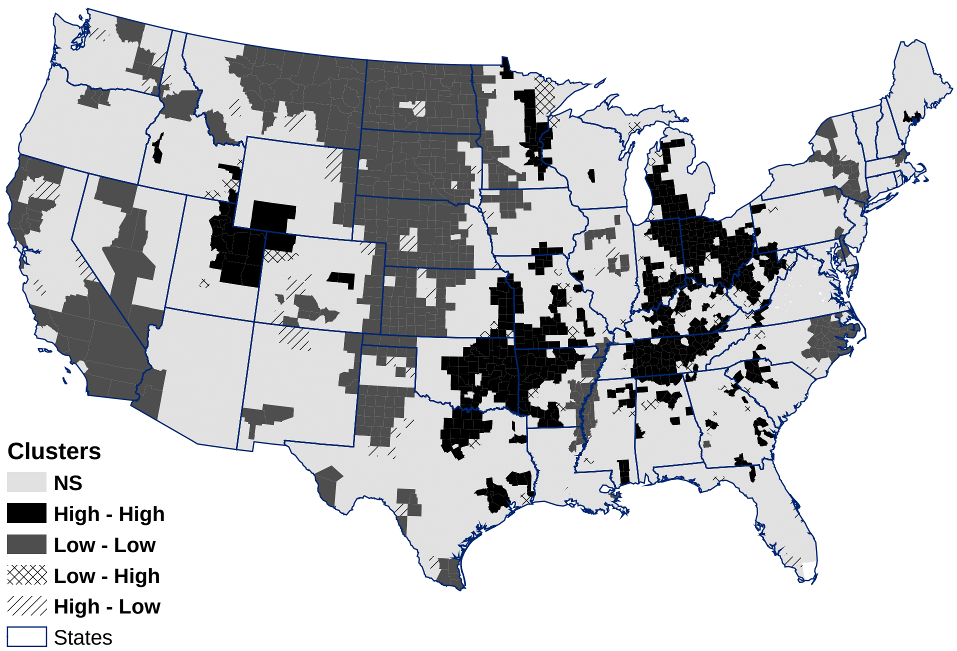
3.7 EMPIRICAL MODEL AND ESTIMATION

A series of models were estimated to determine the final model for the estimation, taking into account the possible endogeneity of government payment variables and spatial dependency of off-farm employment. First, to determine whether the government payment variables are endogenous, the Wu-Hausman test was performed on the model specified in equation 20, setting ρ*, W, and* λ to null. The government payment variables were instrumented with five-years lagged percent of farms with sales>=$100,000 (as used in El-Osta et al. 2004); nine ERS farm production regions such as Heartland, Northern Crescent, Northern Great Plains, Basin and Range, Prairie Gateway, Fruitful Rim, Mississippi Portal, Eastern Upland, and Southern Seaboard (reference); the Palmer drought index for 2001 (March, April, May August and September); and respective spatially-lagged government payment variables (W*GP). The spatial weight matrix used here is constructed using the standard first-order contiguity (LeSage 1999). Wu-Hausman test results showed that the government payments variables violate the exogeneity assumption of OLS, suggesting that government farm payments and off-farm employment are required to be jointly estimated. In a subsequent step, models were estimated using an instrumental variable two-staged least squares (IV/2SLS) method.

Second, before conducting formal tests to determine if spatial dependency is a problem in the IV/2SLS model, a spatial analysis was performed to explore the extent to which spatial dependency is apparent at the local level. Figure 3.1 illustrates the scatter map of counties with statistically significant local Moran's I (LISA scatter plot) based on 95%

percentiles. The spatial clusters of high prevalence of principal farm operators' off-farm employment (hot spots) are concentrated

Figure 3.1 Spatial Concentration of the Share of Principal Farm Operators Who Worked Off-Farm (>=200 Days), 2002



in or near the Appalachian region; the Ozarks; in the Denver, Colorado region; and in the southern Great Lakes region encompassing Michigan, Ohio and northern Indiana. Similarly, spatial clusters of low prevalence of principal operators' off-farm employment (cold spots) are located through the Northern Great Plains southward into Texas; in a narrow band along the Mississippi; in Southern California; and in a band along the Eastern coastal region where farms located in densely-populated regions are often farmed intensively. There are relatively few outliers, indicating strong spatial dependence in off-farm employment participation rates in the U.S.

The exploratory analysis presented above, however, does not formally test whether spatial correlation is a problem in the data and it also does not suggest which spatial specific econometric model is appropriate for the given problem. Therefore a series of formal tests including the Moran's I and asymptotic Lagrange Multiplier (LM) tests were conducted. Tables 3.1 and 3.2 present the results of the formal diagnostic tests of spatial dependency of off-farm employment of principal farm operators for the models with and without including farm enterprises as defined according to North American Industrial Classification Systems (NAICS). The Moran's I statistics and asymptotic LM-based tests results presented are conditional on the explanatory variables introduced in the IV/2SLS models. The unconditional (univariate) Moran's I for the dependent variable is estimated to be 0.45, which is quite high, indicating a strong spatial correlation in the data.

Table 3.1 Diagnostic Tests for Spatial Dependency of Participation Effect Models

Model	**TGPM**		**CRWRPM**		**CCCLPM**		**OFFPPM**	
Test[1]	Without	With	Without	With	Without	With	Without	With
Moran's I	0.262	0.250	0.258	0.249	0.269	0.252	0.266	0.254
I-stat	25.407	24.422	25.000	24.252	26.102	24.562	25.756	24.777
LM Error	609.734	555.479	590.016	547.529	643.907	561.819	626.896	572.054
LM Lag	660.092	573.257	655.239	587.715	690.458	587.033	667.858	570.803
Robust LM Error	34.215	48.076	30.828	42.158	41.612	51.293	37.430	56.999
Robust LM Lag	84.572	65.854	96.050	82.345	88.163	76.508	78.392	55.749

[1] All test results are significant at 0.1 % level of significance

Table 3.2 Diagnostic Tests for Spatial Dependency of Scale Effect Models

Model	**GP_APFM**		**CRWRP_APFM**		**CCCLP_APFM**		**OFFPP_APFM**	
Test[1]	Without	With	Without	With	Without	With	Without	With
Moran's I	0.264	0.265	0.265	0.242	0.271	0.260	0.272	0.258
I-stat	25.310	25.538	24.420	22.511	24.033	23.222	25.071	24.006
LM Error	604.334	607.469	560.640	468.208	541.876	497.856	591.310	533.907
LM Lag	604.807	589.994	583.327	487.871	608.108	538.035	589.106	544.892
Robust LM Error	47.412	64.721	45.357	47.191	28.640	41.547	55.179	53.279
Robust LM Lag	47.885	47.246	68.043	66.854	94.873	81.726	52.975	64.264

[1] All test results are significant at 0.1 % level of significance

The highly significant conditional Moran's I statistics confirm that the spatial correlation is a serious problem to be addressed in estimating the off-farm response of U.S. principal farm operators. The Moran's I coefficients range from 0.25 to 0.27 in the case of the *participation effect* models and from 0.24 to 0.26 in the case of the *scale effect* models. Further, the formal asymptotic Lagrange Multiplier (LM) tests and their robust forms show that chi-squared statistics for those tests are highly significant across the models (Tables 3.1 and 3.2).

The formal test results suggest an appropriate spatial econometric model that accounts for spatial dependency in both the lagged dependent variable and error terms and also considers endogenous government program variables. As chi-square statistics for robust LM-Lag and LM-Error tests are large and in many cases close to each other, instead of selecting between the spatial lag and spatial error model as suggested in Anselin (2005), the general form of the spatial model that nests both spatial lag and error terms is adopted following the suggestion of LeSage (1999). The final model for the estimation, in compact form, takes the following form:

$$OFF=\alpha + \rho W{*}OFF + \gamma GP + X\beta + \mu \qquad (20)$$

where $\mu= \lambda W\mu + \varepsilon,\ \varepsilon \sim N(0, \sigma^2_{\varepsilon})$

and OFF is a $n{\times}1$ vector of the dependent variable, defined as percent of principal farm operators who worked off-farm for >=200 days in a year, ρ is a spatial autoregressive parameter (or spatial autocorrelation coefficient if W is row-standardized), W is the standard first-order contiguity spatial weight matrix of dimension $n{\times}n$, $W{*}OFF$ is the spatially-lagged dependent variable, GP represents the government farm payment variables which are assumed to be endogenous to off-farm employment, X is an $n \times k$ matrix of observations of exogenous variables, β is a $k \times 1$ vector of parameters to be estimated, and ε is an $n \times 1$ vector of error terms. The λ is a spatial autoregressive parameter similar to ρ, but for the error lag $W\mu$. As mentioned before, $W*OFF$ as an explanatory variable induces correlation with the error term similar to presence of an endogenous variable regardless of the correlation structure of the errors (see Anselin and Bera 1998).

Handling the system of equations with a spatially-lagged dependent variable and spatial dependency in the error term is complex. Kelejian and Prucha (2004) suggest a Feasible Generalized Spatial Two-Stage Least Squares (FGS2SLS) procedure that involves a three-step procedure based on the GMM estimator to deal with this kind of estimation issue. Alternatively, as discussed before, the Maximum Likelihood (ML) method is widely used in spatial analysis but is computationally constrained when the data set is very large and the weight matrix is not row-standardized. The final model (20), therefore, was estimated using the FGS2SLS estimator as suggested by Kelejian and Prucha (2004), which is briefly described below.

The estimation of models using the FGS2SLS estimator involves three steps. In the first step, the model parameters (ρ, γ, and β) in equation (20) were estimated using IV/2SLS using the instrumental matrix H. The instruments used for the government payments variable are already reported. For the lagged dependent variable, i.e., W*OFF, spatially-lagged exogenous variables (W*X) were used as instruments. It should be noted that equation (20) implicitly embodies the system of equations. In compact form, this model can be expressed as

$$Y_j = Z_j \delta_j + \mu_j , \tag{21}$$

where $\mu_j = \lambda_j W \mu_j + \varepsilon_j$, $Z_j = (WY_j, X_j, \overline{X}_j)$, and $\delta_j = (\rho_j, \beta_j, \gamma_j)$, and where j is the j^{th} equation representing each endogenous variable (e.g., GP, W*OFF, and OFF) and $\overline{X}_j$ represents endogenous government payment variables.

Consider H as an instrumental matrix. The predicted value of endogenous variables is estimated as $\widetilde{Z}_j = H(H'H)^{-1} H'Z_j$. The IV/2SLS estimator of δ_{jIV} is given by $\hat{\delta}_{jIV} = [\widetilde{Z}_j ' Z]^{-1} \widetilde{Z}_j ' Y_j$. The disturbances term we obtained is $\hat{\mu}_j = Y_j - Z_j \hat{\delta}_j$.

