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CONSUMPTION INSURANCE UNDER UNCERTAINTY: THE CASE OF NEPAL DURING MAOIST INSURGENCY

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We test the implication of the full consumption insurance hypotheses in the presence of violent conflict due to the Maoist People's War using household survey data from Nepal. We find that food consumption is more vulnerable than non-food consumption if we do not account for the non-linear relationship between the consumption and the level of violence. The level of food consumption vulnerability, however, is not severe for the households with low levels of education and income. Contrary to the common notion of vulnerability of low-caste/ethnic group, we find complete consumption insurance for this socially excluded social group. This result is surprising as the socially disadvantaged caste/ethnic group has been considered more vulnerable in Nepal.

Keywords: Consumption Insurance; Nepal; Violent Conflict; Consumption Vulnerability

JEL Classification: D1, O17, R2

1. Introduction

In most of the developing countries credit and insurance markets are either poorly functioning or completely absent leaving households exposed to different kinds of risks. But, surprisingly, various studies show that households in developing countries are mostly insured against idiosyncratic shocks even in the absence of formal credit or insurance

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mechanisms. It is believed that informal social mechanisms and institutions may fill the gap in the absence of formal credit and insurance markets. Any attempt to provide formal insurance may crowd-out those existing social insurance systems. But, during civil wars and violent conflicts, the probability of reneging on contracts would be high as violent conflicts or civil war probably destabilizes the existing social institutions, and the contract enforcement would be weaker if the borrower threatens violence. Such behavior may compel households to opt for costly self-insurance, destabilizing the age-old social insurance system that would otherwise help the community to share the risks in times of need.

The full consumption insurance hypothesis asserts that in the case of risk-sharing and resource pooling, individual household consumption would be related to the aggregate consumption of the community regardless of the household's resources change. But, such risk-sharing and resource pooling may be absent during violent conflicts due to the breakdown of the traditional norms and networks. If this is the case, then as asserted in Mace (1991), the growth rate of per capita household consumption would be more closely related to household income growth rather than to aggregate consumption growth of the community. Such expectations about the nature of relationships between household consumption and household income and aggregate consumption of the community permit an empirical distinction between the two benchmarks of risk sharing and autarky even in the situation of violent conflict.

The objective of this paper is to investigate the extent households can insure their consumption against idiosyncratic shocks during such violent conflicts. In earlier studies of the theory of full consumption insurance, shocks such as illness, unemployment, and the likes are considered as idiosyncratic. In this study we consider a different set of shocks. In addition to the income shock, we also consider negative shocks such as natural disaster. Given the over-a-decade old violent conflict in Nepal, we control for the number of people killed due to the Maoist People's War in the villages. Here, our main goal is to investigate the following issues: Can the local traditional institutions guard against the consumption loss of households during times of violent conflict or natural disasters by pooling their resources?

Basically, our interest is to investigate to what extent households are insured against income shocks, as analyzed in the existing literature as well as against other non-traditional shocks such as natural disasters. For our analysis, we derive the implications of the full consumption insurance theory and use data from Nepalese household surveys for the empirical investigation. Our effective insurance community is different from Grimard (1997) where insurance community is among the ethnic groups. In Nepal, there are over hundred ethnic groups, and villages are highly heterogeneous in terms of ethnic groups. Therefore, we identify the primary sampling unit (PSU) as an effective insurance community for several reasons. PSU used in the survey is the smallest local political and administrative unit of Nepal. In Nepal, provision of the local public goods, utilities, and other developmental projects (schools, health facilities, drinking water, etc) are mostly based on the PSU boundaries. Local clubs and self-help groups are also based on the

PSU and they compete with other clubs and groups from other PSUs. This helps to create cooperation among the villagers within the PSU, and we expect that villagers extend their support to other villagers from the same PSU in times of need.

A PSU as identified in the survey is a village (also called *ward*) with less than 400 households, with average of 115 households in the villages. Within a PSU, households are geographically close to each other and can enforce informal insurance by creating credible threat of non-cooperation in case of non-compliance by any participating household.[1] In such a small community, each household can get signals about other household's income or wealth, and households can work together so that they can establish regular contact to enforce an informal implementation mechanism by creating trust, a necessary element that determines the success or failure of any informal social insurance within networks. Such a closely-knit community would be able to lower the transaction costs by creating trust (Jarillo 1990), prevent moral hazard and incentive-related problems, and solve the Pareto optimal planning problem for the community where households pool their resources and insure each other using informal mechanisms if they are allowed to interact for a long period of time (Fafchamps 1992). Such informal insurance systems may take a variety of forms, such as interest free loans, exchange of labor, rent free access to cultivating land, grain transfers in times of need, etc. (as in Platteau 1991). In a large community, these criteria are unlikely to be met, partly because of the free-rider (monitoring) problem and partly because of the transaction cost, contrary to the small or closely-knit community.

The theory of full consumption insurance predicts that household consumption should depend on aggregate shocks but not on idiosyncratic shocks. Theoretical works by Diamond (1967) and Wilson (1968) show that a household's consumption does not depend on idiosyncratic income shocks once aggregate shocks are taken into account under a Pareto-optimal consumption plan. Using data from the Panel Study on Income Dynamics (PSID) of US households, Cochrane (1991) finds some support to the theory of consumption insurance, but not against all types of shocks.

Several researchers have tested the hypothesis of full consumption insurance. Mace (1991) reports mixed support for the theory of full consumption insurance using a panel from the US Consumer Expenditure Survey (1980–83). Townsend (1994) provides evidence of risk-sharing among the villagers in rural India where formal credit and insurance markets are absent. Using the same PSID date set, Hayashi et al. (1996) find no support for intra- as well as inter-family full risk-sharing. Using a panel data set from Indonesia, Gertler and Gruber (2002) document imperfect consumption insurance over major illnesses as a measure of idiosyncratic shock. More recent studies (Skoufias 2003; Mu 2006) reject the hypothesis of perfect consumption insurance in Russia, but find that food-consumption is better protected than non-food consumption.

