RAINFALL UNCERTAINTY AND OCCUPATIONAL CHOICE IN AGRICULTURAL HOUSEHOLDS OF RURAL NEPAL*

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Abstract

Although agriculture is the main occupation in rural Nepal, evidence suggests that households strive to diversify their sources of income. This paper investigates why this is the case. Using household data from the World Bank and information on rainfall for the various rural districts of Nepal, we find that occupational choice is highly correlated to the uncertainty associated with historical rainfall patterns. Where the head is employed in agriculture, other family members are less likely to choose agriculture as an occupation in districts where rain is more uncertain. Estimates indicate that for a 1% increase in the coefficient of variation of rain, there is a 0.61% decrease in the probability of choosing the same occupation as the household head, where the head is classified as self-employed in agriculture. The negative effect of rainfall uncertainty on occupational choice is less evident in households that have access to credit, and in households with relatively high levels of human capital.

Keywords: Diversification, Occupational choice, Rainfall, Nepal

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Section 1: Introduction

Agriculture is the main occupation in most South Asian countries, particularly Nepal. Households in rural areas of Nepal have extensive experience in cultivating agricultural crops; and in raising agricultural livestock. Income from the production and sale of crops and livestock constitutes a major source of household earnings and consumption. Recent statistics indicate that agriculture and livestock (agro-industry) together contribute almost 60% of Nepal's GDP, and employ approximately 90% of the population.[1]

Despite the overwhelming prevalence of agriculture as the main occupation in rural Nepal, empirical evidence suggests that households in these regions also strive to diversify their sources of income. Thus, it is not uncommon to see other household members engaged in non-agricultural activities (particularly, non-agricultural self-employment activities) in families where the household head is employed in agriculture. Using data from Nepal, this paper investigates why rural households diversify their choice of occupations, and what underlies household incentives to invest in activities that are removed from agriculture.

The question of why households diversify their choice of occupations is important for several reasons. First, determining the underlying cause for diversification will help explain what appears to be a fairly widespread, yet relatively little-researched phenomenon in the rural areas of many developing countries. Of the 2388 households in our rural sample, 2132 (89.28%) had heads who were classified as either wage employed or self employed in agriculture. Of the 2132 households with heads in agriculture, 482 households had at least one other member engaged in either wage or self employment in *non-agriculture*. That is, more than one fifth (22.61%) of the households with heads in agriculture had other household members employed in non-agriculture. This is not an insignificant proportion; yet, relatively little attention in the economic development literature has been devoted to explaining this fact.

Second, if diversification is tied to the need to stabilize total household income, identifying the cause will assist in improving security and reducing the vulnerability of poor households. Third, if diversification appears to be a necessary strategy in some regions, and if resource scarcities limit the ability of impoverished households to diversify, then outside interventions may be warranted. Such interventions can be effective only when the underlying incentives for diversification are clear.

One of the main sources of uncertainty in agricultural communities is likely to be the variability of regional rainfall patterns. Some of this variability may be associated with seasonality, and thus anticipated to some degree. However, there is evidence that within-season variations in rainfall can be large, and, in turn, can have sizeable consequences on the scale of agricultural output. The following extract (reported verbatim) from an editorial in one of the major newspapers in Nepal highlights the effects of inter- and intra-seasonal variations in rain:

> In Nepal, agriculture is basically weather dependent... *Approximately 75 per cent of the total variation in wheat yield can be explained by rainfall distribution.* ...In … Nepal … agricultural production is highly dependent on rainfall.[2] (italics added for emphasis)

The editorial proceeds to describe how the lack of irrigation infrastructure has compounded the effects of rain uncertainty:

> … Agricultural productivity of Nepal is poor… *Since, most of the farmers have to depend on the suitable weather condition to come to commence their farm activity, seasonal variation in climate has a remarkable implication in Nepalese agriculture.*[3] (italics added for emphasis)

The editorial concludes with the following segment:

> In recent years there have been growing number of studies on economic aspects of weather forecasts, or of climatic control, and on the whole field of economics and especially risk taking in agriculture. *However, in Nepal weather and climate data are seldom used in economic decision making and proper attention has not been given in this field.*[4] (italics added for emphasis)

Although research and government institutions may not have as yet used "weather and climate data" to devise ways to stabilize income from agriculture, this study shows that households in Nepal are cognizant of the risk associated with weather. A strategy that households appear to have developed to counteract this risk is diversification of occupational choice. In order to obtain preliminary evidence of this strategy in our sample of rural households, the majority of whom are engaged in agriculture, we construct a diversification index (indicator variable) that equals one if at least one worker within the home is employed in non-farm work. The index equals zero otherwise. We then run a regression of total income of the household on a measure of rainfall uncertainty (discussed below), the diversification index, the interaction of uncertainty with the diversification index, and other household and village characteristics. Results indicate that although rainfall uncertainty has a negative effect on total income in household that do not diversify, we cannot reject the null hypothesis that uncertainty has *no* effect on total income in rural households that diversify and engage in *both* farm and off-farm work. Hence, there is evidence in these data that diversification of occupations is an effective strategy to insure against rain shocks.[5]

Since the diversification index developed above is likely to be endogenous, we model it directly and study the structure of household occupational choice in the presence of rainfall variability. Using data on rainfall and the 1995-96 World Bank household survey on Nepal, we find that choice of occupation is very sensitive to regional rainfall patterns. In households where the head is classified as either self-employed or employed for wages in agriculture, other household members are less likely to choose agriculture as an occupation in areas where the coefficient of variation of rainfall (our measure of rainfall uncertainty) is high. The effect of coefficient of variation of rainfall is most pronounced in households that bear the highest risk, that is, where the head is classified as self-employed in agriculture. In such households, historical uncertainty in rainfall patterns has the strongest, most significant effect on occupational choice. Although other determinants of occupational choice such as age, gender, education, as well as village and regional characteristics also have the hypothesized effects, the magnitude of these effects is relatively small. Hence, our results indicate that one of the main reasons for diversification in sources of income in rural Nepalese households is shocks associated with rain.

We also investigate the effect of credit on diversity of occupational choice in the presence of rainfall uncertainty. We find that the effect of this uncertainty on occupational choice is less evident in rural households with access to credit, particularly consumption credit and credit used to finance business/farm investments. This underlines the fact that facilitating access to credit is one of several important mechanisms to insure poor households against seasonal rainfall shocks.

Section 2 presents a review of the literature in this area. Sections 3 and 4 discuss our data and empirical methodology, respectively. Results are presented and interpreted in section 5, and section 6 concludes. All tables and figures are shown at the end of the paper.

Section 2: Literature Review

Even though consumption smoothing by the poor is well documented in the literature, most of the focus has been on strategies to mitigate risk *ex-ante* through conservative production choices, or on ways to cope with income shocks *ex-post* via credit and/or transfers and remittances. The role of weather shocks in inducing off-farm work, and to a related extent, the importance of diversifying economic activities as a means to smooth income, is relatively little researched. In a comprehensive review of the poor's attitudes towards risk and the coping strategies they employ, Morduch (1995) notes this gap in the literature by emphasizing the importance of both income smoothing and consumption smoothing. Other work that has highlighted the risk-mitigating and risk-coping strategies of the poor include Dercon (2002), which notes that "entry constraints" often limit the ability of the poor to smooth income. Related studies that discuss the role of precautionary savings, crop choice in smoothing income (and consumption), intra-household patterns of risk sharing, and the effect of aggregate weather-related shocks on long run outcomes (health, education, and lifetime earnings) include Dercon (1996), Dercon and Krishnan (2000), Dercon and Hoddinott (2003).