In the second step, spatial autoregressive parameters (λ) were estimated using the the Generalized Method of Moments (GMM) procedure (Kelejian and Prucha 2004). The disturbances obtained from the first step were used as predictors of ε_j, where $\varepsilon_j = \mu_j - \lambda_j W \mu_j$. The GMM estimator considers three moments of the error term. Pre-multiplying the expression for the error term by the spatial weight matrix W, we obtain $W\mu_j - \lambda_j W^2 \mu_j = W\varepsilon_j$. Consider that,

$W\mu_j = \overline{\mu}_j$, $W^2 \mu_j = \overline{\overline{\mu}}_j$, and $W\varepsilon_j = \overline{\varepsilon}_j$. Based on this relationship we have,

$$n^{-1} \mu_j ' \mu_j + \lambda_j^{\,2} n^{-1} \overline{\mu}_j ' \overline{\mu} - 2\lambda_j n^{-1} \mu_j ' \overline{\mu}_j = n^{-1} \varepsilon_j ' \varepsilon_j$$

$$n^{-1} \overline{\mu}_j ' \overline{\mu}_j + \lambda_j^{\,2} n^{-1} \overline{\overline{\mu}}_j ' \overline{\overline{\mu}} - 2\lambda_j n^{-1} \overline{\overline{\mu}}_j ' \overline{\mu}_j = n^{-1} \overline{\varepsilon}_j ' \overline{\varepsilon}_j$$

$$n^{-1} \mu_j ' \overline{\mu}_j + \lambda_j^{\,2} n^{-1} \overline{\mu}_j ' \overline{\overline{\mu}} - \lambda_j n^{-1} [\mu_j ' \overline{\overline{\mu}}_j + \overline{\mu}_j ' \overline{\mu}_j] = n^{-1} \varepsilon_j ' \overline{\varepsilon}_j \tag{22}$$

Then the three moments of interest in terms of error terms can be expressed as

$$E[n^{-1}\varepsilon_j{}'\varepsilon_j] = \sigma_j{}^2$$

$$E[n^{-1}\bar{\varepsilon}_j{}'\bar{\varepsilon}_j] = n^{-1}\sigma_j{}^2 tr(W'W)$$

$$E[n^{-1}\varepsilon_j{}'\bar{\varepsilon}_j] = 0 \tag{23}$$

Rearranging moment conditions and system of equations, we get

$$g_j = G_j\theta_j \tag{24}$$

The estimators of g_j, and G_j, can be expressed as,

$$\tilde{g}_j = n^{-1}[\tilde{\mu}'_j\,\tilde{\mu}'_j\,, \tilde{\bar{\mu}}'_j\,\tilde{\bar{\mu}}'_j\,, \tilde{\mu}'_j\,\tilde{\bar{\mu}}'_j\,]' \tag{25}$$

$$\tilde{G}_j = n^{-1}\begin{bmatrix} 2\tilde{\mu}'_j\,\tilde{\bar{\mu}}'_j & -\tilde{\bar{\mu}}'_j\,\tilde{\bar{\mu}}'_j & n \\ 2\tilde{\bar{\bar{\mu}}}'_j\,\tilde{\bar{\mu}}'_j & -\tilde{\bar{\bar{\mu}}}'_j\,\tilde{\bar{\bar{\mu}}}' & tr(W'W) \\ (\tilde{\mu}_j{}'\tilde{\bar{\bar{\mu}}}_j + \tilde{\bar{\mu}}_j{}'\tilde{\bar{\mu}}_j) & -\tilde{\bar{\mu}}_j{}'\tilde{\bar{\bar{\mu}}}_j & 0 \end{bmatrix} \tag{26}$$

$$\tilde{\theta}_j = (\tilde{\lambda}_j, \lambda_j{}^2, \tilde{\sigma}_j{}^2)' \tag{27}$$

Empirically, $g_j = G_j\theta_j + \tau_j$, where g_j and G_j are observable and θ_j are parameters to be estimated. τ_j is vector of residuals as $\tau_j = g_j - G_j\theta_j$. The generalized moment estimator $\tilde{\theta}_j = (\tilde{\lambda}_j, \tilde{\sigma}_j{}^2)$ is defined as a nonlinear least squares estimator that minimizes the quadratic in residual, $\tau_j{}'\tau_j$, which can be expressed as

$$(\tilde{\lambda}_j, \tilde{\sigma}_j{}^2) = \text{argmin}\left[g_j - G_j\begin{bmatrix}\lambda_j \\ \lambda_j{}^2 \\ \sigma_j{}^2\end{bmatrix}\right]'\left[g_j - G_j\begin{bmatrix}\lambda_j \\ \lambda_j{}^2 \\ \sigma_j{}^2\end{bmatrix}\right] \tag{28}$$

In the last step, the estimated consistent autoregressive parameter (λ) is utilized to estimate the generalized spatial 2SLS models that account for the spatial autocorrelation in the disturbances. This involves estimation of the Cochrane-Orcutt type transformed model of the form specified in equation (20) using the estimated autoregressive parameters. Consider,

$$Y_j^*(\lambda_j) = (Y_j\text{-}\lambda WY_j) \text{ and } Z_j^*(\lambda_j) = (Z_j\text{-}\lambda WZ_j). \tag{29}$$

Then the equation (20) becomes

$$Y_j^*(\lambda_j) = Z_j^*(\lambda_j)\delta_j + \varepsilon_j \tag{30}$$

Since λ_j is not known, the generalized moment estimator of λ_j is substituted by $\tilde{\lambda}_j$ and the feasible generalized spatial two-stage least squares (FGS2SLS) estimator ($\hat{\delta}_j^F$) of δ_j is obtained by the following expression

$$\hat{\delta}_j^F = [\hat{Z}_j^*(\tilde{\lambda}_j)'\hat{Z}_j^*(\tilde{\lambda}_j)]^{-1}\hat{Z}_j^*(\tilde{\lambda}_j)'Y_j^*(\tilde{\lambda}_j) \tag{31}$$

where $\hat{Z}_j^*(\lambda_j) = H(H'H)^{-1}H'Z_j^*(\lambda_j)$

The parameter estimates for the vector of exogenous variables were obtained by estimating the transformed model using H as the instrument matrix. Kelejian and Prucha (1999) have demonstrated that the estimates and variance obtained in the model hold the asymptotic properties of the feasible generalized least squares estimator.

For the estimation of this model, Matlab routines in LeSage's Matlab Spatial Econometric Tool Box and SAS routines were used. The SAS routine was used for non-linear least squares estimation of consistent spatial parameters at the second step.

One of the issues related to the estimation of a system of equations with a spatial component is the technique of obtaining predicted values of the endogenous variables. Henry *et al.* (2001) report two ways of obtaining predicted values of endogenous variables that enter into the second stage estimation of spatial lag models. The first technique suggested is to obtain a spatially-weighted predicted endogenous variable as the product of the predicted value of the dependent variable obtained by regression on the exogenous variable and the spatial weight matrix, i.e., $W[X(X'X)^{-1}X'Y] = W[XB]$ (Anselin 1980 citied in Henry *et al.* 2001) The next technique is to obtain the predicted value of the endogenous variable by regression of the spatially-lagged dependent variable on instruments, i.e., $X(X'X)^{-1}X'WY = XB_W$. As suggested in Kelejian and Oates (1989), Henry *et al.* (2001) state that the estimators in the first method are inconsistent but are consistent in the second method. This paper uses the second method.

Two sets of specifications were used to model the off-farm response of principal farm operators for each of the independent variables of interest. The first set is represented by Model-I that does not include farm specialization variables but includes dummy variables for the top five leading dairy-producing states. The second set represented by Model-II is the expanded model that nests the Model-I with share of farm specialization variables for 1997 but excludes the dairy state dummy variables. Farm specialization variables are expected to proxy the farm characteristics at the county-level. The dairy dummy variables are included in the first model to help adjust the extent of effect of government support of dairy, which is excluded in the government payments data due to its indirect nature of support. Government payments to peanuts and sugar are also not accounted in the available data; however, this factor is not adjusted in the models.

Data and Variables

County-level data are primarily drawn from the 2002 U.S. Census of Agriculture. Data are also drawn from other sources including the U.S. Census Bureau county characteristics; ERS/USDA to identify counties in different farm resource regions and for Beale codes; Regional Economic Information System, Department of Commerce for wage and farm proprietors' income; and National Oceanic Administration for climate data. All counties in the U.S. except those in Alaska and Hawaii have been used. For some variables included in the models, data for all the counties are not available for disclosure reasons. One way to supplement such missing data is through imputation using an appropriate technique. But imputation of missing data is likely to inflate the spatial dependency in the data. Therefore, only counties with complete data for variables in the specific model being estimated are considered. The sample size for all participation models is the same (n=3001) but it is different for the scale effect models depending on the type of farm payments considered in the models. The number of observations in the scale effect models range from 2497 to 2931. The variables, their descriptions, and data sources are given in Table 3.3.

Dependent Variable: As mentioned previously, the dependent variable is defined as the county-level percent of principal farm operators who worked off-farm at least 200 days in the last year prior to the survey. The 2002 U.S. Census of Agriculture counted an off-farm work day, if the principal operator worked at least four hours a day off the farm. The threshold for off-farm work defined in this study seems very large. As a result, the influence of any variable on the off-farm employment change may have a limited range. However, given that the variable specified is of county-level share and county-average of share of principal farm operators working off-farm is only 38%, it seems to be not an issue as there is a three-fourth of principal farm operators who have not yet met that threshold of off-farm employment.

Independent Variables: Government farm payments and spatial lags that account for the spatial dependency problem are variables of interest. Government farm payments are separated into two groups. 1) county-level percent share of farms receiving government payments (referred as *participation effect* models) and 2) the amount of money transferred, measured in terms of payment per farm (referred to as *scale effect* models). For both models, the government payment variables are specified as: 1) government payments of any type (TOTAL); 2) Conservation Reserve Program and Wetland Reserve Program (CRWRP) payments; 3) Commodity Credit Corporation Loans (CCCL) payments; and 4) Other Federal Farm Programs (OFFP) payments. The average value calculated is based on the number of farm receiving the payments as reported by USDA. To estimate the net effect of independent variables of interest, the principal farm operator's characteristics (e.g., age and gender), farm household characteristics (e.g., number of farm operators, farm size, land ownership, factor productivity and farm specialization), and local/regional characteristics including market variables (e.g., rural-urban indicator, changes in value of agricultural land, wages, changes in population, and education) are controlled.