There are several new studies on the efficient risk sharing hypothesis (Ligon 1998, Albarran an Attanasio 2003 and Dubois et al. 2008) that are focusing on asymmetric information aspects of informal contract, such as limited commitment constraint or moral

[1] Using data from the Phillipines, Fafchamps and Gubert (2005) show that the informal insurance systems tend to spread risk over households who live in proximity and have similar income and occupations.

hazard problems. Our paper does not focus on the asymmetric information issue, but covers the abnormal situation of violent conflict in Nepal that broke in 1996 where we control for the number of people killed during the violent conflict. Our study explores how the violence has affected the patterns of consumption insurance in Nepal, which itself is an interesting issue. In order to analyze the effect of the violence (number of people killed during the violence) on the consumption insurance, we use interaction terms of violence with the growth rate of per capita household income and village per capita consumption. Without the use of such interaction terms, the extent of violence seems to have negative effect on the household's per capita consumption growth which does not hold once we use the interaction terms. We also analyze the consumption vulnerability of historically excluded low-caste group, different from the ethnic groups that Grimard (1997) analyzed. This sub-division of the sample to test consumption insurance hypothesis for the low-caste/ ethnic households is different from what Grimard (1997) did using Cote d'Ivoire data. Grimad categorizes all sampled households accordingly to their ethnicity and tests the full consumption insurance hypothesis for the entire sample, where the complete risk-sharing within ethnic group is rejected. As a part of our analysis, we consider one specific low-caste that has been suffering social exclusion for centuries, and understanding informal risk sharing arrangement within low-caste group is an interesting issue given that current policy debate in Nepal is how to bring such excluded groups into the mainstream. In our sample, the share of this socially disadvantaged low-caste group is about 33%, a sizable number. Contrary to the popular belief that the consumption of this low-caste group is more vulnerable than the rest, we find a complete risk sharing within this socially excluded low-caste group.

The paper is organized as follows. In Section II, we review the theory of full consumption insurance and derived testable hypotheses from the theory. Section III provides the description of the data used for empirical analysis. In Section IV, we summarize the econometric methodology adopted for the analysis followed by the empirical results in Section V. The final section concludes.

2. Consumption Insurance: Basic Theory and Hypotheses

The basic theory presented here resembles to Cochrane (1991), Mace (1991) and Townsend (1994). Consider an economy with N households where household h has a time separable, state contingent utility $U[C_{ht}(s_{\tau 1}), \delta_{ht}(s_{\tau 1})]$ that depends on household consumption $C_{ht}(s_{\tau 1})$ at time t, event τ and preference shifters $(\delta_{ht}(s_{\tau 1}))$. Also assume that each household has a finite time horizon (T), and experiences a variety of events $(s_{\tau 1})$ at time t with probability $\pi(s_{\tau 1}) \in [0,1]$ and $\tau = 1, 2, \ldots, S$, where each event is a collection of states of the world. In the absence of formal credit and insurance markets, if all of the households pool their resources and insure each other against idiosyncratic shocks, then the risk-sharing Pareto-optimal consumption allocation can be derived from the social planner's perspective that maximizes a weighted sum of the individual households' life-time utilities given the budget constraint. The optimization of the planning problem generates the equality of weighted marginal utilities across households as the equilibrium condition. The *ex-ante* uncertainty disappears once the households realize state τ. By taking the ratio of two first order conditions for an individual household at two different dates, we can get:

$$\rho_h \frac{\pi(s_{\tau t+1}) E[U_C(C_{h(t+1)}, \delta_{h(t+1)})]}{U_C(C_{ht}, \delta_{ht})} = \frac{\mu_{t+1}}{\mu_t} \tag{1}$$

Equation (1) indicates that the discounted growth rate of marginal utility is constant across households, where r$_h$ is the subjective time discount rate of household *h*. It is determined by the growth rate of the Lagrange multiplier, which is unrelated to household's income or the endowment. As the Lagrange multiplier is a function of the aggregate resources available to the community at two different dates and not the individual household's resource growth, the full consumption insurance hypothesis predicts that the growth rate of the household's marginal utility is independent of the growth rate of the individual household's resources.

In order to put the full consumption insurance hypothesis to an empirical test, we need to derive the form of the equation that needs to be estimated. For this purpose, we consider a Constant Relative Risk Aversion (CRRA) utility function with multiplicative preference shocks (Mace 1991; Cochrane 1991):[2]

$$U(C_{ht}, \delta_{ht}) = e^{\sigma \delta_{ht}} \frac{1}{\sigma} (C_{ht})^{\sigma}, \tag{2}$$

where $(1 - \sigma)$ is the coefficient of relative risk aversion that is assumed constant across households, and we need $\sigma < 1$ for concavity. The marginal utility with respect to C_{ht} is given by

$$U_C(C_{ht}) = e^{\sigma \delta_{ht}} (C_{ht})^{\sigma - 1} \tag{3}$$

Combining (1) with (3) and taking natural logs gives

$$\ln\left(\frac{C_{h(t+1)}}{C_{ht}}\right) = \frac{1}{1-\sigma}\left(\ln\left(\frac{\mu_{t+1}}{\mu_t}\right) - \sigma(\delta_{h(t+1)} - \delta_{ht}) - \ln(\rho_h)\right) \tag{4}$$

Equation (4) implies that for CRRA utility function there is a positive linear relationship between the growth rate of individual household consumption and the growth rate of aggregate consumption. As indicated by (4), we specify our econometric model as

$$\Delta \ln C_{ht} = \alpha + \beta . \Delta \ln C_t^A + \delta . \Delta \ln Y_{ht} + \gamma . \Delta X_{ht} + u_{ht} \tag{5}$$

where $\Delta \ln C_{ht}$ is the per capita household consumption growth rate, $\Delta \ln C_t^A$ is a vector of an aggregate shock to the community (aggregate consumption growth, and natural disaster at the community level), $\Delta \ln Y_{ht}$ is a idiosyncratic shock to individual households (households' income growth), ΔX_{ht} is a vector of other control variables (e.g., number of people killed in the village due to the conflict, and amount of remittances received by households) and change in the preference shifters of the household (e.g., changes in household size, age and

[2] Given our short panel data with several years' gap in between, we use a growth rate model which can be derived from the power utility function.

sex compositions between two dates[3]). u_{ht} is the error term that captures the measurement errors of the dependent variable and the change in the household's unobservable preference shifters.