Although the literature on consumption smoothing by the poor is relatively well-developed, as noted above, previous work on the underlying causes of occupational diversity in developing countries is not voluminous. Economic studies that exist focus on the rise of the non-farm sector in recent times, and do not adequately address the role of weather shocks in explaining why a given household may choose both on-farm and off-farm work. A few exceptions include Shucksmith et al. (1989) and Ellis (2000). Shucksmith et al. (1989) considers farm household strategies in various regions of the U.K., and the role these strategies play in facilitating diversification into off-farm work. Ellis (2000) documents the link between livelihoods and occupational diversity in developing countries and is among the first to introduce terms such as “risk strategies”, “asset strategies”, and “coping behavior”.[6] The study notes that in response to crises, agricultural households tend to follow a set sequence of actions where the primary aim is a conservation of assets.[7] One of the very first actions in the sequence of events noted in Ellis (2000) is diversification (a pursuit of different sources of income).

In a theoretical examination of the costs and benefits of learning in environments exposed to uncertainties of various types, Menon and Subramanian (2007) find that the optimal choice of occupations for risk-averse agents depends crucially on both aggregate (common) and idiosyncratic risk. Focus (which occurs, for example, when all workers in a household choose to specialize in the same occupation) allows faster learning over time, but is more risky due to common occupation-specific shocks. The study concludes that both the level and nature of risk (whether it is permanent or can be “learnt away”) are important in the optimal focus-diversification choice.

Other empirical research in the literature on off-farm work and its role as a diversification strategy has emphasized the tension between “pull” and “push” factors. Pull factors that might induce households to enter into off-farm work generally include the possibility of high remuneration and the low level of risk associated with non-farm activities; push factors include the scarcity of land and the need to self-insure by engaging in *ex-ante* risk-mitigating and income-smoothing mechanisms. Although the necessity of insuring income against weather shocks as a “push” factor for off-farm work has been noted (Lanjouw and Lanjouw, 2001, Deininger and Olinto, 2001), evidence on the effect of such shocks on household occupational choice is limited. For instance, in the discussion of weather shocks as a motivating factor for off-farm work, Lanjouw and Lanjouw (2001) note the importance of off-farm income in smoothing total income across agricultural seasons, and in stabilizing total income by reducing risk through diversification. However, little empirical evidence is provided for the effect of weather shocks on occupational choice, or for the smoothing and stabilizing effects of non-farm income.

Deininger and Olinto (2001) use data from Colombia to argue that although the non-farm sector provides an important avenue for income diversification (and risk-reduction), because of a linear relationship that they document between total income and specialization, households stand to gain by choosing a single source of income. Again, there is no specific consideration of the influence on non-farm employment of uncertainties associated with regional rainfall patterns.

In analyzing determinants of diversification in rural Peru, Escobal (2001) highlights the critical roles of both “private assets” (access to credit and individual ability as proxied by education) and “public assets” (presence of roads and other infrastructure variables) in determining whether households choose alternate sources of income. However, Escobal (2001) does not consider the role of rainfall shocks in household occupational choice. Furthermore, access to credit is treated as an exogenous variable.

Other work that has evaluated the non-farm sector in developing countries includes Lanjouw (2001). However, this study is focused on documenting the rise of the non-farm sector; there is little consideration of the role that rainfall shocks play in diversification of occupational choice at the household level.

The effect of rainfall uncertainty on measures of household vulnerability is analyzed in Christiaensen and Subbarao (2004). Using repeated cross-sectional data with retrospective information on rainfall, the authors show that households in the arid regions of rural Kenya have the most volatile levels of consumption. This is because these households are exposed to the largest rainfall shocks. This study also considers the effect of “risk exposure” variables (size of landholdings, proportion of workers employed in the public sector, income shares from pensions and non-agricultural activities), and “coping capacity” variables (household size, dependency ratio, proportion of literate adults in the household, and so on) on consumption levels. However, the analysis reflects the effect of such variables on household vulnerability (real expenditure), not household occupational choice.

Finally, the sensitivity of occupational choice to rainfall uncertainty has been noted in several studies on climate risk. In particular, Eakin (2005) notes that households in three agricultural communities of Central Mexico cope with rainfall uncertainty by engaging in a diverse range of activities. These include migration to urban centers, selling livestock, increasing their participation in non-farm work, borrowing in informal credit markets, and when possible, re-planting existing plots of land with crops that are more resistant to rain shocks. However, the study presents qualitative evidence in the form of case studies; no quantitative evidence is provided. Similarly, Smit et al. (2000) outlines the importance of adaptation to climate variability in developing countries where weather shocks such as droughts, floods, and storms are severe and recurrent. Other work on adaptation to rainfall uncertainty through the appropriate choice of crops and livestock includes Thomas et al. (2007), which documents a switch away from crops to livestock management in areas where rain is unpredictable. Other studies that find farmers focusing on livestock in dry regions include Mendelsohn and Seo (2007); Seo and Mendelsohn (2006) goes a step further in analyzing farmer's choice of species of livestock in regions with warm temperatures and low precipitation.

This research contributes to the literature in three ways. First, we provide an explanation for why households in rural areas of developing countries may choose to invest in both on-farm and off-farm work by studying the effect of rainfall uncertainty on occupational choice. This work thus builds a bridge between existing studies of vulnerability that do not focus on occupational choice and existing studies of the non-farm sector that do not consider rainfall shocks. Second, we analyze how access to credit (differentiated by loan purpose) tempers the effect of rainfall uncertainty on occupational choice. Third, we provide some evidence that improving levels of human capital and physical infrastructure (paved roads, electricity) may also serve to reduce the vulnerability of the poor to rain shocks.

Section 3: Data

Data used in this research are from the Nepal Living Standards Survey (NLSS) carried out by the World Bank and the Government of Nepal in 1995/96. The NLSS, a nationally representative survey, includes information on 275 wards (communities), 73 districts, 3,373 households, and approximately 20,000 individuals. Because the survey provides detailed information on household characteristics, education, occupational activities, and credit, NLSS 1995/96 is particularly appropriate for purposes of this study.

Of the 3,373 households in the complete sample, 2388 are rural. We focus only on the rural sample since the effect of rainfall uncertainty is likely to be most pronounced in this sub-set of households. The 2388 rural households are located in 66 of the 73 districts for which we have information. Nepal has 75 districts in total, but two of these (Rasuwa and Mustang) were not surveyed because the size of their populations was too low. Although these 2388 rural households include over 12,000 individuals, for purposes of estimation, we focus on those who are between 10-65 years of age (working age population).[8] Thus, the rural sample that we use for estimations comprises 2388 households and 8939 individuals who live in 194 wards (communities) located in 66 districts of Nepal. Finally, the NLSS sample was selected using a multi-stage stratified sampling procedure. Thus, all estimations as well as summary statistics are adjusted with weights to correct for the fact that the distribution of households in the sample is different from the distribution of households in the true population.

The NLSS data classifies workers into four occupational categories: wage-employed in agriculture, wage-employed in non-agriculture, self-employed in agriculture, and self-employed in non-agriculture.[9] As noted above, approximately 89% of rural households have heads who are employed in agriculture. Of these, about 22% have at least one household member engaged in non-agricultural work (wage or self-employment); approximately 6% have two or more household members engaged in non-agricultural work. Thus, diversification into off-farm work for farm households appears to be quite prevalent in these data.

Summary statistics for the variables included in the estimations are presented in table 1. The summary statistics are differentiated by the level at which information is available – at the individual level, at the household level, at the ward level, and at the district level. We begin by discussing variables that are available at the individual level (the first panel of table 1). Individual level variables represent information for all household members between the ages of 10 and 65 (working age population) who are not household heads. The first three individual level variables constitute the set of dependent variables in the Logit estimations below. Table 1 reports that about 54% of individuals in rural Nepal are employed in the same occupation as the household head. Where the head is classified as either self-employed or employed for a wage in agriculture, approximately 66.5% of individuals are likewise employed; 66.7% of individuals work in the same occupation as the household head, where the head is classified as self-employed in agriculture (in these data, very few household heads are classified as wage-employed in agriculture). These proportions indicate that although a relatively large number of individuals work in the same occupation as their household head, complete specialization in occupational choice does not occur.