Age. The life-cycle hypothesis (Huffman 1980, Sumner 1982) suggests that age can influence the off-farm employment decision because of its relation to the individual's ability to make off-farm employment remunerative. According to this hypothesis, individuals increase work effort in earlier years to accumulate assets for future use. Similarly, the off-farm employment decision is like to be influenced by the intention of building up human capital (Mishra and Goodwin 1997) and taste and preferences (Goodwin and Bruer 2003) that differ by age. To capture the life-cycle effects, in the literature both age and age-squared terms are considered. But, as the 2002 U.S. Census of Agriculture provides the age of the principal farm operator in age classes, age is classified here into three categories: young: county-level percentage of principal farm operators < 35 years, middle-aged: 35-64 years (considered as reference) and older: >= 65 years.

Gender. The gender status of principal farm operators may be relevant to off-farm employment decisions due to differing gender roles of men and women. Women are often more responsible for household work including taking care of younger children. Therefore, a higher share of women principal farm operators at the county level is expected to have a negative influence on off-farm employment. This variable is specified as percent of principal operators who are women.

Number of Farm Operators. From the supply-side perspective, the farms with large number of operators are more likely to release some labor for off-farm employment as a strategy to diversify income sources. Conversely, from the demand-side perspective, farms may have more operators because of size of production, which may discourage off-farm employment. Similarly, the numbers of farm operators may have no effect on off-farm employment if the numbers of operators well match with size of farm. 2002 US census of agriculture collected information on total numbers of farm operators, which include person who operates a farm. The operator may be owner, a member of the owner's household, a hired manager, a tenant, a renter, or a sharecropper.

Farm Size. Large-sizes farms are expected to have a higher labor demand that discourages off-farm employment. On the other hand, the size of the farm operation can also be influenced by the time allocated to off-farm employment. If farm operators are more involved in off-farm employment, they may reduce the size of the farm production. Therefore, farm size can be endogenous to off-farm employment. In this study, as farm size is a control variable, to circumvent the complexity of estimation, a five-year lag of average farm size ($Acre_{t-5}$) is used instead of the current value which would likely be endogenous. It is expected that off-farm employment and farm size are negatively related. The land area of a farm is considered as an operating unit consisting of land owned and operated as well as land rented from others.

Land Ownership. The tenure regime of farm land is relevant as it is argued that the opportunity cost of rental land is relatively greater than that of owned land (Serra *et al.* 2003). Tenant farm operators, therefore, may have greater incentives to efficiently work on farm as compared to operators who own the farm. Farm ownership is classified into three categories: 1) full owners – those who actually own the land; 2) part owners – those who partially own land and also rent in land; and 3) tenants – those who fully rent in land. The full owner category is treated as the reference category. The other two variables are measured as the percent of the farms at the county level that are partly owned and fully rented in. One might suspect that land ownership and farm size may be correlated. The correlation coefficient for average farm size per farm in acre in 1997 and the farm ownership categories in 2002 are not much correlated. For instance, the Pearson correlation coefficient with full owner farm is -0.26, and with part owner farms and tenant farms 0.19 and 0.25, respectively. Incorporation of these variables is expected to tease out the net effect of one variable controlling the other.

Farm Specialization. The North American Industrial Classification Systems (NAICS) classifies farms into ten categories, with the following categories included as variables: grains and oils; dairy and milk; sheep and goats; vegetables and melons; greenhouse, nursery and floriculture; fruits and nuts; beef and cattle; hogs and pigs; poultry and eggs. The farm specialization may be relevant to off-farm employment decisions due to the seasonal nature of farming and labor demand. For instance, dairy farming requires labor input consistently throughout the year, while grain production does not and labor demand is seasonal. Therefore, compared to principal operators of grain-producing farms, those producing milk likely to have less flexibility for pursuing off-farm employment.

Value of Farm Land. The value of farm land may be relevant for off-farm employment of principal farm operators. Farms that experience an increase in land value may reflect a higher quality of land and higher marginal value of labor allocated to such land, reflecting a higher expected income from land. The value of land may also be influenced by the proximity to urban areas and the land use restrictions. This variable is specified as the ratio of per acre value of land, building and forage land in 2002 as compared to 1997. It is expected that an increase in the ratio of value of land decreases the propensity of off-farm employment; however, this has to be viewed in terms of value of fixed assets.

Factor Productivity. The off-farm work decision may also be influenced by the variation in the inherent quality of land and other factors of production. However, data on these factors are not available. Total factor productivity (TFP), the ratio of total farm outputs (all crops and livestock) to total inputs (capital, labor, and intermediate inputs), is expected to proxy these quality factors. Principal farm operators who have higher factor productivity from the operations are expected to find greater incentive to engage in farm than off-farm as compared to those with lower farm productivity. Ahearn *et al.* (2005) find that a decrease in factor productivity increased off-farm work. Since the farm productivity data are not available at farm or even at county-level, the six-year lagged state level total factor productivity index (Alabama=1) for 1996 is used. The lagged term used here is assumed to avoid the possible endogeneity of TFP to off-farm employment.

Again, state-level total factor productivity and the ratio of land value in 2001 to 1997 may be highly correlated as they proxy in part the quality of land. The correlation coefficient is only 0.12. In fact, the ratio of value of land measure the growth in the value which many not necessarily dependent mainly on the quality of land but also other factors such as land use restriction.

Urban Influence. The characteristics of counties such as metro- and non-metro represent local labor market opportunities, which are generally higher in metro counties. These designations also reflect the commuting time to and from off-farm employment, which is typically lower in metro counties. Commuting time also increases the cost of employment. Therefore, compared to principal operators in metro counties, those in non-metro counties are expected to be less involved in off-farm employment. In practice, researchers categorize counties as metro and non-metro. In this study, to capture more comprehensively the effects of local characteristics, metro counties are treated as the reference and non-metro counties are further divided into three categories: Rural-I (non-metro counties with more than 2500 urban population adjacent to metro counties); Rural-II (non-metro counties with more than 2500 urban population nonadjacent to metro counties); and Rural-III (non-metro counties with less than 2500 urban population, adjacent or nonadjacent to metro counties).

Off-Farm Wage. The wages that farm operators can earn from off-farm work are important as these wages serve as the opportunity cost of time allocated to farm work. The data do not provide the actual wages that farm operators earn from off-farm employment. However, as used in Goodwin and Bruer (2003), the county-level average annual earnings per job are used as a proxy. It is generally assumed that farm operator's off-farm response to wage earning prospects may not be immediate; therefore, one period lagged average annual earnings per job ($AWPG_{2001}$) is used. Farm operators' time allocation to farm and off-farm activities not only depends on offered wages but also on the relative risk of income from farm and off-farm activities. The relevance of risk-averse behavior of farm operators in labor allocation decisions is well reported (Goodwin and Bruer 2003; Goodwin and Mishra 2004). To capture the relative risk of income from off-farm employment, the coefficient of variation (CV) of wage measured over the last five years is used. We expect a positive sign on the wage and negative sign on the wage dispersion variables.

Education. Educational attainment of principal farm operators may affect time allocation to off-farm employment as it affects the marginal value of time in off-farm and farm work (Sumner 1982). Generally, operators with higher levels of education are expected to have higher marginal values of time in off-farm than farm employment, resulting in a higher propensity to work off-farm. The 2002 U.S. Agricultural Census data do not include the education level of principal farm operators. Therefore, the share of adults in the county with attainment of different education levels is included in the estimations with the following categories being considered: below high school (reference), high school degree completed, at least a bachelor's degree completed.

3.8 RESULTS

Descriptive Results

Table 3.3 reports the summary statistics for all variables included in the models. In 2002, about 38 percent of principal farm operators had off-farm employment for at least 200 days. Significant variation in the county-level share of off-farm employment of principal operators in the U.S. is observed (Figure 3.2). Two-fifths of counties have at least 40% of principal farm operators employed in off-farm jobs for at least 200 days annually. These counties are clustered in or near the Appalachian region; the Ozarks; in the Denver, Colorado region; and into the southern Great Lakes region including Michigan, Ohio and northern Indiana. Counties with low shares of principal farm operators working off-farm for at least 200 days are concentrated on the West Coast and in the Midwest.

Figure 3.2 Quintiles of Principal Farm Operators Working Off-Farm >= 200 days, 2002

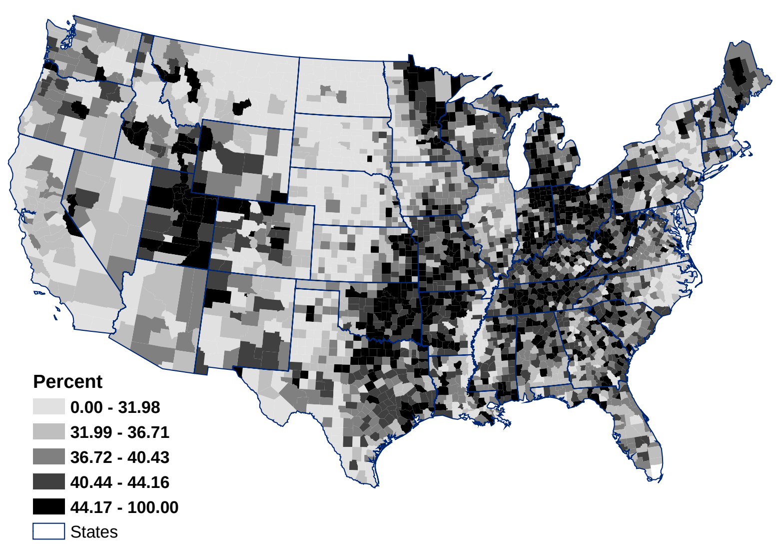
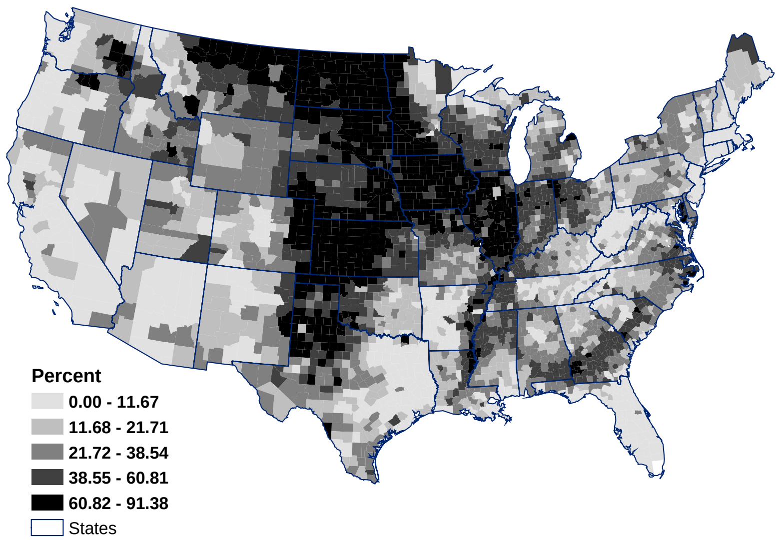


Figure 3.3 Quintiles of Farms Receiving Selected [4]Government Farm Payments (Total), 2002



Nearly 35% of farms received at least one type of government payment. Two-fifths of counties have at least 38% of farms receiving government payments of any type. Interestingly, these counties are concentrated in those regions where the share of principal farm operators working off-farm is low (Figure 3.3), suggesting a negative association between off-farm employment and government income transfers. In terms of type of payments, the percent of farms receiving CRWRP payments was greatest, followed by percent of farms receiving OFFP and CCCL payments. But in terms of income transfer per farm by payment type, the pattern is just in contrast. The average payments received by CCCL farms was greatest ($23,053), followed by payments of OFFP per farm ($9,431) and payments of CRWRP per farm ($4,192).