Generally, parametric panel data are affected by functional form, and generalization of preference shocks. While running a regression based on (4), the right hand side variables must be uncorrelated with the error terms, including unobservable preference shocks and measurement errors. In order to capture the aggregate shocks, we use aggregate consumption growth as a righ hand side variable. Cochrane (1991) argues that the use of aggregate consumption growth taken over the sub-sample being studied, not the entire population of the community, may not serve its purpose due to the small sample. To avoid the correlation issue raised by Cochrane, we use the village specific aggregate consumption growth of the entire households, not the aggregate consumption growth of the sub-sample being studied.

The growth rate specification of (5) avoids the correlation from time-invariant omitted unobserved household characteristics, and hence avoids problems of omitted variables bias. This specification is similar to Mace (1991), Cochrane (1991), Townsend (1994), and many other studies. We use the generalized method of moments (GMM) technique for estimation. The full consumption insurance theory described above generates two testable hypotheses.

H1: Given that households in their insurance community pool resources and insure each other for unforeseen shocks, then the per capita growth rate of household consumption should grow linearly at the aggregate growth rate of community level consumption, *i.e.*, $\beta_{\Delta \ln C_t^A} = 1$.

H2: As the household level resources do not enter into the first order conditions (1), the effect of idiosyncratic shocks on the growth rate of per capita household consumption should be zero, *i.e.*, $\beta_{\Delta \ln Y_{ht}} = 0$.

In empirical settings, we will test these two hypotheses jointly as predicted by the theory as

H3: $\beta_{\Delta \ln C_t^A} = 1$ and $\beta_{\Delta \ln Y_{ht}} = 0$.

Inclusion of more shocks may change the number of parameters to be tested, but the basic idea remains the same. We will test these hypotheses individually as well as jointly, using one or more idiosyncratic shocks.

3. Data Descriptions

The data for this research come from two rounds of Nepal Living Standard Survey (NLSS) conducted in 1995/96 and 2003/04 by the Nepal Central Bureau of Statistics (CBS) in collaboration with the World Bank. Both of these surveys follow the World Bank's Living Standards Measurement Survey (LSMS) methodology and a two-stage stratified

[3] One can make a point that the level of education can be a good candidate for the preference shifters. Within the given analytical framework, the level of education affects income, not consumption. Therefore, the level of education is used as an instrument, not as an argument of the growth rate of the household consumption.

sampling is used to collect nationally representative samples. In both rounds, two sets of questionnaires, at the household and the community level, are administered and the data are collected during a one-year period to cover a complete cycle of agricultural activities and to capture seasonal variations in different variables. In the first round of NLSS (1995/96), 3373 households are included in the survey and in the second round (2003/04), the sample size is 3912 households. Along with these main surveys, CBS also collected panel data from 962 households around the country during both surveys. We use panel data for this research along with the data from the main surveys. Other than the village level aggregate consumption, and violence related information, all other variables used in this paper are drawn from the panel aspect of the NLSS.

The conflict-related data are collected from the Informal Sector Services Center (INSEC), a not-for-profit national human rights organization in Nepal. The number of deaths in the villages due to the violent conflict since 1996 are obtained from the annual reports (1996–2004) of the INSEC, and aggregated up to 2004. Another source of our data is the population census of 2001. In our panel data or full NLSS samples, small numbers of households are chosen from each Primary Sampling Unit (PSU) to collect household information. Due to the small sample, any single household consumption may have a significant effect on the community (PSU) level consumption. In order to avoid the influence of an individual household on the community level consumption aggregate, a variable that we use as a measure of aggregate shocks in the community, we use village level average consumption. The NLSS samples do not have the village level consumption information. In order to overcome this deficiency we use the information from population census for imputing the household consumption using the micro-level estimation techniques (Elbers et al. 2003).

Basically, we use the full NLSS samples to impute expenditures for the households that are enumerated in the population census as the census data do not have the households' welfare measures such as income or expenditures. We use the following procedure for imputation. Let y_h be the household h's expenditure obtained from the NLSS survey. A regression of y_h on a vector of covariates X_h, where X_h are chosen so that they are available in the NLSS as well as in the census data, is estimated using the generalized least squares method. Then the estimated model is used to impute the census household expenditures from which we computed community (village) level expenditures. Elbers et al. (2003) provides the methodological details of the survey-to-census imputation of the household income/expenditures. List of variables use for micro-level estimates and the first-stage regression results are provided in the appendix.

4. Econometric Method

This section describes the econometric method used for estimating the model presented in equation (5) and testing the hypotheses implied by the theory. In our panel data we have two observations for each household, and these observations are several years apart. Therefore, we use the CRRA utility function in order to test the proposed hypotheses as this functional form allows us to use growth rates of the relevant variables, not just the difference.[4] As noted in Cochrane (1991) and Hayashi et al. (1996), the panel data with longer gaps may be a blessing in disguise as it helps to avoid certain deficiencies present in the more frequent panel data with shorter horizon. The longer period allows more households to receive shocks while the timing problems that result from using a discrete-time model to study time aggregates would be reduced.[5]

For analytical purposes, we disaggregate the total household expenditure into food-expenditure and non-food expenditure. As we use the household's expenditure growth rates as the dependent variable, ordinary least squares (OLS) would be the starting point for econometric estimation. But, as specified in (8), the growth rate of household income enters as a right-hand-side variable, and measured income is likely to be correlated with the measurement error in household consumption that violates the fundamental assumption of OLS. The Anderson-Rubin endogenity test (Baum, Schaffer and Stillman 2003) shows that some of the right-hand variables are endogenous. So, inferences from OLS estimates would not be valid for hypotheses testing.

An alternative to the OLS is two-stage least squares (TSLS) or instrumental-variable (IV) estimation that take into account the endogeneity of income or some other variables used as right-hand side variables. Both of these methods basically inherit the basic assumption of homoskedasticity from the OLS. In our sample data, the White-Koenker test (White 1980; Koenker 1981) shows that the errors in IV-method are heteroskedastic. If the error terms exhibit heteroskedasticity of unknown form, as in our sample, then the inference about hypothesis testing under IV-method is again invalid even if one uses standard errors robust to heteroskedasticity (Dufour 2003) and diagnostics for endogenity and over-identifying restrictions would also be invalid (Baum et al. 2003). Furthermore, the household surveys that we are using are designed using multi-stage stratified cluster-sampling. In such a situation it is possible that error terms are correlated within but not across the clusters. The consequence of such clustering effect resembles that of the presence of heteroskedasticity where traditional IV estimation becomes problematic. As an alternative to IV estimation, we use the generalized methods of moments (GMM) that provides valid estimates in the presence of heterogeneity of unknown form (Hansen 1982).