Other variables for which information is available at the individual level include age, gender, literacy, and marital status. Descriptive statistics for these variables are as shown in the topmost panel of table 1.

Next, we discuss variables at the household level (the second panel of table 1). Of these, the share of workers classified as self-employed in agriculture and share of workers classified as wage-employed in non-agriculture are the dependent variables in the second set of estimations (seemingly unrelated regression models) presented in the paper. Information for these variables in table 1 indicates that on average, 30% of household members are classified as self-employed in farm work, and 2.4% of household members are classified as wage-employed in off-farm work. Approximately 42% of households (predicted) have access to credit. Of the 2132 rural households with heads in agriculture, 1357 (63.6%) have an outstanding loan or a loan that was contracted in the previous twelve months that has already been repaid.

Household heads are on average 45 years old, 9.8% of them have completed primary school, and approximately 87% are male. Almost 90% of households own livestock, and the average number of females in rural households is about 3. Where dependents are defined as those below the age of 5 and those above 65, the average dependency ratio in the sample of rural households is 0.18. In the list of individual and household level variables, the number of males and females, the dependency ratio, the gender of the household head, education of the individual and household head, as well as the indicator of livestock ownership, are measures of the household's ability to cope with risk ("coping capacity" variables in the Christiaensen and Subbarao (2004) terminology). By determining the scale of agricultural operation, land ownership, in particular, measures how much risk the household is exposed to ("risk exposure" variables in the Christiaensen and Subbarao (2004) terminology).

Descriptive statistics for variables at the ward (community) and district levels are presented in the third and fourth panels of table 1. Of these, the first variable listed at the district level pertains to rainfall uncertainty. A measure of the coefficient of variation of rain is constructed by dividing standard deviation of rain by mean rainfall during the "monsoon" months of the year (June, July, and August). The construction of the coefficient of variation of rain is discussed in detail below. We focus on June, July, and August, since most of the annual rainfall precipitation in Nepal arrives in these summer months. Thus, much of the seasonality in rain patterns in Nepal is anticipated (rainfall is expected to be relatively high during the months of June, July, and August, and low during the remaining months of the year). In order to study the effect of rainfall uncertainty on occupational patterns, we need a measure of *unanticipated* changes in expected annual rainfall patterns. Thus, in order to ensure that our measure of rainfall shocks captures uncertainty *within* months of the year when rainfall levels are already expected to be relatively high, we construct the measure of rain uncertainty using precipitation data from the three “monsoon” months in the 20 year time-span from 1971 to 1990. The measure of rain shocks we construct thus conditions on anticipated seasonality.

Continuing our discussion of the descriptive statistics in the third and fourth panels of table 1, ward-level variables used in our estimations include indicators of infrastructure development, such as the presence of electricity, markets, and paved roads. The third panel of table 1 also presents information on the average price of irrigated and un-irrigated cultivable land in the ward. These variables capture the effect of land quality in our specifications. Our analysis also conditions on ecological regions – mountainous, terai (low-lying tropical, alluvial land and grass-lands, that are a continuation of the Gangetic plain in India), and hill. Descriptive statistics for these variables are reported in the fourth panel of table 1. See figure 1 for a map of these regions.

Information on Rainfall

Before describing the source of our rain data, it is useful to discuss the administrative structure in Nepal. Nepal is divided into five development regions – Far Western, Mid-Western, Western, Central, and Eastern. These five regions in turn are divided into 75 districts. These districts are further disaggregated into 58 municipalities and 3913 village development committees (VDCs). Each municipality consists of between 9 and35 wards; each VDC is composed of 9 wards.

Data on rainfall in Nepal were obtained from the Global Historical Climatology Network (GHCN) data base of the International Research Institute for Climate and Society (IRI) at Columbia University. IRI compiles the GHCN data base using monthly precipitation data from the U.S. National Climatic Data Center (NCDC). Monthly rainfall information in the GHCN data base is available for 66 rain stations in Nepal, located across 41 districts. However, three of these districts are absent in the NLSS 1995/96 survey; we can thus directly match precipitation information from 59 rain stations located in 38 districts to the household data. District level data is the most disaggregate level at which information on precipitation is publicly available for

Nepal. Since rainfall patterns are not markedly different within districts, use of rain data at this level is likely to accurately reflect precipitation uncertainties experienced by households residing in these districts.

The NLSS household and community surveys were fielded in 1995/96, thus, we use retrospective information on rainfall from the GHCN data base only from 1971 to 1990. This prevents time overlaps, and allows us to capture the influence of historical rainfall patterns on subsequent occupational choice behavior at the household level. The five-year gap also allows occupational behavior at the household level to be well-entrenched. Rain data are used to construct a coefficient of variation (COV) measure for each of the 38 districts. Since much of the seasonality in rain patterns is expected (rainfall is relatively high during the summer monsoon months of June, July, and August, and low during the remaining months of the year), we construct the measure of rain uncertainty using precipitation data from the three "monsoon" months during the 20 year time-span from 1971 to 1990. Hence, our measure of rainfall shocks captures uncertainty *within* months of the year when rainfall levels are expected to be relatively high. The measure of rain shocks we construct thus takes anticipated seasonality into account.

As noted above, the rural households in our sample are located in 66 of the 73 districts for which we have NLSS information. However, the IRI rain data are directly available for only 38 of these 66 districts. Using GIS software (ArcGIS Spatial Analyst) we were able to grid rainfall data and compute estimated variability contours for the remaining 28 districts for which direct rainfall information is missing. We thus have complete COV measures for all of our 66 rural districts. The district-level COV measures were subsequently matched to households in corresponding districts using the district name in which the household is situated. Each household in the sample was thus associated with a district-level measure of rainfall uncertainty in the "monsoon" months of the year from 1971 to 1990.

Section 4: Empirical Methodology

We begin by formulating an empirical model of occupational choice where we hypothesize that the need to reduce the vulnerability of total household income influences the choice of occupations by working members other than the head (referred to as “non-heads” from now on). As noted above, one of the main sources of uncertainty in rural agricultural communities is the variability of rain. In light of this, we expect that the choice of occupations by non-heads will tally directly with rainfall uncertainty. That is, in districts where the variance of rainfall is high, more non-head household members will choose occupations unrelated to agriculture. Such patterns will be particularly evident in households with heads employed in agriculture.

Where the dependent variable is a dummy indicating whether a non-head household member chooses the same occupation as the household head, we model choice using the following Logit specification:

$$\ln\left(\frac{P_{ijw}}{1-P_{ijw}}\right) = \beta_1 + \beta_2 X_{1ijw} + \beta_3 X_{2jw} + \beta_4 X_{3w} + \beta_5 COV_w + \mu_{ijw} \text{ --- (1)}$$

where P_{ijw} is the probability that non-head member *i* in household *j* in ward (region) *w* is engaged in the same occupation as his/her household head. X_{1ijw} and X_{2jw} are exogenous variables specific to member *i* and household *j* that influence the choice of occupations. These variables include individual characteristics such as age and gender, and household characteristics such as land ownership, number of males and females over 10 years of age in the household, and the total number of dependents. X_{3w} are variables specific to the ward that affect occupational choice; these include presence of electricity and markets in the ward, as well as the average quality of land in the ward.

COV_w is the coefficient of variation of rain, and the hypothesis that increased uncertainty in rain will lead to smaller probabilities of non-heads choosing the same occupation as their household head is borne out if β_5 is negative and significantly different from zero. The estimates of equation (1) are presented in the first three columns of table 2.

Access to Credit

If households have access to credit, then diversification in occupational choice in order to insure household income against rainfall shocks may be less urgent as compared to the case where such access is absent. This is because households in which credit constraints do not bind can borrow to supplement income during times of hardship. This implies that rainfall uncertainty will have a less pronounced effect on employment choice in households that can borrow. Rainfall variation will have the strongest effects on occupational choice in households that are the most likely to be credit-constrained, that is, the poorest households.