[4] Direct cash payments received by the farm operators in 2002, including disaster payments, loan deficiency payments, payments from Conservation Reserve Programs (CRP), the Wetlands Reserve Programs (WRP), other conservation programs, and all other federal farm programs. It does not include Commodity Credit Corporation (CCC) proceeds and federal crop insurance payments (http://www.nass.usda.gov/census/census02/volume1/al/al2appxa.pdf).

Table 3.3 Variables Included in the Models, Descriptions, and Summary Statistics

Variables	Descriptions	Mean	SD
Dependent Variable			
OFF[1]	% principal farm operators worked >=200 days off the farm last year, 2002	37.972	7.406
Independent Variables			
GPF02[1]	% farms receiving government farm payments regardless of payment type (TOTAL), 2002	34.847	23.894
CRWRP02[1]	% farms receiving Conservation Reserve and Wetland Reserve Program (CRWRP) payments, 2002	13.439	14.617
CCCL02[1]	% farms receiving Commodity Credit Corporation Loans (CCCL) payments, 2002	5.094	6.516
OFFP02[1]	% farms receiving Other Federal Farm Program (OFFP) payments, 2002	25.821	17.408
AGPF02[1]	Government payments average per recipient farm ($1,000), 2002	8.856	7.980
ACRWRP02[1]	CRWRP payments average per recipient farm ($1,000), 2002	4.192	4.521
ACCL02[1]	CCCL payments average per recipient farm ($1,000), 2002	23.053	29.274
AOFFP02[1]	OFFP payments average per recipient farm ($1,000), 2002	9.431	8.927
Principal Farm Operator's Characteristics			
$POAge_{35}02$[1]	% principal farm operators age < 35 years, 2002	5.611	2.865
$POAge_{65+}02$[1]	% principal farm operators age >=65 years, 2002	26.473	5.758
PWPO02[1]	% principal farm operators who are women, 2002	26.662	6.004
PPOWH02[1]	% principal farm operators who are white, 2002	85.160	15.659
Farm/Farm Household Characteristics			
ANOPTR02[1]	Average number of operators, 2002	1.461	0.112
AFSA97[1]	Average farm size (100 acre), 1997 (adjusted)	6.464	13.790
PARTOWN02[1]	% farms operated by part owners, 2002	26.593	9.044
TENANT02[1]	% farms operated by tenants, 2002	7.553	5.504
RVLBPA[1]	Ratio of per acre value of land, building and forage land in 2002 to 1997	1.317	0.338
PDAIRY97[1]	% farms classified (NAICS) as dairy and milk producers, 1997	3.504	7.253

PFRUIT97[1]	% farms classified (NAICS) as fruits and nuts producers, 1997	2.938	7.850
PGRENH97[1]	% farms classified (NAICS) as greenhouse, nursery and floriculture producers, 1997	3.624	7.274
PHOG97[1]	% farms classified (NAICS) as hog and pig producers, 1997	2.206	2.972
PSHEEP97[1]	% farms classified (NAICS) as sheep and goats producers, 1997	1.732	3.270
PPOULT97[1]	% farms classified (NAICS) as poultry and eggs producers, 1997	1.954	4.808
PVEG97[1]	% farms classified (NAICS) as vegetables and melon producers, 1997	1.873	3.198
PGRAIN97[1]	% farms classified (NAICS) as oil/grain producers, 1997	23.810	25.103
PBEEF97[1]	% farms classified (NAICS) as beef and cattle producers, 1997	35.154	22.813
County/Regional Characteristics			
PCOLLEGE[2]	% people 25+ years with at least high school degree but not bachelor's degree, 2000	16.277	7.460
PHIGHSCH[2]	% people 25+ years with at least bachelor's degree, 2000	61.070	6.809
RURAL-I[3]	Non-metro 2500+ urban population adjacent to metro	0.267	0.442
RURAL-II[3]	Non-metro 2500+ urban population nonadjacent to metro	0.179	0.383
RURAL-III[3]	Non-metro rural<2500 urban population, adjacent or nonadjacent to metro	0.215	0.411
TFP96[4]	State-level total factor productivity index, 1996 (Alabama=1)	1.045	0.209
AWPJ01[5]	Annual average wage per job, 2001($1000)	23.652	4.977
CVAWPJ[5]	Coefficient of variation of average wage per job (1997-2001)	6.002	2.022
DAIRYST	Dummy for five leading dairy producing states, 2002	0.112	0.315
POPCH[2]	% change in population between 1997 and 2000 (*10)	11.159	15.997

Data Sources: 1= 2002 Agricultural Census, U.S. Department of Agriculture
2= U.S. Census Bureau
3= Beale Codes, Economic Research Service, USDA
4= http://www.ers.usda.gov/Data/AgProductivity/#datafiles
5= Bureau of Economic Analysis (BEA), Regional Economic Information System (REIS)

Participation Effects

Results for the effect of participation in government payments regardless of payment type (TOTAL) are presented in Table 3.4 and by payment type are presented in Tables 3.5 through 3.7. One of the key objectives of this study was to ascertain whether or not the spatial dimension is important in estimating the relationship between government farm payments and off-farm employment of U.S. principal farm operators. Across all estimated models the coefficients for ρ and λ are considerably large. It is to be noted that, as mentioned previously, the FGS2SLS routine does not provide a standard error for λ, therefore, there are no significant test results for it but for ρ. In all participation effect models, ρ coefficients are positive and highly significant, revealing evidence of a strong positive spatial spillover effect of off-farm employment among principal farm operators. *Ceteris paribus*, each percent increase in off-farm employment of principal operators from neighboring counties contributes 0.44% to 0.58% increases in off-farm employment of principal farm operators in a county. Similarly, 36% to 37% of the error in off-farm employment in one county is positively influenced by the errors in off-farm employment in neighboring counties.

As expected, net of other factors, participation in government farm payments (TOTAL) negatively contributes to the off-farm employment of principal farm operators. Every percent increase in farms receiving government payments of any type (TOTAL) decreases the off-farm employment of principal farm operators by 0.05% (Table 3.4).

Table 3.4 Model Predicting Percent Principal Farm Operators Working Off-Farm>=200 Days, U.S., 2002 [Participation Effect: Total Government Payments]

Parameters	**Model-I**						**Model-II**					
	IV/2SLS			***FGS2SLS***			***IV/2SLS***			***FGS2SLS***		
	Coeff	Sig	t-stat	Coeff	Sig	t-stat	Coeff	Sig	t-stat	Coeff	Sig	t-stat
CONS	67.151	***	27.907	23.614	***	12.091	63.098	***	26.251	23.887	***	12.115
GPF02	**-0.070**	*******	**-8.694**	**-0.043**	*******	**-4.373**	**-0.079**	*******	**-7.899**	**-0.048**	*******	**-3.925**
$POAge_{35}02$	0.205	***	4.991	0.160	***	4.229	0.163	***	4.094	0.146	***	3.951
$POAge_{65+}02$	-0.224	***	-10.502	-0.255	***	-12.420	-0.259	***	-11.749	-0.304	***	-14.493
PWPO02	-0.131	***	-4.492	-0.035		-1.216	-0.129	***	-4.541	-0.056		-1.998
PPOWH02	0.020	*	2.414	-0.013		-1.363	0.017	*	2.101	-0.012		-1.270
ANOPTR02	-9.221	***	-6.658	-5.717	***	-4.357	-6.292	***	-4.643	-3.574	**	-2.771
AFSA97	-0.044	***	-5.051	-0.023	*	-2.513	-0.069	***	-7.699	-0.051	***	-5.481
RURAL-I	-0.091		-0.311	-0.076		-0.291	-0.399		-1.417	-0.250		-0.971
RURAL-II	-0.649		-1.940	0.155		0.460	-1.229	***	-3.799	-0.393		-1.189
RURAL-III	-2.589	***	-7.263	-1.373	***	-4.033	-2.971	***	-8.559	-1.818	***	-5.429
PARTOWN02	-0.147	***	-8.714	-0.102	***	-5.835	-0.175	***	-10.486	-0.129	***	-7.369
TENANT02	-0.470	***	-20.049	-0.336	***	-13.501	-0.459	***	-19.782	-0.347	***	-14.171
RVLBPA	0.130		0.407	-0.682	*	-2.269	0.575		1.843	-0.299		-1.019
PCOLLEGE	-0.040		-1.988	0.012		0.622	-0.017		-0.876	0.021		1.107
PHIGHSCH	0.118	***	5.602	0.100	***	4.504	0.080	***	3.907	0.080	***	3.679
AWPJ01	0.045		1.748	0.037		1.479	0.102	***	3.923	0.078	***	3.142

CVWPJ	-0.074		-1.357	-0.087		-1.745	-0.116	**	-2.188	-0.105	*	-2.163
POPCH	0.022	**	2.848	0.011		1.432	0.005		0.700	0.001		0.120
TFP96	-5.355	***	-9.955	-2.370	**	-3.534	-2.761	***	-4.981	-0.454		-0.670
DAIRYST5	-3.046	***	-8.644	-1.990	***	-4.452						
PDAIRY97							-0.102	***	-6.312	-0.123	***	-6.655
PFRUIT97							-0.102	***	-6.958	-0.049	***	-3.008
PGREENH97							-0.176	***	-8.996	-0.153	***	-7.688
PHUG97							0.154	***	3.893	0.071		1.640
PSHEEP97							0.091	**	2.750	0.138	***	3.645
PPOULT97							-0.152	***	-6.843	-0.139	***	-5.591
PVEG97							-0.065		-1.764	-0.040		-1.121
PBEEF97							0.031	***	3.846	0.034	***	3.753
ρ				**0.543**	*****	**13.797**				**0.466**	*****	**12.370**
λ				**0.370**						**0.370**		
R-Squared	0.431			0.362			0.478			0.401		
F-Ratio	112.863	***		80.434	***		100.943	***		71.092	***	

* *=p<0.05* ** *=p<0.01* ****=p<0.001*

Table 3.5 Model Predicting Percent Principal Farm Operators Working Off-Farm>=200 Days, U. S., 2002 [Participation Effect: Conservation Reserve and Wetland Reserve Programs (CRWRP) Payments]