The GMM makes use of the orthogonality conditions to allow efficient estimation in the presence of heterogeneity of unknown form, but it still requires strong instruments for the endogenous variables.[6] If model is poorly identified, then as discussed in Hansen, Heaton and Yaron (1996), continuously- updated GMM provides better estimates that

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[4] In such a specification, the time invariant fixed effects are removed when the observations are first differenced. Given that consumption and income are in logarithms, it accounts for potential differences in the inflation rate across communities (Skoufias 2003).

[5] But the longer periods may also capture the change in living standards over many years rather than the effects of the sudden shocks that might more plausibly be insured (Cochrane 1991). If short term income is dominated by transitory income changes, such as remittances, the orthogonality conditions may have low power in GMM estimation (Hayashi, Atonji and Kotlikoff 1996).

[6] The validity of the instruments is a serious issue in GMM estimation, where instrument validity implies orthogonal to the errors but correlated to endogenous regressors. If instruments are irrelevant or weak, then the sampling distributions of GMM as well as IV statistics are non-normal and standard GMM and IV point estimates, hypothesis tests, and confidence intervals are unreliable.

have several advantages over the TSLS, IV, or simple GMM, such as more reliable test statistics and insensitivity to parameter-dependent scale factors.[7] We use the continuously-updated GMM method (also called continuously-updated estimation (CUE)) in which the test statistic is robust in the light of weak instruments.

5. Empirical Analysis

Basic Information

For the empirical analysis, we divide per capita total household consumption into food and non-food consumption and use their growth rates, *GRHPCFCON* and *GRHPCNFCON*, respectively as dependent variables. Following Ravallion and Chaudhuri (1997), we are treating food and non-food consumption as separable and estimating these equations separately. The major explanatory variables are the growth rate of per capita consumption (*GRVPCCON*) at the village level, and the growth rate of household per capita income (*GRHPCINC*). The first explanatory variable (*GRVPCCON*) is used as a proxy for aggregate shocks to the households in the given community, and the *GRHPCINC* is used as proxy of idiosyncratic shocks at the household level.

We also use the number of people killed during 1996–2004, cumulative deaths due to the Maoist rebels (*MKILL*) as well as the cumulative total deaths (*TOTKILL*), in the villages as an additional regressor.[8] Definitely, these variables measure shocks to the households.[9] In our data set, we have the total number of deaths in each village, but we do not have a separate account of the deaths where one can match which household in the given community lost their family member. Therefore, we use violence related shocks as an additional control variable.

Along with the variables that are used to measure various shocks to the households, we also use three additional variables as a measure of preference shifters of the households. They include the change in the household size (*DHHZIZE*), the change in the age (*DHHAGE*)

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[7] For a regression model: $y = X\beta + u$, if $E(X_t u_t) \neq 0$, one can use the IV method for estimation, which is a special case of GMM. If the error variance is heteroskedastic, then one needs to use GMM. The basic idea of the continuously updated GMM estimator (CUE) can be summarized as follows (Hansen, Heaton and Yaron 1996). The moment conditions is given by $E[\varphi(X_t, \beta)] = 0$, where β is k-dimensional vector of interest, $\varphi(.)$has $n \geq k$ coordinates, and $\left\{T^{-1/2} \sum_{t=1}^{t} \varphi(X_t, \beta)\right\} \rightarrow N(0, V(\beta))$. An efficient GMM estimator of the parameter vector β is constructed by choosing β_c (consistent estimator of β) that minimizes $[T^{-1} \sum_{t=1}^{T} \varphi(X_t, \beta_c)]'[V_T(\beta_c)]^{-1}[T^{-1} \sum_{t=1}^{T} \varphi(X_t, \beta_c)]$, where $V_T(\beta)$ consistent (but infeasible) estimator of covariance matrix that also works as a weighting matrix in GMM estimation. Instead of taking the weighting matrix as fixed, if we consider an estimator in which the covariance matrix is continuously updated as β_c changes in the above minimization problem, then we get an alternative GMM estimator, called the continuously-updated estimator (CUE).

[8] As the number of deaths due to government forces is about two-thirds of the total, and it is highly correlated with the total number of deaths, we exclude this measure from our analysis. Our approach of cumulating regressors resembles Cochrane (1991), where right hand side variables are cumulated for three years, and the growth rate of the dependent variable (food consumption) was measured for a three-year period, not as a year-to-year basis. The longer period analysis can be viewed as a test of the change in the standard of living over many years (rejection of full consumption may indicate slow changes in the living standards over many years).

[9] Our assumption is based on the fact that in an average less than one person is killed per village during 1996–2004 conflict indicating very low probability that the sampled households lost any of their members (Nepal et al. 2011).

and sex (*DHHSEX*) compositions of the households. An obvious advantage of our panel data with few years span is apparent here since we can observe significant changes in these preference shifters that may be absent in the case of more frequent panel data.

The main idea of the full consumption insurance hypothesis is that the growth of per capita consumption will not depend on changes in household resources that are uncorrelated with shifts in preferences once the growth in community resources is taken into account. We use household per capita income growth as a measure of idiosyncratic shocks. In developed countries, a large share of the household income is typically insured, but in developing countries, such as Nepal, household income is not insured at all, indicating that household income serves as a better proxy for the idiosyncratic shocks. Still, household income alone may not capture all types of risks and shocks; we also include natural disaster (floods) as a direct measure of shocks.

Obtaining an accurate measurement of household income or expenditure through surveys is difficult. Deaton (2000) asserts that in many surveys, household consumption and income suffer significant levels of measurement error. Also, the number of people killed in the given village may depend on several factors including political activities of the rebels, presence of social capital in the community, presence of security forces, population density, distributional issues like inequality, and so on. Table 1 shows a wider cross-sectional variations in household consumption, income and the measure of violence, such as *MKILL* (number of people killed by Maoist) and *TOTKILL* (total deaths due to the violence), indicating that there is a good deal of measurement error in our data. Therefore, we suspect that the growth rate of household per capita income (*GRHPCINC*) and the number of people killed (*MKILL* and *TOTKILL*) may be endogenous. The Anderson-Rubin endogenity test (Baum *et al*. 2003) shows that these two variables are actually endogenous. We use household and community characteristics that are expected to be correlated with the growth rate of household per capita income and the violence but orthogonal to the error term, as instruments to correct for endogenity.[10]

In order to see the relevancy and sufficiency of these instruments, and the need of the particular estimation method, we perform several statistical tests as described in section IV. All of these test statistics are summarized in the respective tables.