In order to analyze how the availability of credit mediates the effect of rain uncertainty on choice of occupations by non-heads, we use a variant of equation (1):

$$\ln\left(\frac{P_{ijw}}{1-P_{ijw}}\right) = \gamma_1 + \gamma_2 X_{1ijw} + \gamma_3 X_{2jw} + \gamma_4 X_{3w} + \gamma_5 COV_w + \gamma_6 \hat{c}_{jw} + \gamma_7 (COV_w * \hat{c}_{jw}) + \eta_{ijw} \quad \text{--- (2)}$$

where $\hat{c}_{jw}$ is the predicted value of a dummy which equals one if household *j* has access to credit (has an outstanding loan or a loan that was contracted in the previous twelve months that has already been repaid), and equals zero otherwise. We use predicted values since credit may be endogenous as discussed below. In equation (2), the effect of rain uncertainty on occupational choice in households that do not have access to credit is captured by the γ_5 parameter. As noted above, we expect γ_5 to be negative. For households with access to credit, the additional effect of uncertainty is measured by the γ_7 coefficient. The total effect of rainfall uncertainty in households with access to credit is then measured by ($\gamma_5 + \gamma_7$). If ($\gamma_5 + \gamma_7$) is not significantly different from zero, then uncertainty associated with variable rainfall patterns has little impact on occupational choices of non-heads in households with access to credit. The estimates of equation (2) are presented in column (5) of table 2.

In order to study whether the effects of consumption or investment credit differs from the effects of credit borrowed for personal reasons, we condition our analysis of equation (2) by the purpose for which a loan was obtained. These results are reported in table 3.

Simultaneous Estimation with Correlated Errors

We conclude our empirical analysis by taking a more aggregate view of occupational choice at the household level. This is accomplished by constructing the share of household workers classified as self-employed in the farm sector and the share of household workers classified as wage-employed in the off-farm sector, and then allowing for the joint optimization of these shares within a household. Workers that are classified as self-employed in agriculture are likely to be the most susceptible to weather shocks; workers classified as wage-employed in non-agriculture bear the least risk in terms of rain uncertainties. Analyzing these two sets of workers thus allows a clear demarcation of the effects of rain variability at the household level. Furthermore, joint optimization allows for correlation between the errors of the share equations at the household level (households jointly decide shares of farm and off-farm workers).

Shares are bounded at 0 and 1, so we take natural logs of shares in order to make the support of the distribution appropriate for use of Zellner's seemingly unrelated regression (SUR) model (see Greene (2003) for details).[10] We use the standard form of this model; a separate equation for the SUR model is thus not presented in this section of the paper. Results of the estimation of the SUR model that allows for correlated errors at the household level are reported in table 4.

Section 5: Results

Dynamics in Rural Nepal

Before discussing our instruments for credit and the estimates from our empirical specifications, it is worthwhile to present an overall context within which our results are to be interpreted. Poverty is widespread in rural Nepal. Some of the micro- and macro-level factors that exacerbate the incidence of poverty include low levels of human capital, dependence on agriculture, relatively high rates of population growth, weak institutions, and inadequate physical and social infrastructure (Prennushi, 1999, Bhatta and Sharma, 2006). Deterioration of the environment (air, water, and soil pollution, and the depletion of land use, land cover, and land productivity) has contributed further to reducing standards of well-being. In recent times, this had led to out-migration, albeit to relatively close locations (Massey et al. 2007). Furthermore, the Maoist insurgency has been pivotal in destabilizing urban and rural life, and in contributing to increased relative deprivation amongst the poor (Seddon and Hussein, 2002, Macours, 2006). In the discussion that follows, we attempt to interpret our results within this framework of life in rural Nepal. However, before that, we discuss the possible endogeneity of credit, and the instruments we use to correct for it.

Instruments for Credit

Credit may be endogenous primarily for two reasons. First, households that are more “able” or have more experience in managing borrowed funds may choose to participate in credit markets; this is the issue of self-selection. Second, some areas may have easier access to credit as compared to other areas; this is the issue of omitted variables at the community level. The presence of either or both of these causes of endogeneity necessitates the use of instruments for credit.

As noted in Pitt and Khandker (1998), a technique motivated by demand theory is to use the price of credit, or the costs associated with learning about the availability of credit, as identifying instruments. The price of credit is the interest rate on the loan, and although the NLSS survey does collect this information, there are a large number of missing values for this variable in the data. Alternatively, we hypothesize that the costs associated with gaining information on credit will be correlated with the level of infrastructural development in the community (ward). Indicators of the presence of a police station, a post office, and telephone and telegraph service in the community are predictors of the costs associated with gaining information on the availability of credit, but conditional on credit, these variables should have little effect on the choice between farm and off-farm work. These variables thus form our set of instruments.

A discussion of the economic validity of these instruments is warranted. First, by proxying for ease of access to credit, instruments such as the presence of a post office and presence of a telephone and telegraph service in the community should directly correct for a large part of the second cause of endogeneity noted above. However, since our instruments are measured at the community (ward) level, they have less power in predicting the within-community variation in credit. One way to allow for within-community variation would be to interact these instruments with variables measured at the household level. However, it is difficult to find household level variables in our data which may be used as exclusion restrictions (that is, conditional on credit, have no effect on occupational choice). Thus for example, we could interact our instruments with education of the household head (to proxy for household "ability"), but education of the household head should be present directly in the occupational choice equations as well. Given this, interactions of the community level variables with education of the household head would not have much power as instruments.[11]

In the first stage of our estimation, a dummy measuring household access to credit is regressed on the set of instruments. A chi-squared test that these identifying instruments are jointly zero is strongly rejected (chi2 (3) =49.40, Prob > chi2 = 0.0000). Thus our instruments are valid. In order to ensure that our instruments have little effect on occupational choice conditional on credit, a Logit model was used to regress the dummy for choice of employment on our set of instruments, the credit variable, and other exogenous regressors in the model.[12] Based on the point estimates from this regression, we cannot reject the null that the effect of our instruments is jointly zero. This means that conditional on credit, our instruments have little effect on occupational choice. This is as required.

Effects of the Coefficient of Variation of Rainfall

Table 2 presents results for the effects of historical rainfall uncertainty on choice of employment of individuals over 10 years of age, who are *not* heads of households (non-heads). Standard errors in table 2 are adjusted for clustering at the household level. As can be seen, results in table 2 are presented in five columns. The first column reports estimates where the dependent variable is an indicator for whether the non-head member is employed in the same occupation as the household head. This is thus a broad classification without any differentiation of agriculture versus non-agriculture. The second column reports estimates where the dependent variable is an indicator of whether the non-head member chooses the same occupation as the head, given that the head is classified as either wage or self-employed in agriculture. The third, fourth, and fifth columns report estimates for the case where the non-head member chooses the same occupation as the household head, given that the head is classified as self-employed in agriculture. The second, third, fourth, and fifth column results are thus specific to choices made in agriculture. Focusing on agriculture is important since this is the occupational category in which choices of employment are likely to be the most sensitive to uncertainties associated with rain. Results in columns three to five consider effects for self-employment in the farm sector alone since as residual claimants, workers classified as self-employed in agriculture are likely to bear the most risk associated with the precariousness of rainfall patterns.

Table 2 shows that although the COV of rain has a negative effect in columns (1)-(3), the effect is significant only in column (3). This means that where the head is self-employed in agriculture, non-heads are *less* likely to choose the same occupation (as the head) in areas where the uncertainty associated with rainfall is large. Using the parameter estimate in column (3), for a 1% increase in the COV of rain, there is a 0.61% decrease in the probability of choosing the same occupation as the head, where the head is classified as self-employed in agriculture. Thus, these data provide evidence that occupational choice at the household level is sensitive to rainfall shocks; households are less likely to specialize in agriculture in regions where rainfall is uncertain.