Parameters	**Model-I**						**Model-II**					
	IV/2SLS			***FGS2SLS***			***IV/2SLS***			***FGS2SLS***		
	Coeff	Sig	t-stat	Coeff	Sig	t-stat	Coeff	Sig	t-stat	Coeff	Sig	t-stat
CONS	67.955	***	28.208	22.696	***	11.512	62.934	***	26.050	21.793	***	11.027
CRWRP02	**-0.089**	*******	**-8.588**	**-0.034**	******	**-2.666**	**-0.078**	*******	**-6.517**	**-0.017**		**-1.200**
$POAge_{35}02$	0.187	***	4.601	0.145	***	3.857	0.142	**	3.584	0.133	**	3.598
$POAge_{65+}02$	-0.213	***	-9.889	-0.255	***	-12.332	-0.265	***	-11.882	-0.316	***	-14.979
PWPO02	-0.096	**	-3.380	-0.010		-0.353	-0.100	**	-3.535	-0.036		-1.310
PPOWH02	0.019	*	2.349	-0.014		-1.553	0.019	*	2.319	-0.012		-1.287
ANOPTR02	-9.954	***	-7.091	-5.499	***	-4.142	-6.624	***	-4.811	-3.101	*	-2.377
AFSA97	0.000	***	-5.228	0.000	*	-2.443	-0.001	***	-8.184	-0.001	***	-5.803
RURAL-I	-0.116		-0.399	-0.122		-0.463	-0.446		-1.577	-0.312		-1.214
RURAL-II	-0.674	*	-2.016	0.120		0.356	-1.298	***	-4.003	-0.449		-1.360
RURAL-III	-2.523	***	-7.048	-1.405	***	-4.123	-3.040	***	-8.709	-1.939	***	-5.793
PARTOWN02	-0.187	***	-11.631	-0.125	***	-7.544	-0.217	***	-13.580	-0.148	***	-8.817
TENANT02	-0.502	***	-21.930	-0.350	***	-14.142	-0.491	***	-21.367	-0.355	***	-14.350
RVLBPA	0.116		0.363	-0.675	*	-2.245	0.579		1.849	-0.275		-0.935
PCOLLEGE	-0.043	*	-2.172	0.008		0.399	-0.026		-1.326	0.016		0.848
PHIGHSCH	0.105	***	5.113	0.089	***	4.026	0.064	**	3.166	0.068	**	3.157
AWPJ01	0.000	*	2.079	0.000		1.715	0.000	***	4.517	0.000	***	3.648

CVWPJ	-0.080		-1.464	-0.091		-1.836	-0.130	*	-2.448	-0.115	**	-2.370
POPCH	0.023	*	2.872	0.013		1.701	0.008		1.001	0.004		0.476
TFP96	-5.423	***	-10.098	-2.407	**	-3.617	-2.921	***	-5.263	-0.441		-0.655
DAIRYST5	-2.987	***	-8.471	-1.927	***	-4.345						
PDAIRY97							-0.101	***	-6.235	-0.119	***	-6.449
PFRUIT97							-0.091	***	-6.276	-0.031		-1.986
PGREENH97							-0.152	***	-7.979	-0.131	***	-6.836
PHUG97							0.150	***	3.775	0.067		1.548
PSHEEP97							0.093	**	2.758	0.155	***	4.082
PPOULT97							-0.133	***	-6.056	-0.123	***	-5.028
PVEG97							-0.040		-1.101	-0.017		-0.465
PBEEF97							0.044	***	5.892	0.049	***	5.854
ρ				**0.582**	*****	**14.995**				**0.515**	*****	**13.824**
λ				**0.363**						**0.362**		
R-Squared	0.431			0.365			0.475			0.404		
F-Ratio	112.863	***		81.540	***		99.624			71.949	***	

** =p<0.05 ** =p<0.01 ***=p<0.001*

Table 3.6 Model Predicting Percent Principal Farm Operators Working Off-Farm>=200 Days, U. S., 2002 [Participation Effect: Commodity Credit Corporation Loan (CCCL) Payments]

Parameters	**Model-I**						**Model-II**					
	IV/2SLS			***FGS2SLS***			***IV/2SLS***			***FGS2SLS***		
	Coeff	Sig	t-stat	Coeff	Sig	t-stat	Coeff	Sig	t-stat	Coeff	Sig	t-stat
CONS	66.508	***	27.582	23.128	***	12.142	62.258	***	26.059	23.764	***	12.695
CCCL02	**-0.260**	*******	**-8.088**	**-0.257**	*******	**-6.674**	**-0.362**	*******	**-8.447**	**-0.363**	*******	**-7.107**
$POAge_{35}02$	0.178	***	4.374	0.166	***	4.425	0.143	**	3.630	0.153	***	4.160
$POAge_{65+}02$	-0.271	***	-12.760	-0.279	***	-13.697	-0.312	***	-14.886	-0.326	***	-16.144
PWPO02	-0.138	***	-4.679	-0.061	*	-2.118	-0.140	***	-4.924	-0.077	**	-2.762
PPOWH02	0.023	*	2.807	-0.010		-1.084	0.022	**	2.769	-0.009		-0.970
ANOPTR02	-8.379	***	-6.096	-5.497	***	-4.267	-5.333	***	-3.980	-3.168	*	-2.504
AFSA97	-0.062	***	-7.033	-0.036	***	-3.908	-0.092	***	-10.398	-0.064	***	-6.916
RURAL-I	-0.225		-0.770	-0.155		-0.591	-0.518		-1.847	-0.307		-1.204
RURAL-II	-0.813	*	-2.437	0.084		0.250	-1.402	***	-4.370	-0.473		-1.444
RURAL-III	-3.131	***	-8.867	-1.596	***	-4.739	-3.564	***	-10.485	-2.032	***	-6.178
PARTOWN02	-0.145	***	-8.447	-0.079	***	-4.404	-0.155	***	-8.883	-0.088	***	-4.725
TENANT02	-0.413	***	-15.791	-0.278	***	-10.379	-0.380	***	-14.537	-0.276	***	-10.377
RVLBPA	0.096		0.299	-0.751	*	-2.505	0.570		1.830	-0.348		-1.192
PCOLLEGE	-0.058	**	-2.932	-2.047	***	-4.637	-0.037		-1.943	0.019		1.015
PHIGHSCH	0.101	***	4.890	0.104	***	4.777	0.059	**	2.947	0.079	***	3.685
AWPJ01	0.060	*	2.335	0.043		1.739	0.111	***	4.311	0.077	**	3.135

CVWPJ	-0.047		-0.846	-0.063		-1.270	-0.084		-1.575	-0.071		-1.463
POPCH	0.029	**	3.765	0.012		1.510	0.012		1.526	0.002		0.218
TFP96	-5.161	***	-9.490	-1.898	**	-2.836	-2.751	***	-4.971	-0.201		-0.300
DAIRYST5	-3.100	***	-8.783	0.014		0.737						
PDAIRY97							-0.126	***	-7.598	-0.156	***	-8.170
PFRUIT97							-0.086	***	-6.068	-0.051	**	-3.320
PGREENH97							-0.162	***	-8.507	-0.160	***	-8.328
PHUG97							0.288	***	6.792	0.165	***	3.651
PSHEEP97							0.104	**	3.147	0.130	**	3.485
PPOULT97							-0.146	***	-6.639	-0.145	***	-5.969
PVEG97							-0.088	*	-2.366	-0.079	*	-2.186
PBEEF97							0.029	***	3.645	0.013		1.399
ρ				**0.541**	*****	**14.582**				**0.468**	*****	**13.263**
λ				**0.362**						**0.364**		
R-Squared	0.429			0.371			0.480			0.412		
F-Ratio	111.946	***		83.671	***		101.641	***		74.372	***	

** =p<0.05 ** =p<0.01 ***=p<0.001*

Table 3.7 Model Predicting Percent Principal Farm Operators Working Off-Farm>=200 Days, U. S., 2002 [Participation Effect: Other Federal Farm Program (OFFP) Payments]

Parameters	**Model-I**						**Model-II**					
	IV/2SLS			***FGS2SLS***			***IV/2SLS***			***FGS2SLS***		
	Coeff	Sig	t-stat	Coeff	Sig	t-stat	Coeff	Sig	t-stat	Coeff	Sig	t-stat
CONS	66.024	***	27.396	22.985	***	12.031	61.838	***	25.938	23.869	***	12.632
OFFPP02	**-0.116**	*******	**-8.604**	**-0.090**	*******	**-5.396**	**-0.146**	*******	**-8.732**	**-0.126**	*******	**-6.264**
$POAge_{35}02$	0.202	***	4.920	0.168	***	4.436	0.164	***	4.141	0.157	***	4.250
$POAge_{65+}02$	-0.244	***	-11.557	-0.262	***	-12.901	-0.281	***	-13.217	-0.307	***	-15.015
PWPO02	-0.146	***	-4.932	-0.054		-1.842	-0.151	***	-5.270	-0.082	**	-2.886
PPOWH02	0.025	**	3.013	-0.009		-0.980	0.022	*	2.780	-0.008		-0.889
ANOPTR02	-8.188	***	-5.981	-5.062	***	-3.928	-5.137	**	-3.840	-2.770	*	-2.186
AFSA97	-0.044	***	-5.018	-0.023	*	-2.548	-0.069	***	-7.808	-0.050	***	-5.354
RURAL-I	-0.126		-0.433	-0.060		-0.229	-0.436		-1.553	-0.217		-0.849
RURAL-II	-0.745	*	-2.234	0.163		0.483	-1.338	***	-4.168	-0.371		-1.125
RURAL-III	-2.714	***	-7.650	-1.360	***	-4.006	-3.092	***	-9.015	-1.747	***	-5.251
PARTOWN02	-0.118	***	-6.460	-0.072	**	-3.717	-0.133	***	-7.234	-0.083	***	-4.212
TENANT02	-0.442	***	-18.140	-0.314	***	-12.289	-0.422	***	-17.530	-0.316	***	-12.564
RVLBPA	0.072		0.225	-0.717	*	-2.387	0.509		1.632	-0.357		-1.219
PCOLLEGE	-0.040		-1.974	0.016		0.842	-0.013		-0.689	0.027		1.439
PHIGHSCH	0.122	***	5.726	0.111	***	4.935	0.087	***	4.231	0.095	***	4.323
AWPJ01	0.034		1.290	0.031		1.249	0.086	***	3.299	0.066	*	2.651