Basic Results

Non-Food Consumption

Table 2 presents the results from the continuously updated GMM (also called CUE) estimates where the dependent variable is the growth rate of household per capita non-food consumption (*GRHPCNFCON*). All together, the results from five different models are presented in Table 2. Model-A1 and Model-A2 are similar except that the former uses *MKILL* and the latter uses *TOTKILL* as a measure of the violent conflict. In the next two models, we add one more explanatory variable, *DFLOOD*, a measure of natural disasters

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[10] See Table 1 footnote for the list of instruments.

Table 1: Variables Definitions and Descriptive Statistics

Variables	Definition	Sample Mean (S.D.) 1995/96	Sample Mean (S.D.) 2003/04
PCHTCON	Household per capita total consumption (₹)	9924 (11589)	19557 (22270)
PCHFCON	Household per capita food consumption (₹)	5820 (6149)	10944 (11813)
PCHNFCON	Household per capita non-food consumption (₹)	4104 (8336)	8993 (16318)
VPCCON	Village per capita Consumption (₹)	9761 (5079)	18094 (11515)
PCHINC	Household per capita income excluding remittance (₹)	11622 (34858)	17352 (25114)
MKILL	Number of deaths due to Maoist in each village	-	2.57 (5.37)
TOTKILL	Number of total deaths in each village	-	7.20 (15.61)
REMITTANCE	Household remittance income (₹)	4637 (45031)	11913 (44725)
HHSIZE	Household size	6.00 (2.74)	5.75 (2.73)
HHAGE	Average age of household members	25.39 (10.24)	29.18 (12.65)
HHSEX	Percentage of male in household	0.49 (0.17)	0.48 (0.18)
FLOOD	Binary variable (1 if flood in the past five years, else 0)	0.17 (0.38)	0.15 (0.36)

Note: Standard deviations within parentheses.

Data sources: *PCHTCON, PCHFCON, FCHNFCON, PCHINC, REMITTANCE, HHSIZE, HHAGE, HHSEX*, and *FLOOD*-- Nepal Living Standard Surveys (Panel) 1995/96 and 2003/04, Central Bureau of Statistics (Nepal) and the World Bank; *MKILL* and *TOTKILL*-- Informal Sector Services Center (INSEC); *VPCCON* -- Survey-to-Census imputation through small area estimates.

Instruments (figures within parentheses are average values):

(*i*) Categorical variables: if the caste/ethnicity is low (31%) or middle (37%), if the electricity is available (36%), if child works (2%), if household owns house (95%);

(*ii*) Household (per capita) level variable: schooling (4.48 years/member), employment (5.32 months/year), illness (3.26days/year); members working in farm (27%); number of livestock (4.2/household);

(*iii*) Change in community level social network indices between 1995/96 and 2003/04: farmer network index (27%), water network index (23%), forest network index (38%), and women network index (39%);

(*iv*) Others: district's population density in 2001 (541/sq km); public facility index (59%).

that also is a measure of aggregate shocks, in order to check the robustness of the model specifications. The last model incorporates the interactions between GRVPCON and violence; and GRPCHINC and violence. These interaction terms will capture whether the violence affected the effectiveness of the consumption insurance as the villages with severe violence could be considered to have more fragile informal risk arrangement.

Before discussing the actual results, the lower-half of Table 2 deserves proper

Table 2: Continuously Updated GMM Estimates (Dep. Var.: Non-Food Exp.)

VARIABLES	**Model-A1**	**Model-A1**	**Model-A3**	**Model-A4**	**Model-A5**
grpchinc	0.058	0.067	0.111	0.129	0.031
	(0.061)	(0.065)	(0.077)	(0.081)	(0.117)
lMtotkill	0.056		0.018		0.119
	(0.048)		(0.054)		(0.195)
grvpcon	0.365***	0.363***	0.340***	0.341***	0.396***
	(0.052)	(0.054)	(0.062)	(0.063)	(0.117)
dHHsize	-0.066***	-0.066***	-0.064***	-0.063***	-0.066***
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
dHHage	0.009***	0.009***	0.008***	0.008***	0.010***
	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)
dHHmale	0.163	0.167	0.155	0.154	0.175
	(0.121)	(0.120)	(0.118)	(0.118)	(0.122)
ltotkill		0.033		0.002	
		(0.038)		(0.041)	
dflood			0.096	0.096	
			(0.109)	(0.109)	
vpcc_mkill					-0.093
					(0.252)
inc_mkill					0.018
					(0.070)
Constant	0.404***	0.407***	0.433***	0.436***	0.385***
	(0.040)	(0.042)	(0.048)	(0.049)	(0.076)
[a] *White-Koenker NR*^{2}	41.65***	41.91***	41.85***	41.65***	43.49***
b Kleibergen-Paap LM Test	52.66***	54.75***	37.21***	39.72***	29.30***
[c] *Hansen J-Stat.* ($\chi 2_{15}$)	6.06	6.40	5.22	5.23	5.99
[d] $\chi 2_{(k)}$ [H0: $\beta_{\Delta \ln C_t^A} = 1$ & $\beta = 0$]	148.73***	139.14***	137.16***	131.98***	37.70***
No of Clusters	92	92	92	92	92
Observations	922	922	922	922	922
R-squared	0.540	0.537	0.544	0.542	0.534

Notes: [a] *White-Koenker* test of the presence of heteroskedasticity of unknown form (H0: disturbance is homoskedastic); [b] Lleibergen-Paap LK Test for under identification (H0: Matrix of reduced form coefficients has rank = k-1 (underindetified)); [c] *Hansen* test of relevancy/ over-identification of all instruments (H0: all instruments are relevant/over ID); [d] Joint hypothesis of full consumption insurance where $k = 1$ (*GRPCHHINC*) for first two models and $k = 2$ (*GRPCHHINC* and *DFLOOD*) for the last two models; Cluster-robust standard errors are within parentheses; ***, **, and * refer to significant at 1%, 5% and 10% level, respectively.

explanation as it reports several tests statistics about the presence of heteroskedasticity, instrument relevance, and under or over-identification issues.[11] The *White-Koenker* test for the presence of heteroskedasticity indicates the strong presence of heteroskedasticity of unknown form in all models. As we are using more than one endogenous variables, the usual first-stage F-statistics or partial R^2 may not provide sufficient information about the relevancy and sufficiency of the instruments.[12] So, we perform the Kleibergen-Paap

[11] We also report these test statistics in all other tables as well.