The first three columns of table 2 also report results for other variables that influence occupational choice. A household head over 65 years of age has a positive effect (in two of the three columns), as does the total amount of land owned (significant in column (2)) and total number of males in the HH. Age and education of the individual, and the total years of wage labor experience for household members, all exert negative effects on agriculture as an occupational choice. The negative coefficient on the literacy variable echoes the low levels of human capital in rural Nepal, and the great benefits that are to be reaped by investing more in education and thus by possibly moving to other occupations that are more remunerative than agriculture. The negative coefficient on the dummy for males is as expected. This is because in Nepal, agriculture employs a relatively large number of young women, particularly after the onset of the Maoist insurgency. Although it is not clear what effect the marriage dummy should have, the negative coefficient on this variable may reflect the fact that given other commitments, married (older) individuals (particularly women) are less likely to be engaged in agriculture. Similarly, as the total number of females increases, there is a higher chance that the average woman in the household is older, and therefore, less likely to be employed in agriculture. As expected, the mountain dummy indicates that agriculture is less likely to engage individuals in the mountainous regions of the country.

The fourth and fifth columns of table 2 report results for occupational choice conditional on credit. In the fourth column of table 2, credit and its interaction with rainfall variability are endogenous (credit is not instrumented for). It is clear from column (4) that although the sign on the credit variable is as expected, credit has no significant effect on occupational choice. The fifth column of table 2 instruments for credit and uses its predicted value. As noted above, the predicted value of having access to credit is obtained from a first stage where access to credit is regressed on exogenous instruments. The use of an estimated variable in a non-linear specification such as the Logit model may potentially lead to bias, but as discussed in Train et al. (1987), this bias is of second order and thus very small.[13] Furthermore, we obtain bootstrapped estimates to adjust the Logit second stage standard errors for the use of a predicted variable from the first stage. The standard errors reported in column (5) of table 2 are thus the bootstrapped standard errors.

The results in column (5) emphasize that for non-heads in credit-constrained households, uncertainty in rainfall has strong negative effects on choice of self-employment in agriculture as an occupation. The credit variable in column (5) has the hypothesized sign and is (marginally) significant; however, its interaction with rain shocks is measured imprecisely. As compared to the insignificant result for credit in column (4), the significant result for credit in column (5) suggests that our instruments have some power in predicting the effect of having access to loans. The *p*-value in column (5) for the sum of coefficients on COV and the interaction of COV with the predicted value of having access to credit indicates that we cannot reject the null that uncertainty has no impact on occupational choice in households with access to credit. This implies that with credit access, diversification in occupational choice is less urgent since households that are not credit-constrained can borrow to buffer income against rain shocks. These data indicate that the effect of rainfall uncertainty is most significant in households that are credit-constrained.[14] Other variables in column (5) have similar effects as discussed above.[15]

Effects of Access to Credit by Purpose of Loan

Column (5) in table 2 indicates that access to credit mitigates the effects of rainfall shocks. This is expected since in households that can borrow for consumption, for example, the need to diversify occupational choice to insure against weather shocks is likely to be less important. The mitigating effect of credit is also expected in the case of households that have borrowed for investment in the past, since such households are likely to have sources of income that are independent of weather outcomes. However, it is unclear whether credit borrowed for personal reasons (marriage/family events, or to purchase consumer durables) will dampen the effect of rain uncertainty on occupational choice. Since those who borrow to finance personal expenditures are likely to be relatively credit-worthy, it is possible that this category of loans will also cushion the effect of rain shocks. The effect of historical rainfall variability on choice of occupations in households that have borrowed for various purposes is presented in table 3. Information on loan purpose is directly available from the NLSS household data.

The dependent variable in all columns of table 3 is an indicator of whether (non-head) individuals choose the same occupation as the household head, where the head is classified as self-employed in agriculture. Heads that are self-employed in agriculture tend to bear the most risk as residual claimants; hence, the effect of credit access on occupational choice is likely to be most evident in this sub-group of households. The first column of table 3 shows estimates for when households have obtained credit to finance consumption needs. As evident, the negative and significant coefficient on COV of rain suggests that individuals are less likely to be classified as self-employed in agriculture in households that lack consumption credit. However, the *p*-value in column (1) indicates that at conventional levels, we cannot reject the null hypothesis that uncertainty has *no* effect on occupational choice in households that have borrowed to finance consumption. Thus as expected, the need to diversify is less pressing when consumption credit is available to insure against rainfall uncertainty. Other variables in column (1) have the same effects as before. In particular, the more educated an individual is in rural Nepal, the less likely he/she is to be self-employed in agriculture.

Column (2) of table 3 presents results for credit borrowed for business or farm use (purchase of inputs, purchase of equipment, purchase of land, purchase of animals, for building improvement, or for other business or farm use). As before, as uncertainty increases, individuals are less likely to be classified as self-employed in agriculture in households that do not have access to investment credit (this coefficient is measured with error). Similar to the case of consumption credit, the *p*-value in column (2) indicates that uncertainty has *no* effect on the occupational choice of individuals in households with access to investment credit. This is as expected since it is likely that in such households, credit has been obtained to finance non-agricultural activities that provide sources of income independent of weather shocks.[16] The effect of rain uncertainty on occupational diversification is thus less evident. Other variables in column (2) have the same effects as before.

The last column of table 3 presents results for credit obtained for personal use (purchase/improvement of dwelling, marriage/family events, purchase of consumer durables, and other personal use). As is clear, rainfall uncertainty again exerts a significant negative effect in households that are credit-constrained. Moreover, results in column (3) show that even though this category of credit in of itself has little effect on the dependent variable, the *p*-value is large enough that we cannot reject the null hypothesis that uncertainty has no effect on occupational choice in households with access to credit for personal use. This is probably because households with access to credit (including credit used for personal reasons) are likely to be wealthier than those households that lack such access; households that are not credit-constrained may independently possess the means to smooth the effects of rain shocks. Other variables in column (3) have the same effects as before.

Seemingly Unrelated Regression Analysis

Table 4 reports the results of the seemingly unrelated regression (SUR) model which allows for correlated errors in the simultaneous estimation of a system of two equations. The dependent variables in this system are the share of household workers classified as self-employed in farm work, and the share of household workers classified as wage-employed in off-farm work. Since the dependent variables now measure shares of workers in farm and off-farm work, the SUR model measures effects at the household level.

The first column of table 4 presents results for the natural log transformation of share of workers classified as self-employed in farm work in the household over one minus the share of workers classified as self-employed in farm work in the household (see bottom of table 4). The second column of table 4 shows results where the dependent variable is the natural log of share of workers classified as wage-employed in non-farm work in the household over one minus the share of workers classified as wage-employed in non-farm work in the household. Since shares are bounded at 0 and 1, the natural log form transforms the dependent variables and allows them to vary between negative infinity and positive infinity. The log transform thus converts the 0-1 bounded share variables to continuous variables, and makes them appropriate for use in the SUR model. Table 4 presents results of the SUR estimation which conditions on historical uncertainty in rainfall.

Estimates for the effect of rainfall uncertainty in the SUR model confirm those in the Logit model; as uncertainty increases, the share of household workers self-employed in farm work decreases (column (1) of table 4). The predicted value of credit (without differentiation by loan purpose) has a negative effect on shares of farm work; however, this is not significant. The *p*-values at the bottom of table 4 confirm that we cannot reject the null that uncertainty in rain has little effect on shares of farm and non-farm work in households with access to credit.

Other variables in table 4 have the hypothesized effects. In particular, age of head increases the share of self-employed agricultural workers, and the share of literate individuals decreases the share of self-employed farm workers in the household (measured imprecisely). As compared to the hill region (excluded regional dummy), the share of wage-employed off-farm workers in households situated in the terai region is negative (but measured with error). This is as expected since most of Nepalese agriculture is concentrated in the terai region.