CVWPJ	-0.071		-1.286	-0.084		-1.684	-0.111	*	-2.104	-0.096		-1.994
POPCH	0.022	*	2.789	0.009		1.166	0.003		0.449	-0.003		-0.340
TFP96	-5.385	***	-10.017	-2.262	***	-3.368	-2.639	***	-4.765	-0.299		-0.442
DAIRYST5	-3.260	***	-9.234	-2.169	***	-4.825						
PDAIRY97							-0.109	***	-6.722	-0.129	***	-7.001
PFRUIT97							-0.103	***	-7.035	-0.059	***	-3.708
PGREENH97							-0.186	***	-9.416	-0.173	***	-8.600
PHUG97							0.157	***	3.984	0.076		1.746
PSHEEP97							0.106	**	3.225	0.140	**	3.721
PPOULT97							-0.164	***	-7.348	-0.153	**	-6.180
PVEG97							-0.088	**	-2.359	-0.073	*	-2.007
PBEEF97							0.029	***	3.710	0.023	*	2.546
ρ				**0.530**	*******	**13.439**				**0.444**	*******	**11.954**
λ				**0.372**						**0.371**		
R-Squared	0.431			0.363			0.481			0.405		
F-Ratio	112.863	***		80.839	***		102.049	***		72.248	***	

** =p<0.05 ** =p<0.01 ***=p<0.001*

Interestingly, the effect of government farm payment participation varies by payment type. The coefficient for participation in CRWRP, which was significant in Model-I, was not significant in Model-II when spatial correlation is accounted for (Table 3.5). On the other hand, the results from models including participation in CCCL payments show negative and highly significant effects on the off-farm employment of principal farm operators even when farm enterprises are controlled and spatial correlation is accounted for in the analysis. For instance, every percent increase in farms receiving CCCL payments decreases the percent of principal farm operators working off-farm by 0.36% (Table 3.6). In the case of models that include participation in OFFP payments, the estimated coefficient is also negative and highly significant (Table 3.7), but the magnitude is almost one-third (i.e., 13%) compared to that for participation in CCCL payments. It is interesting to note that, although only 5% of farms received some amount of CCCL payments compared to 25% percent of farms that received OFFP payments, in terms of magnitude of effect, participation in CCCL had a three-time greater negative effect on off-farm employment as compared to the participation effect of OFFP. This can be attributed to the amount of payments per farm which is very high for CCCL payments, close to four times greater than the average OFFP payments per farm. Also, it could be that the extent of effect on the off-farm employment decision is related to the magnitude of level of participation. The type of payment with currently lower shares of participation may be higher in effect on off-farm employment as compared to that with the currently higher shares of participation. This makes it of interest to examine the relationship between the scale of payments and off-farm employment, which is presented in the following section.

Scale Effects

The results presented above assess the effect of prevalence of participation in government farm payments, but do not indicate the extent to which government income transfers influence off-farm employment response of principal farm operators. To address the latter question, models were estimated introducing government payments measured as county-level payments per farm as important independent variables. Tables 3.8 through 3.11 report the results of the effect of average government payments (TOTAL) and by payment type on off-farm employment of principal farm operators. As in the participation models, results show that spatial lag parameters are positive and highly significant, revealing the existence of strong spatial spillover effects of off-farm employment of operators. The off-farm employment of principal farm operators in neighboring counties contributes a 40% to 56% increase in off-farm employment in a county. The spatial spillover effect operating through error terms is very high, ranging from 38% to 40%. This result again confirms that spatial correlation is a serious problem to be addressed when analyzing off-farm employment of principal farm operators in the U.S.

The models measuring the scale effects provide interesting results. The estimated coefficient for average government payments of any type (AGPF02) is negative and highly significant (Table 3.8). This result is as expected and consistent with previous studies. Each thousand dollar increase in government payments per farm decreases the off-farm employment of principal farm operators by 0.29%. This result indicates that government farm payments as supplemental income makes leisure more affordable and principal farm operators reallocate labor from off-farm employment. The analysis using

Table 3.8 Model Predicting Percent Principal Farm Operators Working Off-Farm>=200 Days, U. S., 2002 [Scale Effect: Average Government Payment Per Farm]

Parameters	Model-I						Model-II					
	IV/2SLS			*FGS2SLS*			*IV/2SLS*			*FGS2SLS*		
	Coeff	Sig	t-stat	Coeff	Sig	t-stat	Coeff	Sig	t-stat	Coeff	Sig	t-stat
CONS	68.185	***	28.045	27.893	***	14.499	64.163	***	26.391	26.368	***	14.127
AGPF02	**-0.307**	*******	**-13.076**	**-0.340**	*******	**-9.364**	**-0.249**	*******	**-9.854**	**-0.287**	*******	**-7.786**
$POAge_{35}02$	0.102	*	2.371	0.068		1.683	0.054		1.259	0.038		0.953
$POAge_{65+}02$	-0.289	***	-13.392	-0.307	***	-14.573	-0.335	***	-15.407	-0.358	***	-16.937
PWPO02	-0.081	**	-2.855	-0.026		-0.908	-0.088	**	-3.083	-0.030		-1.074
PPOWH02	-0.008		-0.922	-0.031	**	-3.417	-0.004		-0.513	-0.030	**	-3.287
ANOPTR02	-3.548	*	-2.518	-2.556		-1.884	-2.255		-1.604	-1.250		-0.928
AFSA97	-0.033	***	-3.928	-0.013		-1.434	-0.065	***	-7.400	-0.041	***	-4.478
PARTOWN02	-0.193	***	-12.097	-0.129	***	-7.737	-0.210	***	-13.111	-0.149	***	-8.840
TENANT02	-0.311	***	-11.657	-0.187	***	-6.561	-0.339	***	-12.599	-0.214	***	-7.475
RURAL-I	-0.481		-1.704	-0.412		-1.607	-0.669	**	-2.431	-0.495		-1.976
RURAL-II	-1.003	**	-3.111	-0.187		-0.562	-1.390	***	-4.415	-0.508		-1.564
RURAL-III	-3.167	***	-9.241	-1.839	***	-5.527	-3.450	***	-10.325	-2.085	***	-6.421
PCOLLEGE	-0.090	***	-4.805	-0.020		-1.030	-0.069	***	-3.690	-0.007		-0.377
PHIGHSCH	0.062	**	3.208	0.075	**	3.511	0.037		1.865	0.057	**	2.673
AWPJ01	0.051		2.020	0.034		1.389	0.116	***	4.556	0.079	**	3.277
CVWPJ	-0.155	**	-2.903	-0.139	**	-2.864	-0.183	**	-3.534	-0.146	**	-3.080

RVLBPA	-0.328		-1.042	-1.021	**	-3.445	0.141		0.455	-0.670	*	-2.302
POPCH	0.032	***	4.219	0.022	**	2.884	0.018	*	2.415	0.012		1.596
DAIRYST5	-2.965	***	-8.611	-2.182	***	-4.911						
TFP96	-5.733	***	-10.900	-2.851	***	-4.274	-3.357	***	-6.113	-0.592		-0.870
PDAIRY97							-0.083	***	-5.240	-0.098	***	-5.386
PFRUIT97							-0.052	**	-3.628	-0.014		-0.895
PGREENH97							-0.154	***	-7.986	-0.171	***	-8.573
PHUG97							0.077		1.939	0.009		0.209
PSHEEP97							0.126	***	3.918	0.152	***	4.119
PPOULT97							-0.133	***	-6.238	-0.139	***	-5.829
PVEG97							-0.050		-1.319	-0.070		-1.919
PBEEF97							0.042	***	6.226	0.033	***	4.127
ρ				**0.424**	*******	**10.236**				**0.401**	*******	**10.461**
λ				**0.384**						**0.388**		
R-Squared	0.465			0.387			0.498			0.418		
F-Ratio	126.395	***		87.453	***		106.662	***		74.438	***	

** =p<0.05* *** =p<0.01* ****=p<0.001*

Table 3.9 Model Predicting Percent Principal Farm Operators Working Off-Farm>=200 Days, U. S., 2002 [Scale Effect: Conservation Reserve and Wetland Reserve (CRWRP) Payments Per Farm]

Parameters	**Model-I**						**Model-II**					
	IV/2SLS			***FGS2SLS***			***IV/2SLS***			***FGS2SLS***		
	Coeff	Sig	t-stat	Coeff	Sig	t-stat	Coeff	Sig	t-stat	Coeff	Sig	t-stat
CONS	63.971	***	25.438	22.765	***	11.992	59.026	***	24.042	23.122	***	12.611
ACRWRP02	**-0.425**	*******	**-10.415**	**-0.199**	*****	**-2.342**	**-0.450**	*******	**-11.159**	**-0.332**	*******	**-4.240**
$POAge_{35}02$	0.107	*	2.395	0.060		1.425	0.068		1.555	0.062		1.484
$POAge_{65+}02$	-0.243	***	-10.849	-0.271	***	-12.258	-0.311	***	-14.000	-0.327	***	-14.921
PWPO02	-0.030		-1.028	0.035		1.212	-0.056		-1.897	0.009		0.310
PPOWH02	0.012		1.438	-0.015		-1.648	0.010		1.251	-0.016		-1.733
ANOPTR02	-5.194	**	-3.654	-4.689	**	-3.465	-2.355		-1.686	-2.525		-1.892
AFSA97	-0.027	*	-2.476	-0.029	*	-2.333	-0.063	***	-5.882	-0.055	***	-4.666
PARTOWN02	-0.234	***	-14.040	-0.166	***	-9.483	-0.249	***	-15.361	-0.183	***	-10.543
TENANT02	-0.439	***	-18.718	-0.326	***	-12.874	-0.429	***	-18.495	-0.321	***	-12.842
RURAL-I	-0.169		-0.585	-0.199		-0.766	-0.403		-1.456	-0.309		-1.223
RURAL-II	-0.561		-1.686	0.281		0.832	-1.059	**	-3.324	-0.148		-0.451
RURAL-III	-2.363	***	-6.624	-1.340	***	-3.939	-2.670	***	-7.816	-1.660	***	-5.009
PCOLLEGE	-0.045	*	-2.301	0.024		1.225	-0.018		-0.937	0.035		1.843
PHIGHSCH	0.124	***	6.092	0.121	***	5.346	0.093	***	4.627	0.104	***	4.693
AWPJ01	0.047		1.799	0.017		0.662	0.117	***	4.549	0.062	*	2.495
CVWPJ	-0.169	**	-2.985	-0.090		-1.739	-0.246	***	-4.547	-0.136	*	-2.729