[12] For a single endogenous variable, $F < 10$ in the first-stage is a cause for concern, but with multiple endogenous variables,

LM test for the under-identification of the moments conditions. The test statistic shows that our models do not suffer from an under-identification problem. An alternative to the Kleibergen-Paap LM test statistics is the Hansen (1982) *J*-statistic. This is a test of the joint hypotheses of correct specification of the model and the orthogonality conditions. The *J*-statistics are sufficiently small so that we cannot reject the null of instrument relevancy and over-identification. Such a failure to reject the null in our sample implies identification and orthogonality of the instruments, the necessary conditions to make any inferences using the estimated coefficients.[13]

As indicated by the test statistics, the models are identified and the instruments are properly chosen.[14] Table 2 presents our first set of results using five models were the dependent variable is the growth rate of household per capita non-food consumption. The only difference in the first two models (Model-A1 and A2) is that Model-A1 has *MKILL* and Model-A2 has *TOTKILL* as an explanatory variable. Model-A3 and Model-A4 have one additional explanatory variable (*DFLOOD*) that is used to test robustness of the model specifications. Regardless of the model specifications, our results indicate that for every 10% increase in village level aggregate consumption, the per capita household consumption increases by 3.6%, an indication of weak association between those two variables. Overall, the results show that there is less than perfect but positive $\left(\beta_{\Delta \ln C_t^A} = 0.36\right)$ association between *GRVPCCON* and *GRHPCNFCON* implying that partial risk-sharing in non-food consumption is taking place among the households in the sampled communities. The coefficient of *GRHPCINC* is positive but insignificant in all models. Numerically, for every 10% increase in the growth rate of the household per capita income, per capita non-food consumption grows in the range of 0.58%–1.3%, depending on the model that we use. Statistically, these coefficients are insignificant, indicating that the growth rate of non-food consumption is not significantly affected by the growth rate of household income. This is an indication of the presence of partial risk pooling in the case of non-food consumption within the given community.[15]

The effect of the violence related shocks (*MKILL* and *TOTKILL*) appears to be positive but insignificant on the growth rate of household per capita non-food consumption indicating that the violent conflict does not tend to affect household's non-food consumption. This result is surprising on the grounds that it is contrary to the *a priori* expectation of a negative effect of conflict on household non-food consumption. The insignificant impact

such a rule of thumb is not applicable (Staiger and Stock 1997).

[13] Since the GMM method suffers the weak identification problem we use CUE, as this procedure is robust to weak identification (Stock, Wright and Yogo 2002)

[14] As we use a relatively larger set of excluded instruments, we also perform redundancy as well as orthogonality tests on a subset of instruments using the 'difference-in-Sargan' test, also called *C-test* (Hayashi 2000). In the case of the redundancy test, the null of redundant instruments is strongly rejected, and in the case of the orthogonality test for a subset of instruments, we failed to reject the null hypothesis that both sets (suspected set and the remaining set) of instruments are orthogonal and valid. As the *C-test* shows that the suspected sub-set of instruments is relevant and we retain all instruments for estimation.

[15] Rupee is the Nepali currency. We measure the remittance in 1000 Rupees in order to account for the scale issue. If we use the growth rate of remittances, it forces us to drop a significant number of households from our analysis as not all households that are receiving remittances in 2003/04 had remittance income in 1995/96.

of violent conflict on non-food consumption can be explained with the widespread poverty in the country (42% households were below poverty line in 1995/96, and the poverty rate in 2003/04 was about 31%), where the non-food consumption share is very small for a majority of households, and this portion of consumption may already be so low or it may be the bare minimum level that is required for survival of the households and cannot go down further even in the face of the violent conflict.[16]

After including an environmental shock (*DFLOOD* in Model-3A and Model-4A), a variable that measures the occurrence of natural disasters, such as flooding in the given community, the basic results do not change. The coefficient of *DFLOOD* is positive but insignificant. This may be due to the fact that village per capita consumption that captures the damage of flood, is included in the regression. As we included both village per capita consumption and household per capita income in the regression, the coefficient of DFLOOD captures the effect of flood other than the village level shocks and household income shocks.[17] However, the joint hypothesis of the full consumption insurance ($\beta_{\Delta \ln C_t^A} = 1$ and $\beta_{GRPCHHINC} = 0$) is strongly rejected at the 1 percent level. It is because of the less than perfect relationship between the aggregate shock and non-food consumption $\left(\beta_{\Delta \ln C_t^A} < 1\right)$ but not because of the significant impact of idiosyncratic shocks ($\beta_{GRPCHHINC} > 0$) on household non-food consumption. The results do not change when we add interactions terms of village per capita consumption growth and violence; and household per capita income growth and violence. In all cases, we use cluster-robust standard errors as our panel data are clustered in the primary sampling units (PSUs), a section of a village from where the sample was taken using two-stage stratified sampling scheme.

Other control variables used to account for the shift in household preferences are the change in household size (*DHHSIZE*), the change in household members' average age (*DHHAGE*) and sex (*DHHSEX*) compositions. The significant negative coefficient of *DHHSIZE* may indicate that the households had new-born babies during the period as the per-capita consumption is calculated giving full weight to all members of the household including children. This result is consistent across different models. The increase in a household's average age has a positive significant effect on the growth rate of the household's per capita consumption, while the change in sex composition has no significant effect on the consumption growth, indicating that the non-food consumption growth is not gender sensitive.