The estimates of the SUR model in table 4 (which allows for correlated decision making at the household level) thus confirm many of the results obtained from the Logit specifications of tables 2 and 3 (which allow for decision making at the individual level). The result that fewer individuals choose agriculture as an occupation in areas where rain is uncertain is thus not specific to the particular functional form we choose.

Section 6: Conclusion

This analysis studies the determinants of occupational diversification in rural Nepal. Using household data and historical information on regional rainfall patterns, we find that although agriculture is the main occupation in rural Nepal, many agricultural households also choose non-farm sources of income. Results of our specifications suggest that this is done primarily to insure total household income against rainfall uncertainty. Modeling the occupational choices of household members other than the head using a Logit specification, we find that for a 1% increase in the coefficient of variation of rain (our measure of rainfall uncertainty), there is a 0.61% decrease in the probability of choosing the same occupation as the head where the head is classified as self-employed in agriculture. Results of a specification that allows for correlated errors in the decision making process at the household level (SUR model) confirm that variability of rainfall has significant effects on the structure of occupational choice within a household. Estimates from the SUR model indicate that the share of household workers classified as self-employed in the farm sector decreases as regional rainfall uncertainty increases. Thus, these data provide significant evidence that the choice of occupations in rural Nepal is very sensitive to weather shocks associated with rain.

Our empirical analysis of occupational choice conditions on credit availability, among other variables. Estimates from both the Logit and SUR models indicate that the effect of rainfall uncertainty on diversification of occupational choice (away from agriculture) is less pronounced in households with access to credit. This may be because households that are not credit-constrained can borrow to insulate total income during times of hardship. Upon differentiation by loan purpose, we find that we cannot reject the null hypothesis that rainfall uncertainty has no effect on diversification incentives when households borrow to finance consumption needs, or when they borrow to finance business/farm investments. This is not surprising particularly in households that obtain investment credit, as it is likely that in such households, credit has been used to finance non-agricultural activities that provide sources of income independent of weather outcomes. Reflecting their relative wealth, rain shocks are also found to exert little influence in households that borrow for personal reasons (marriage/family events or for other personal use). In a country where poverty is already widespread (recent estimates suggest that the poverty rate in rural Nepal is 47%), uncertainty in income arising from weather shocks can lead to increased vulnerability and deprivation.[17] Our analysis provides evidence that poor households in regions of the developing world such as rural Nepal try to overcome this uncertainty by choosing supplementary sources of income that are removed from agriculture.

Endnotes

1. http://www.new-agri.co.uk/01-3/countryp.html. December 12, 2005.
2. http://www.gorkhapatra.org.np/pageloader.php?file=2005/01/23/editorial/editorial2. Accessed on March 17, 2006.
3. http://www.gorkhapatra.org.np/pageloader.php?file=2005/01/23/editorial/editorial2. Accessed on March 17, 2006.
4. http://www.gorkhapatra.org.np/pageloader.php?file=2005/01/23/editorial/editorial2. Accessed on March 17, 2006.
5. Since the diversification index is endogenous, and since the purpose here is only to provide preliminary evidence to motivate our (more rigorous) analysis that follows, these results are not reported in the paper. They are available upon request.
6. Ellis (2000), p. 44-45.
7. Ellis (2000), p. 44.
8. Household heads are included in the sample even if they are over 65 years of age.
9. If the household owns land and the head of the household is classified as self-employed in agriculture, other family members who work on the same land are also classified as being self-employed in agriculture.
10. Share of farm workers is transformed to ln(share of farm workers/(1-share of farm workers)), and share of off-workers is transformed to ln(share of off-farm workers/(1-share of off-farm workers)).
11. The basic regressions of tables 2 and 3 were estimated using such interactions as additional instruments. Credit effects in tables 2 and 3 did not alter much.
12. The dummy for choice of employment was an indicator for whether a member chooses the same occupation as the household head, where the head is self employed in agriculture. Results were the same when the other two indicators (discussed below) of occupational choice were used as dependent variables.
13. Ordinary least squares (OLS) estimations of linear probability models were also conducted. Linear probability models are unbiased asymptotically, although they do not exhibit the minimum variance property. OLS estimations of linear probability models gave the same results as the Logit models; these are not reported.
14. Various tests were conducted to ensure that the demographic structure of households is not endogenous. First, in order to test whether diversification in occupational choice is possible only in households with more working age adults, the model in column (5) of table 2 was re-estimated with only those individuals who reside in households with fewer than the mean number of working age adults in the full sample. The results of column (5) table 2 remain unchanged. Second, simple averages were calculated to ensure that non-head males did not leave (to form their own households) more in cases where the original household's head is wage-employed in agriculture. Again, there is no evidence for such a systematic pattern in these data.
15. The NLSS data has no explicit distinctions between full and part-time work. However, using hours worked per day, a dummy for part-time work was constructed. On the basis of this constructed dummy, the results of column (5) table 2 were re-estimated for full and part-time workers. It was found that in both cases, the original results of column (5) table 2 remain unchanged. Hence, the distinction between full and part-time work does not affect the results.
16. In households with heads self-employed in agriculture, mean farm income is about 30,420 Nepali Rupees. In such households, mean non-farm income is only about 1/6th that amount (approximately 5420 Nepali Rupees). In the complete date, mean non-farm income is approximately 1/3rd of mean farm income. These estimates indicate that compared to returns from agriculture, sources of non-agricultural supplementary income provide lower expected return. Hence, they are probably chosen only to reduce risk.
17. http://www.nssd.net/country/nepal/nep08.htm. Accessed on December 12, 2005.

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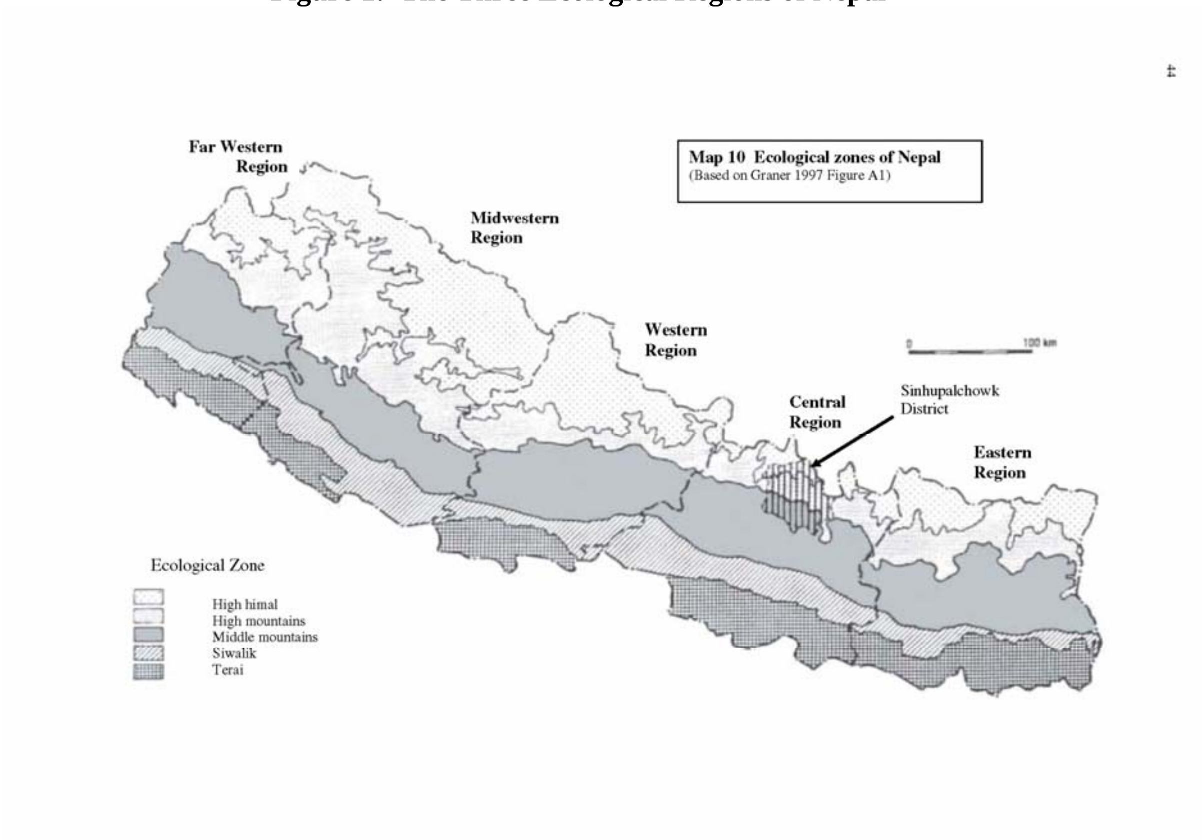
Figure 1: The Three Ecological Regions of Nepal