RVLBPA	-0.200		-0.610	-0.570		-1.818	0.333		1.052	-0.328		-1.081
POPCH	0.034	***	4.237	0.016		1.983	0.016	*	2.051	0.006		0.824
DAIRYST5	-3.590	***	-10.223	-2.353	***	-5.073						
TFP96	-6.949	***	-12.539	-3.363	***	-4.704	-4.206	***	-7.439	-1.413		-1.993
PDAIRY97							-0.130	***	-8.098	-0.128	***	-6.738
PFRUIT97							-0.077	***	-5.024	-0.026		-1.546
PGREENH97							-0.184	***	-9.252	-0.157	***	-7.560
PHUG97							0.120	**	3.142	0.059		1.366
PSHEEP97							0.152	***	4.130	0.186	***	4.392
PPOULT97							-0.151	***	-7.056	-0.138	***	-5.622
PVEG97							-0.002		-0.048	-0.024		-0.627
PBEEF97							0.056	***	8.718	0.051	***	6.655
ρ				**0.504**	*****	**11.250**				**0.419**	*****	**10.323**
λ				**0.399**								
R-Squared	0.483			0.389			0.534			0.433		
F-Ratio	135.931			88.193	***		123.208	***		79.149	***	

** =p<0.05   ** =p<0.01   ***=p<0.001*

Table 3.10 Model Predicting Percent Principal Farm Operators Working Off-Farm>=200 Days, U. S., 2002 [Scale Effect: Commodity Credit Corporation Loan (CCCL) Payments Per Farm]

Parameters	**Model-I**						**Model-II**					
	IV/2SLS			***FGS2SLS***			***IV/2SLS***			***FGS2SLS***		
	Coeff	Sig	t-stat	Coeff	Sig	t-stat	Coeff	Sig	t-stat	Coeff	Sig	t-stat
CONS	69.085	***	25.223	23.255	***	10.994	63.130	***	23.323	23.461	***	11.457
ACCL02	**-0.046**	*******	**-5.851**	**-0.065**	*******	**-5.506**	**-0.045**	*******	**-5.253**	**-0.078**	*******	**-6.196**
$POAge_{35}02$	0.061		1.278	0.062		1.418	0.014		0.294	0.040		0.942
$POAge_{65+}02$	-0.274	***	-11.317	-0.273	***	-11.704	-0.324	***	-13.478	-0.339	***	-14.546
PWPO02	-0.066	*	-2.074	0.013		0.402	-0.089	**	-2.834	-0.002		-0.064
PPOWH02	0.006		0.589	-0.032	**	-3.155	0.002		0.226	-0.036	**	-3.593
ANOPTR02	-7.797	***	-5.186	-5.287	**	-3.774	-4.245	**	-2.836	-2.013		-1.437
AFSA97	-0.059	***	-6.144	-0.042	***	-4.260	-0.086	***	-8.996	-0.068	***	-6.885
PARTOWN02	-0.216	***	-12.198	-0.127	***	-7.004	-0.237	***	-13.604	-0.153	***	-8.420
TENANT02	-0.422	***	-15.434	-0.262	***	-9.032	-0.421	***	-15.887	-0.277	***	-9.890
RURAL-I	-0.404		-1.284	-0.413		-1.477	-0.647	*	-2.144	-0.540		-1.993
RURAL-II	-0.816	*	-2.273	0.280		0.783	-1.284	**	-3.712	-0.257		-0.737
RURAL-III	-3.399	***	-8.893	-1.648	***	-4.541	-3.722	***	-10.115	-2.054	***	-5.826
PCOLLEGE	-0.085	***	-4.027	0.000		0.018	-0.059	**	-2.858	0.003		0.142
PHIGHSCH	0.106	***	4.759	0.113	***	4.826	0.074	**	3.362	0.084	**	3.664
AWPJ01	0.066	*	2.300	0.031		1.168	0.137	***	4.847	0.079	***	2.986
CVWPJ	-0.062		-1.060	-0.078		-1.501	-0.128	*	-2.274	-0.102	*	-2.034

RVLBPA	0.072	*	0.205	-0.725	*	-2.229	0.617		1.820	-0.292		-0.926
POPCH	0.032	**	3.772	0.020	*	2.466	0.015		1.743	0.011		1.376
DAIRYST5	-2.880	***	-7.591	-1.713	**	-3.633						
TFP96	-6.388	***	-10.625	-2.340	**	-3.137	-3.838	***	-6.214	-0.541		-0.721
PDAIRY97							-0.109	***	-6.379	-0.157	***	-7.997
PFRUIT97							-0.070	***	-4.534	-0.017		-1.055
PGREENH97							-0.167	***	-7.721	-0.194	***	-8.803
PHUG97							0.178	***	4.423	0.095	*	2.156
PSHEEP97							0.085	*	2.293	0.090	*	2.188
PPOULT97							-0.130	***	-5.170	-0.170	***	-6.152
PVEG97							-0.076		-1.764	-0.111	*	-2.669
PBEEF97							0.052	***	6.703	0.024	*	2.563
ρ				**0.566**	*******	**13.897**				**0.496**	*******	**12.921**
λ				**0.375**						**0.379**		
R-Squared	0.452	*		0.394			0.501			0.436		
F-Ratio	120.154			90.063			107.949	***		80.121	***	

** =p<0.05 ** =p<0.01 ***=p<0.001*

Table 3.11 Model Predicting Percent Principal Farm Operators Working Off-Farm>=200 Days, U. S., 2002 [Scale Effect: Other Federal Farm Program (OFFP) Payments Per Farm]

Parameters	**Model-I**						**Model-II**					
	IV/2SLS			***FGS2SLS***			***IV/2SLS***			***FGS2SLS***		
	Coeff	Sig	t-stat	Coeff	Sig	t-stat	Coeff	Sig	t-stat	Coeff	Sig	t-stat
CONS	67.478	***	26.842	27.185	***	14.079	63.085	***	25.210	25.804	***	13.610
AOFFP02	**-0.225**	*****	**-10.875**	**-0.254**	*****	**-8.068**	**-0.172**	*****	**-7.811**	**-0.205**	*****	**-6.443**
$POAge_{35}02$	0.087		1.951	0.053		1.295	0.032		0.729	0.025		0.622
$POAge_{65+}02$	-0.279	***	-12.490	-0.296	***	-13.664	-0.327	***	-14.557	-0.345	***	-15.818
PWPO02	-0.075	*	-2.537	-0.018		-0.609	-0.085	**	-2.848	-0.021		-0.722
PPOWH02	-0.006		-0.672	-0.029	**	-3.038	-0.003		-0.295	-0.028	**	-2.982
ANOPTR02	-3.699	*	-2.575	-3.017	*	-2.238	-1.875		-1.312	-1.818		-1.361
AFSA97	-0.001	***	-6.617	0.000	***	-4.099	-0.001	***	-9.931	-0.001	***	-6.769
PARTOWN02	-0.223	***	-13.373	-0.158	***	-9.108	-0.241	***	-14.632	-0.174	***	-10.068
TENANT02	-0.336	***	-12.571	-0.222	***	-7.798	-0.360	***	-13.416	-0.240	***	-8.387
RURAL-I	-0.376		-1.306	-0.421		-1.635	-0.592	*	-2.117	-0.496		-1.967
RURAL-II	-0.928	*	-2.801	-0.130		-0.382	-1.336	***	-4.152	-0.369		-1.117
RURAL-III	-3.086	***	-8.698	-1.846	***	-5.410	-3.284	***	-9.556	-1.988	***	-5.988
PCOLLEGE	-0.079	***	-4.068	-0.001		-0.059	-0.057	**	-2.928	0.013		0.683
PHIGHSCH	0.083	***	4.114	0.090	***	4.018	0.053	**	2.618	0.071	**	3.197
AWPJ01	0.000		1.713	0.000		0.548	0.000	***	4.393	0.000	*	2.261
CVWPJ	-0.163	**	-2.887	-0.119	*	-2.338	-0.216	***	-3.946	-0.136	*	-2.752

RVLBPA	-0.150		-0.459	-0.738	*	-2.393	0.356		1.109	-0.419		-1.385
POPCH	0.033	***	4.109	0.020	*	2.541	0.019	*	2.451	0.010		1.324
DAIRYST5	-3.091	***	-8.802	-2.241	***	-4.949						
TFP96	-6.216	***	-11.194	-2.975	***	-4.234	-3.965	***	-6.927	-1.246		-1.761
PDAIRY97							-0.090	***	-5.617	-0.097	***	-5.173
PFRUIT97							-0.067	***	-4.262	-0.010		-0.568
PGREENH97							-0.167	***	-8.339	-0.168	***	-8.114
PHUG97							0.116	**	2.951	0.030		0.699
PSHEEP97							0.120	**	3.229	0.148	**	3.544
PPOULT97							-0.141	***	-6.531	-0.134	***	-5.544
PVEG97							-0.046		-1.144	-0.060		-1.545
PBEEF97							0.046	***	6.641	0.033	***	4.022
ρ				**0.414**	*******	**10.089**				**0.415**	*******	**10.957**
λ				**0.400**						**0.396**		
R-Squared	0.485			0.399			0.523			0.436		
F-Ratio	137.024	***		91.965	***		117.858	***		80.033	***	

** =p<0.05   ** =p<0.01   ***=p<0.001*

payment types measured in terms of averages per farm provide quite a different picture compared to the effects of participation in payment types. In the case of CRWRP payments per farm the coefficient is negative and highly significant even when the farm specialization variables and spatial correlation are accounted for. For instance, every thousand dollar increase in CRWRP payments per farm decreases off-farm employment by 0.33% (Table 3.9). Recall that the coefficient for CRWRP in the participation model was not statistically significant. More importantly, the magnitude of the coefficient is larger than the coefficient for other payment types. For instance, each thousand dollar increase in CCCL payment per farm contributes a 0.08% decrease in off-farm employment of principal farm operators (Table 3.10). Similarly, the same of increase in OFFP payment per farm decreases the off-farm employment of principal farm operators by 0.20% (Table 3.11). It seems that again the extent of off-farm response to income transfer from government is dependent on the magnitude of transfer. Ahearn *et al.* (2006) also find that the difference in the extent of off-farm employment impact of government payments between 1996 and 1999 was attributed to magnitude of transfer, operating in a negative fashion. The greater impact of conservation payments also could be due to greater income effect as the payment is essentially decoupled, making leisure more affordable and off-farm employment less preferable. On the other hand, the smaller impact of commodity related payments to off-farm employment could be due to mix effects as the transfer may not be fully decoupled. The income transfer not only makes leisure more affordable and off-farm employment less attractive, but it also to some extant relaxes borrowing constraints and increase farm labor demand. The scale effect results suggest that if we aim to decrease off-farm employment of principal farm operators, we need to focus on the payment types that are now smaller in terms of payment amounts per farm and payment decoupled. The results also show that the participation effect and scale effect results provide different views of the extent to which off-farm employment is influenced by government payments.