Food Consumption

Table 3 presents the continuously updated GMM estimates when the dependent variable is the growth rate of household per capita food consumption (*GRHPCFCON*). Here we use the same set of right hand side variables as before. The coefficient of *GRVPCCON*

[16]In our sample, the share of non-food consumption ranges from 1%–88% with the mean share 35%, implying that, on average, about 65% of total household expenditure goes to food consumption. In the case of low income households, the share of non-food consumption on total expenditure is even smaller indicating that food-consumption may have suffered heavily due to the violent conflict.

[17] One explanation of the insignificant effect of natural disasters on household's consumption growth is that in the event of flooding, government provides relief packages that may prevent household's consumption from falling.

is significantly higher than (what we have in Table 2) for non-food consumption. The coefficient of 0.70 (approximately close to all four models) indicates that for every 10% increase in *GRVPCCON*, in an average, there is 7% increase in the growth rate of per capita household food consumption. The impact of per capita household income is significant and much higher in food consumption than for the case of non-food consumption. This may due to the fact that, in Nepal, a significant fraction of households is below poverty line, and there is an unmet demand for food consumption. When income increases, households tend to spend more on food consumption. NLSS data suggests that in 1995/96, about 47% of the households had less than adequate consumption while that percentage came down to 29% in 2003/04.

Here, we can observe some fundamental differences between the results presented

Table 3: Continuously Updated GMM Estimates (Dep. Var.: Food Exp.)

VARIABLES	Model-B1	Model-B2	Model-B3	Model-B4	Model-B5
grpchinc	0.218***	0.191***	0.191***	0.161**	0.133
	(0.071)	(0.068)	(0.066)	(0.065)	(0.144)
lMtotkill	–0.157***		–0.145***		0.181
	(0.049)		(0.048)		(0.200)
grvpcon	0.718***	0.672***	0.748***	0.675***	0.839***
	(0.061)	(0.065)	(0.061)	(0.065)	(0.102)
dHHsize	–0.053***	–0.057***	–0.057***	–0.060***	–0.058***
	(0.009)	(0.009)	(0.008)	(0.008)	(0.010)
dHHage	0.013***	0.012***	0.012***	0.012***	0.015***
	(0.003)	(0.003)	(0.002)	(0.002)	(0.003)
dHHmale	-0.007	–0.003	0.029	0.018	-0.035
	(0.142)	(0.142)	(0.138)	(0.140)	(0.136)
ltotkill		–0.087**		–0.070*	
		(0.035)		(0.036)	
dflood			–0.055	-0.033	
			(0.041)	(0.046)	
vpcc_mkill					–0.421
					(0.273)
inc_mkill					0.045
					(0.088)
Constant	0.066	0.083*	0.051	0.076	–0.030
	(0.045)	(0.049)	(0.044)	(0.049)	(0.070)
[a]*White-Koenker nR2*	*38.92****	*42.84****	*39.99****	*43.56****	34.87***
[b]*Kleibergen-Paap LM Test*	37.33***	39.68***	52.46***	54.74	24.13**
[c]*Hansen J-Stat.* (χ^2_{15})	17.50	19.53	17.88	19.68	16.59
[d]$\chi 2_{(k)}$ [H0: $\beta_{\Delta \ln C_t^A} = 1$ & $\beta = 0$]	24.20***	27.72***	23.73***	27.95***	2.53
No of Clusters	92	92	92	92	92
Observations	922	922	922	922	922
R-squared	0.572	0.582	0.589	0.597	0.562

Notes: [a, b, c,] and d see Table 2 footnotes. Joint hypothesis of full consumption insurance where $k = 2$ for first two models and $k = 3$ for the last two models; Cluster-robust standard errors are within parentheses; ***, **, and * refer to significant at 1%, 5% and 10% level, respectively.

in Tables 2 and 3. In the case of food consumption, the effect of violence is negative and significant, indicating that household food security may have declined due to the violence. The coefficient of *LMKILL* (-0.157 in Model-B1 and -0.145 in Model-B3) suggests that for every 10% increase in violence due to the Maoist in the given community, the growth rate of food consumption declines by 0.015%. This number is significantly smaller (0.009% in Model-B2 and 0.007% in Model-B4) in the case of *LTOTKILL*, indicating that the negative impact of violence among villagers may be different depending on who was responsible for creating the terror in the village. However, regardless of who killed the people in a village, the impact of violence on household food consumption is negative.

In Model-B5, we include two interaction terms, growth rate of village per capita consumption and violence, and growth rate of household per capita income and violence, in order to capture whether the violence affected the effectiveness of the consumption insurance. It may also be the case that the negative coefficient of violence in the food consumption just captures the effect of the two interaction terms. Our results (Model-B5) indicate that the Maoist violence may have helped the community to safeguard their consumption against the fluctuations in household income. In this model, the joint significant test of full consumption insurance for food consumption cannot be rejected even at 10% level. This is a surprising result but given the actual circumstances on the ground, it seems reasonable. Maoist had adopted a policy of redistributing captured land from absentee landlords to the locals, to be cultivated communally (Nepal *et al* 2011). This redistributive policy adopted by the Maoist may have helped to increase the informal insurance for food consumption.

One might argue that the households may adopt costly and inefficient self-insurance activities during the violent conflict as conflict imposes higher transaction costs and contract enforcement becomes costly if the borrower threatens violence. In the face of uncertainty about the future due to the high intensity violent conflict, it would be hard to find the lender and households may be forced to opt for autarky. In the case of autarky, the household's consumption is more closely related to household income than to the community level aggregate consumption, a scenario that is absent in our data. In both consumption categories (non-food and food) the coefficient of aggregate consumption is positive and significant, and always greater than the coefficient of household income, suggesting that even under high-intensity conflicts, some form of risk sharing is taking place within the villages of Nepal.

Accounting for Fixed Effect

Ravallion and Chaudhuri (1997) criticize the idea of using village level consumption growth (Townsend, 1994) as a measure of aggregate risks. For robustness check of our results presented so far, we also use village fixed effect estimator. Table 4 presents the results from village fixed effect estimators. As we can see, the coefficients of most of GRPCHHINC is insignificant for the non-food consumption, while the coefficient of GRPCHHINC is significant in the case of food consumption indicating that food consumption is not fully insured while non-food consumption is insured better than the food consumption.