Source: http://www.odi.org.uk/publications/working_papers/wp218/map10_p44.pdf. (March 23, 2006)

Table 1 – Descriptive Statistics

VARIABLES AT THE INDIVIDUAL LEVEL	MEAN	STD. DEV.
Dummy for same occupation as head#	0.5358	0.4988
Dummy for same occupation as head, head in agriculture#	0.6646	0.4722
Dummy for same occupation as head, head SE in agriculture#	0.6666	0.4715
Age in years	25.8499	10.7591
Dummy for male	0.5099	0.4999
Dummy for can read and write	0.2790	0.4485
Dummy for individual is married	0.6211	0.4851

VARIABLES AT THE HOUSEHOLD LEVEL	MEAN	STD. DEV.
Share of workers SE in agriculture in HH#	0.3000	0.2008
Share of workers WE in non-agriculture in HH#	0.0237	0.0652
Total loan amount of the HH (in 100,000s)	0.0911	0.3103
COV*Total loan amount of the HH (in 100,000s)	0.0371	0.1380
Dummy for having access to credit	0.6308	0.4827
Predicted value of having access to credit	0.4203	0.3336
COV*Predicted value of having access to credit	0.1727	0.1471
Dummy for having taken a consumption loan	0.7485	0.4340
Predicted value of having taken a consumption loan	0.2581	0.3127
COV*Predicted value of having taken a consumption loan	0.1124	0.1417
Dummy for having taken a business loan	0.6162	0.4865
Predicted value of having taken a business loan	-0.2925	0.3072
COV*Predicted value of having taken a business loan	-0.1316	0.1424
Dummy for having taken a personal loan	0.5391	0.4986
Predicted value of having taken a personal loan	-0.6575	0.5458
COV*Predicted value of having taken a personal loan	-0.2947	0.2575
Age of head in years	44.5258	14.2652
Dummy for male head	0.8727	0.3333
Dummy for land ownership	0.8616	0.3453
Dependency ratio	0.1775	0.1809
Number of dependents in HH	1.0527	1.0668
Number of females (10 or more years of age) in HH	3.3063	2.2906
Number of males (10 or more years of age) in HH	2.1939	1.3437
Dummy for household owns livestock	0.8966	0.3045
Total years of wage labor experience for HH members	0.6178	0.7369
Total years of self employment experience for HH members	2.0549	1.5327
Age of head is 65 years or older	0.1061	0.3080
Head is illiterate	0.6912	0.4621
Dummy for head has completed primary school	0.0981	0.2976
HH owns more than the mean level of land in sample	0.4165	0.4931
Share of literate people in household	0.2906	0.2774
Total number of workers in agriculture in household	3.5544	2.1844

# Denotes dependent variable. There are 8939 individuals in the sample who are between 10-65 years of age and are classified as household workers. There are 2388 households, 194 wards, and 66 districts in the sample.

Table 1 continued – Descriptive Statistics

VARIABLES AT THE WARD LEVEL	MEAN	STD. DEV.
Dummy for electricity in ward	0.2159	0.4126
Dummy for market in ward	0.2542	0.4366
Dummy for paved road in ward	0.2539	0.4364
Dummy for electricity or market or paved road in ward	0.4451	0.4983
Average price per unit of irrigated cultivable land (in millions)	0.0711	0.0892
Average price per unit of un-irrigated cultivable land (in millions)	0.0494	0.0625
Dummy for police station in ward	0.3690	0.4840
Dummy for post office in ward	0.7425	0.4384
Dummy for telephone service in ward	0.3424	0.4757
Population of ward	968.2849	1024.8450

VARIABLES AT THE DISTRICT LEVEL	MEAN	STD. DEV.
Coefficient of variation of rain 1971-1990	0.4029	0.0941
Dummy for mountain region	0.0868	0.2837
Dummy for terai region	0.3774	0.4884
Dummy for hill region	0.5358	0.5025

There are 8939 individuals in the sample who are between 10-65 years of age and are classified as household workers. There are 2388 households, 194 wards, and 66 districts in the sample.

Table 2 - The Effect of Historical Rainfall Uncertainty on Occupational Choice

	(1)	(2)	(3)	(4)	(5)
COV of rain	-0.4784	-0.3741	-0.9401*	-0.9665*	-1.8789*
	(0.4485)	(0.4261)	(0.4248)	(0.4437)	(0.9213)
Age in years	-0.0386**	-0.0542**	-0.0579**	-0.0579**	-0.0581**
	(0.0036)	(0.0042)	(0.0044)	(0.0044)	(0.0058)
Dummy for male	-0.9964**	-1.7005**	-1.8470**	-1.8485**	-1.8485**
	(0.0669)	(0.0919)	(0.0949)	(0.0947)	(0.1147)
Dummy for can read and write	-0.2985**	-0.4486**	-0.4533**	-0.4498**	-0.4531**
	(0.0930)	(0.1256)	(0.1289)	(0.1302)	(0.1262)
Dummy for individual is married	-0.3295**	-0.4871**	-0.4685**	-0.4675**	-0.4735**
	(0.0913)	(0.1114)	(0.1175)	(0.1177)	(0.1372)
Total years of wage labor experience	-0.6720**	-0.9212**	-1.1269**	-1.1259**	-1.1226**
for HH members	(0.0594)	(0.0584)	(0.0601)	(0.0601)	(0.0704)
Total years of self emp. experience	-0.0094	0.1068**	0.1786**	0.1766**	0.1779**
for HH members	(0.0357)	(0.0379)	(0.0400)	(0.0402)	(0.0451)
Number of females (10 or more years	0.02	-0.0318	-0.0494*	-0.0471*	-0.0468
of age in HH)	(0.0276)	(0.0229)	(0.0223)	(0.0229)	(0.0334)
Number of males (10 or more years	0.2709**	0.3101**	0.3054**	0.3102**	0.3033**
of age in HH)	(0.0409)	(0.0413)	(0.0429)	(0.0444)	(0.0490)
Number of dependents in HH	-0.0271	0.0393	0.0594	0.0548	0.058
	(0.0567)	(0.0473)	(0.0474)	(0.0475)	(0.0639)
Age of head is 65 years or older	-0.4265*	0.5449**	0.6267**	0.6498**	0.6225**
	(0.1901)	(0.1558)	(0.1652)	(0.1683)	(0.2104)
Dummy for head has completed	-0.0016	-0.1582	-0.1525	-0.1535	-0.1382
primary school	(0.1216)	(0.1114)	(0.1171)	(0.1157)	(0.1433)
Dummy for male head	0.0972	0.0271	-0.0294	-0.0336	-0.0141
	(0.1539)	(0.2012)	(0.2246)	(0.2250)	(0.2478)
HH owns more than the mean	0.062	0.3035**	0.1221	0.1248	0.1135
level of land in sample	(0.0888)	(0.0854)	(0.0831)	(0.0837)	(0.0987)
Average price per unit of un-irrigated	-1.199	-1.3168	-1.5838	-1.7217	-1.6523
cultivable land in ward (in millions)	(1.2190)	(1.2187)	(1.2190)	(1.2623)	(1.4777)
Average price per unit of irrigated	-0.4678	0.0147	-0.3105	-0.2037	-0.2161
cultivable land in ward (in millions)	(0.8865)	(0.9501)	(0.9354)	(0.9737)	(1.1187)
Dummy for ward has electricity or	-0.1792†	-0.0394	-0.1131	-0.1100	-0.1236
paved road or market center	(0.1000)	(0.0870)	(0.0851)	(0.0851)	(0.1061)
Dummy for mountain region	-0.1988†	-0.2879**	-0.3397**	-0.3377**	-0.3099**
	(0.1075)	(0.1018)	(0.1034)	(0.1035)	(0.1195)
Population of ward	0.0002**	0.0002**	0.0002**	0.0002**	0.0002**
	(0.0001)	(0.0001)	(0.00005)	(0.00005)	(0.0001)
Credit				-0.2186	-0.9477‡
				(1.1251)	(0.6537)
COV*Credit				0.3113	1.8989
				(2.2156)	(1.4955)
Sum of COV and interaction coefficients				-0.6552	0.0201
p-value that sum=0				0.7570	0.9818