Effects of Other Factors

Other factors affecting off-farm employment were introduced as controls to net out the effect of the independent variables, with the results for those variables briefly summarized below. Among the principal operator's characteristics**,** age appears to be important factor determining off-farm response. Across the models measuring participation effects of government farm payments (Tables 3.4 through 3.7), compared to middle-aged principal farm operators the estimated coefficients for younger operators are positive and highly significant and for older operators are negative and significant. In the case of models incorporating scale effect variables (Tables 3.8 through 3.11), the coefficient for younger operators is positive and significant only in the IV/2SLS models in Model-I. The coefficient is insignificant when spatial correlation bias is corrected and Model-II is adopted. However, the coefficients for older operators are consistent with results obtained from models incorporating participation effect variables.

Gender of principal farm operators appears to be another important factor. In the participation effect model, except in CRWRP model, the share of female principal farm operators in the county is statistically negatively related with off-farm employment than males. However, in models incorporating scale effect variables, the coefficients are not statistically significant in spatial models. It is likely that gender deferential in off-farm employment may also attribute to their level of participation in government farm payments and income transfer, in addition to their gender roles. Similarly, the race of the principal farm operator stands out as an important covariate. In models incorporating the participation effect of government payments, the coefficient for white principal farm operator is positive and significant but is not significant when spatial correlation bias is corrected. In the case of the scale effect model with government payments, the coefficient is negative and significant only when spatial correlation bias is corrected, except in CRWRP model. Results show that the extent to which the race of the principal farm operator is important depends on the type of model, which indicates that the relationship between off-farm employment and racial background is moderated by government payments.

Among farm/household characteristics, number of farm operators per farm is an important factor that may affect off-farm employment. Results show that in models incorporating a participation effect variable for government payments (Tables 3.4 through 3.7), the average number of operators and off-farm employment are negatively related even when spatial correlation bias is corrected. However, in the scale effect models, the coefficients are not statistically significant.

The coefficient for the five years lagged average farm size is negative and significant across all models (Tables 3.4 though 3.11). This indicates that as farm size increases, more labor is demanded on the farm and less labor is released for off-farm employment.

This also may result from an increase in the value of marginal productivity of labor in farming relative to off-farm work. Ownership of farm land is another factor considered in the analysis. As compared to principal farm operators from farms operated by full owners, those from farms operated by part-owners and tenants are less involved in off-farm employment. The coefficients for tenants are substantially greater than that for part-owner farm operators, indicating that as the opportunity cost of ownership of land increases, principal farm operators choose to allocate less time to off-farm employment.

Model-II is the expanded vision of Model-I, incorporating the shares of lagged farm specializations. As compared to farms classified as grain and oil producers, an increase in the lagged shares of farms classified as dairy and milk producers greenhouse, floriculture and nursery producers; and poultry and eggs producers decreases the share of principal farm operators employed off-farm. This relationship may be attributed to the seasonal nature of farm enterprises and labor demand. Similarly, as compared to farms specializing in grain and oil production an increase in the lagged share of farms specializing in beef production increases the off-farm employment of principal farm operators.

In comparison to operators of farms in metro counties, principal farm operators of farms in non-metro locations -- and especially those in locations with less than a 2500 urban population (adjacent or nonadjacent to metro counties) -- are less involved in off-farm employment. This result is consistent across all models even after spatial correlation is corrected. The coefficients of other rural counties such as those with more than 2500 urban population adjacent to or nonadjacent to metro locations are negative and significant in the IV/2SLS models, and the statistical significant disappears when the spatial correlation bias is corrected. This is potentially due to clustering of non-metro counties. Results indicate that the prevalence of off-farm employment among principal farm operators is more concentrated in counties with greater access to labor markets.

Because of the absence of off-farm wage data for principal farm operators, the average annual wage per job in the non-farm sector was used. This variable in part captures the opportunity cost of labor in the farm production sector. Results show that across all models, even after taking into account spatial dependency of off-farm employment, the coefficient for average annual wage per job is positive and significant; indicating that an increase in off-farm wage increases the time allocated to off-farm employment. Results also show that the coefficient of the CV of average annual wage per job is negative and significant, indicating that principal farm operators are risk averse as far as off-farm wage prospects are concerned.

Although there is farm support for dairy and milk producers, farm program payment data do not reflect this support because it is indirect. Thus, a dummy variable for the leading five dairy producing states is used in Model-I. Results show that in all models (Tables 3.4 through 3.11) the estimated coefficient is negative and highly significant, showing that principal farm operators from counties in states with high concentrations of dairy farms are less involved in off-farm employment than other states. This could have been due to larger income effect of income transfer to dairy sector than the likely effect associated with borrowing constraints.

Education attainment of principal farm operators is a relevant variable for off-farm employment. Principal operators from counties with higher percentages of adults with high school degrees were more likely to participate in off-farm employment. This result is consistent across the estimated models and even when spatial correlation bias is taken into account. The coefficient for the share of the adult population with at least a bachelor's degree was negatively significant in Model-I, but became insignificant when spatial correlation was corrected.

Six-year lagged state-level total factor productivity index appears to be another important factor influencing the off-farm employment decision of principal farm operators. Except in the spatial model with farm specialization variables (Model-II), in all other models (aspatial and spatial but without farm enterprises) the coefficient of total factor productivity is highly significant and negative. This result indicates that, controlling other factors, an increase in factor productivity increase marginal value of labor, hence encouraging allocating more labor in the farm than off-farm. The insignificant coefficient of total factor productivity in the spatial model presented in Model-II suggests that the effect of factor productivity is moderated by farm enterprises and also by the spatial autocorrelation in the off-farm employment.

3.9 CONCLUSIONS

This study provides insights into the relationship between U.S. government farm payments and off-farm employment of principal farm operators while taking into consideration two estimation issues: *spatial dependency* and *endogeneity* of government payments which have been ignored with few exceptions in past studies. Results provide strong evidence that county-level off-farm employment of principal farm operators in the U.S is spatially correlated. The effects of government payment variables as well as other explanatory variables are substantially altered when spatial correlation bias is corrected in the models, highlighting the fact that estimates obtained from models ignoring spatial dependency in off-farm employment are misleading. Study findings also offer additional evidence of the impact of government farm payments on labor allocation to off-farm employment. Consistent with the results of most previous studies, the off-farm employment decisions of principal farm operators are found to be negatively responsive to farm-related income transfers from government, suggesting a stronger income effect of income transfers. However, the magnitude of effect and even the significance vary by the type of payment and also by the way government payment variables are considered (scale versus participation).

In terms of the share of farms receiving payments, Commodity Credit Corporation Loan (CCCL) payments appear to have the greatest impact followed by Other Federal Farm Programs (OFFP) payments, while the Conservation Reserve and Wetland Reserve (CRWRP) payments are not statistically significant. On the other hand, when the effect of government payments is measured in terms of average payments (payment per farm), the opposite pattern is found: the CRWRP program is substantially stronger in effect than either OFFP payments or CCCL payments. The stronger negative impact of conservation payments suggests that this payment is essentially decoupled and makes allocation of labor for leisure more attractive relative to off-farm employment. The smaller off-farm employment impact of commodity-related payments suggests that in addition to an income effect, the income transfer may have eased up borrowing constraints for investment in farms. This is why --despite the fact that the amount of commodity-related payments per farm is very high-- the income effect is not as high as that is observed with conservation payments. It is also plausible that as shown by Ahearn *et al.* (2006), the off-farm employment impact of marginal changes in payments seems related with magnitude of payments; the impact is higher if the magnitude of payments is lower and vice versa.

Results also show that other factors including the principal operator's characteristics are important factors affecting off-farm employment. The effects of gender and race are strong but the effects become less important when corrections are made for spatial correlation. Among farm and household factors, the average number of operators, ownership of farm land, and scale of production exert stronger effects. Similarly, the five-year lagged farm specialization variables and state-level factor productivity appear to be important determinants of off-farm employment. Among county and regional characteristics, urban influence, education of adults, off-farm wage and its dispersion are found to be important factors.

Study findings suggest that the spatial correlation problem cannot be ignored when estimating off-farm employment decisions of principal farm operators. This may not be, however, possible with farm-level data if geo-spatial data are not available. In light of the impact of government farm payments that greatly vary by payment type and also by the way the variable is specified, the policy implications that can be drawn are not straight forward. This becomes even more complex if we consider the distribution of payments by farm types (size of farm), which are highly skewed. Policy consideration of a strong cap on payments seems important.

It should be recognized that data used for this study are aggregate county-level data primarily from the 2002 U.S. Census of Agriculture. This makes it impossible to consider some of the salient farm and farm household characteristics that would be possible with farm-level data. An example is the work decision of the farm spouse. Government farm payment variables included in the models are also not inclusive of all types of farm support from the public sector. For instance, these variables do not include income transfers to dairy, peanuts and sugar. Therefore, the estimates obtained for government payments need to be interpreted cautiously. Farm adjustment and off-farm response of farms receiving multiple payments may be quite different from farms receiving single payments. Such adjustments may also depend on the farm structure including diversification of farms. For instance, the influence of government payments can be expected to vary by farm size and nature of enterprises and also by whether proprietors are full owners or tenants. Farm-level data may provide an avenue to address these issues. But farm-level data may not allow controlling for spatial correlation between off-farm employment if farm-specific geo-spatial data are not available. Data are already collected at the farm-level that would also allow such analyses. Given the critical nature of research on farm policy and its impacts, use of these data linked to receipt of government payments is critical.

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Faculty Research Associate, Population and Ecology Research Laboratory (PERL), The University of Michigan, USA/Tribhuvan University, Nepal, March 1998-December 2001

Lecturer of Agricultural Economics, Tribhuvan University, Nepal, January 1998-December 2001

AWARDS AND HONORS

College of Agricultural Sciences Competitive Graduate Research Grant, 2005

Thomas C. and Jackie M. Floore Memorial Scholarship, The Pennsylvania State University, 2003, 2005

Population Policy Communication Fellowship, Population Reference Bureau, 2005-2006

University of Michigan exchange program award for training in 53rd Annual Summer Institute, 2000

British Council Scholarship, for M.S. and P.G.D in Agricultural Economics trainings, 1995-1997

Gold Medal, in recognition of the first class first position in B.Sc. Agriculture, 1987

PUBLICATIONS

Bhandari, P., Sundar S. Shrestha and D. J. Ghimire. 2007. "Sociocultural and Geographical Disparities in Child Immunization in Nepal." *Asia and Pacific Population Journal* 22(1), In press.

Shrestha, S. S. and P. Bhandari. 2006. "Environmental Security and Labor Migration in Nepal." PRI Working Paper 06-08, Population Research Institute, The Pennsylvania State University.

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PRESENTATIONS

Shrestha, S. S., Jill L. Findeis, and S. M. Smith. 2006. "Spatial Aspects of Government Farm Payments and Farm Structure in the U.S." Southern Regional Science Association Annual Meeting, St. Augustine, Florida, March 30-April 1.

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