The dependent variable in column (1)-same occupation as head, in column. (2)-same occupation as head, head in agriculture, and in columns (3)-(5) – same occupation as head, head SE in agriculture. Models include a constant term – these are not reported due to lack of space. Standard errors clustered at HH level in columns (1)-(5). Bootstrapped standard errors in parenthesis in column (5). Credit in column (4) is the total loan taken by the HH. Credit in column (5) is the predicted value of having access to credit. The interaction term (COV*Credit) is constructed correspondingly. ‡ Significant at 12% level; † Significant at the 10% level; * Significant at 5% level, ** Significant at 1% level.

Table 3 - The Effect of Credit by Purpose of Loan

	(1)	(2)	(3)
COV of rain	-2.0715**	-0.2014	-1.5531†
	(0.7429)	(0.6547)	(0.8900)
Predicted value of having taken a loan	-1.8271*	-1.4174*	0.4544
	(0.8053)	(0.6783)	(0.4860)
COV*Predicted value of having taken a Loan	3.7884*	2.9865†	-0.8773
	(1.8384)	(1.6177)	(1.1227)
Age in years	-0.0580**	-0.0582**	-0.0581**
	(0.0057)	(0.0058)	(0.0060)
Dummy for male	-1.8454**	-1.8510**	-1.8488**
	(0.1092)	(0.1087)	(0.1090)
Dummy for can read and write	-0.4558**	-0.4645**	-0.4519**
	(0.1280)	(0.1236)	(0.1232)
Dummy for individual is married	-0.4768**	-0.4759**	-0.4712**
	(0.1406)	(0.1353)	(0.1410)
Total years of wage labor experience for HH members	-1.1177**	-1.1254**	-1.1248**
	(0.0659)	(0.0729)	(0.0665)
Total years of self employment experience for HH members	0.1821**	0.1771**	0.1775**
	(0.0423)	(0.0441)	(0.0461)
Number of females (10 or more years of age in HH)	-0.0459	-0.0492	-0.0474
	(0.0320)	(0.0330)	(0.0324)
Number of males (10 or more years of age in HH)	0.2996**	0.3019**	0.3044**
	(0.0491)	(0.0538)	(0.0476)
Number of dependents in HH	0.0537	0.0636	0.059
	(0.0608)	(0.0607)	(0.0622)
Age of head is 65 years or older	0.6231**	0.6192**	0.6227**
	(0.1964)	(0.1971)	(0.2055)
Dummy for head has completed primary school	-0.1295	-0.1636	-0.1427
	(0.1428)	(0.1509)	(0.1441)
Dummy for male head	-0.0109	-0.0093	-0.0197
	(0.2587)	(0.2574)	(0.2461)
HH owns more than the mean level of land in sample	0.114	0.1047	0.1155
	(0.0987)	(0.0968)	(0.1009)
Average price per unit of un-irrigated cultivable land in ward (in millions)	-1.5905	-1.6924	-1.6725
	(1.5717)	(1.4554)	(1.5588)
Average price per unit of irrigated cultivable land in ward (in millions)	-0.2656	-0.1889	-0.2161
	(1.2201)	(1.0687)	(1.1501)
Dummy for ward has electricity or paved road or market center	-0.1556	-0.1078	-0.1135
	(0.1079)	(0.1102)	(0.1126)
Dummy for mountain region	-0.2825*	-0.3393**	-0.3232**
	(0.1212)	(0.1175)	(0.1175)
Population of ward	0.0002**	0.0002**	0.0002**
	(0.0001)	(0.0001)	(0.0001)
Constant	4.3666**	3.4797**	4.1319**
	(0.4531)	(0.4234)	(0.4849)
Sum of COV and interaction coeffs.	1.6953	2.8082	-2.4418
p-value that sum=0	0.2198	0.2184	0.1994

Consumption loan in column (1), business loan in column (2), personal loan in column (3). Bootstrapped standard errors clustered at the household level in parenthesis. The dependent variable in all three columns equals 1 if individual chooses same occupation as head and head is SE in agriculture. † Significant at the 10% level, * Significant at the 5% level, and ** Significant at the 1% level.

Table 4 - Seemingly Unrelated Regression Analysis

	(1)	(2)
COV of rain	-1.5820*	-1.4926
	(0.7667)	(1.5498)
Predicted value of having access to credit	-0.8310	-0.8989*
	(0.5376)	(0.3696)
COV*Predicted value of having access	2.4376*	2.1367*
to credit	(1.2380)	(0.8525)
Total years of wage labor experience	-0.3947**	-0.0616†
for HH members	(0.0545)	(0.0342)
Total years of self employment experience	0.1832**	-0.0174
for HH members	(0.0307)	(0.0202)
Number of females (10 or more years	-0.0075	-0.0542**
of age in HH)	(0.0192)	(0.0123)
Number of males (10 or more years	-0.0620†	-0.0650**
of age in HH)	(0.0353)	(0.0246)
Dependency ratio	-0.0724	
	(0.2743)	
Age of head in years	0.0087**	0.0025
	(0.0029)	(0.0020)
Head is illiterate	-0.0491	0.0629
	(0.0971)	(0.0669)
Dummy for male head	0.1401	-0.0925
	(0.1141)	(0.0803)
Share of literate people in HH	-0.1828	0.0250
	(0.1621)	(0.1105)
HH owns more than the mean level of	-0.0183	-0.0437
land in sample	(0.0747)	(0.0536)
Total number of workers in agriculture	0.1256**	
in HH	(0.0213)	
Dummy for HH owns livestock	-0.2733	-0.3773
	(0.5598)	(0.3946)
Dummy for electricity in ward		-0.1262
		(0.0783)
Dummy for paved road*dummy for	-0.1358	0.0406
market center	(0.1578)	(0.1150)
Average price per unit of un-irrigated	-0.2071	1.1995
cultivable land in ward (in millions)	(1.1303)	(0.8309)
Average price per unit of irrigated	-1.1533	-1.0923
cultivable land in ward (in millions)	(0.9222)	(0.6667)
Dummy for mountain region	-0.1156	-0.0755
	(0.1087)	(0.0772)
Dummy for terai region		-0.0380
		(0.0717)
Population of ward	0.0001*	-0.00001
	(0.00004)	(0.00003)
Sum of COV and interaction coeffs.	0.8556	0.6441
p-value that sum=0	0.2321	0.1935

Dependent variable in (1) = ln(share of SE workers in ag. in HH/(1-share of SE workers in ag. in HH)), in (2) = ln(share of WE workers in non-ag. in HH/(1-share of WE workers in non-ag. in HH)). Models include a constant term – these are not reported due to lack of space. Bootstrapped standard errors obtained but not reported as they were the same as those above. † Significant at 10% level, * Significant at 5% level, ** Significant at 10% level.