Our results may appear surprising at a first glance. We need to understand distribution of

Table 4: Continuously Updated Fixed Effect GMM Estimates

VARIABLES	Non-Food Consumption	Food Consumption
gr_pchinc	0.098	0.153**
	(0.079)	(0.068)
HHsize	–0.067***	–0.059***
	(0.011)	(0.010)
HHage	0.009***	0.014***
	(0.003)	(0.003)
HHmale	0.202	0.104
	(0.145)	(0.126)
Observations	921	921
R-squared	0.129	0.138
# of Villages	91	91

Standard errors in parentheses; ***, **, and * refer to significant at 1%, 5% and 10% level, respectively

total expenditure on food and non-food consumption, and sufficiency of food consumption at the household level. In Nepal, food consumption absorbs about 65% of total household expenditures, and in 1995/96, about 45% households reported that their food consumption was less that adequate. This indicates unmet demand for food consumption for the majority of the households, and household food consumption expenditure would grow with household income.

Figure 1 shows the scatter plot of the growth rate of per capita income vs. growth rate of per capita consumption of the sample households. The plot indicates that there were households who suffered income loss during the study period. We also plot the growth rate of non-food expenditure against food expenditure by the income status (poor vs. non-poor). Figure 2 indicates that there are fewer non-poor households who suffered food consumption loss compared to that of poor households indicating that poor households are more vulnerable to food insecurity.

Vulnerability to Food Consumption

In this sub-section we explore the level of food consumption vulnerability of households based on their characteristics. We identify three such characteristics: socially disadvantaged low caste/ethnicity (*LOW-CASTE*), low education (*LOW-EDU*), and low income (*POOR*).[18] In our sample, about 32% households are from socially disadvantaged, low caste/ethnic groups that are considered as the most deprived social group in Nepal. Over 35% of households have a very low education level, and 50% are relatively poor.[19] We identify these characteristics

[18] Banerjee and Dulfo (2007) document the economic lives of the poor/extremely poor households from 13 different countries. They find that poor have very little access to formal insurance, and consumption is strongly affected by variations in incomes, thus providing evidence of consumption vulnerability of the poor.

[19] We identify the socially disadvantaged households as the so-called 'untouchables', and other households with similar social status. In the NLSS surveys, households are identified based on their caste/ethnicity that we use for identifying the low caste/ethnic households. For expositional purpose, we use two years or less of average household schooling to identify the

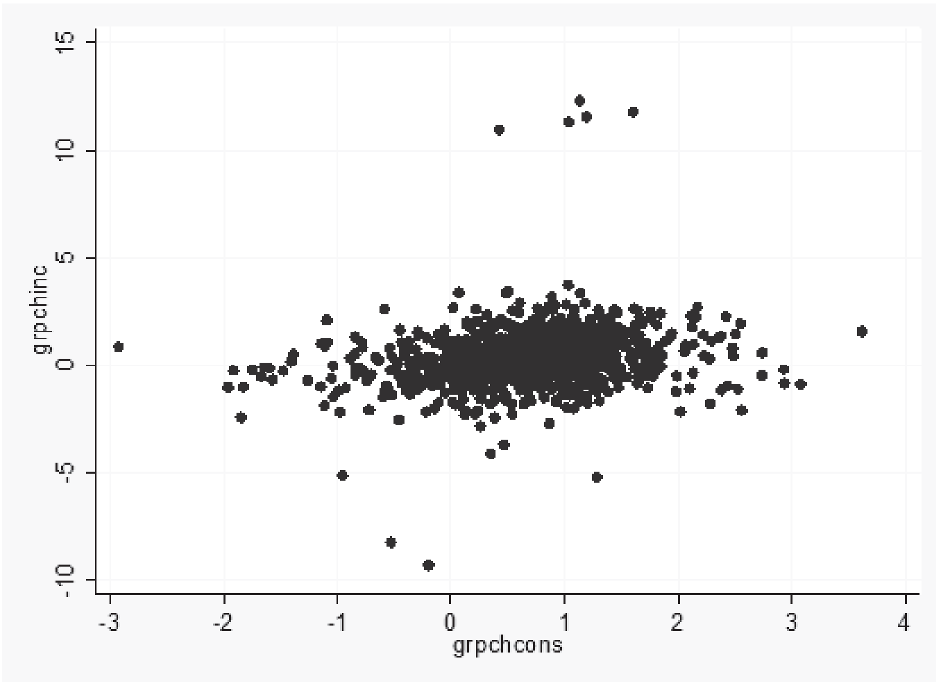
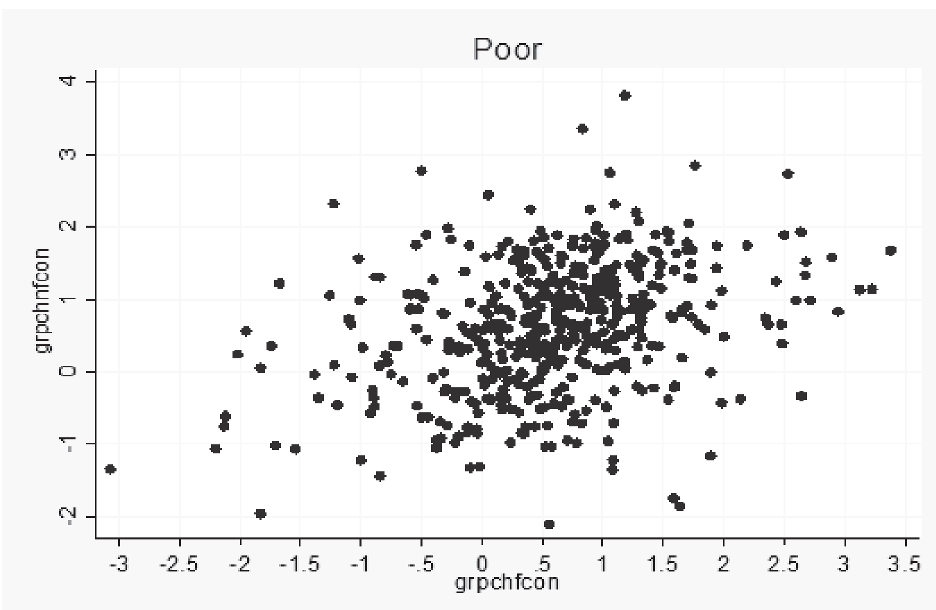


Figure 1: Per-capita Income vs. Consumption Growth Rates, 1994–2004



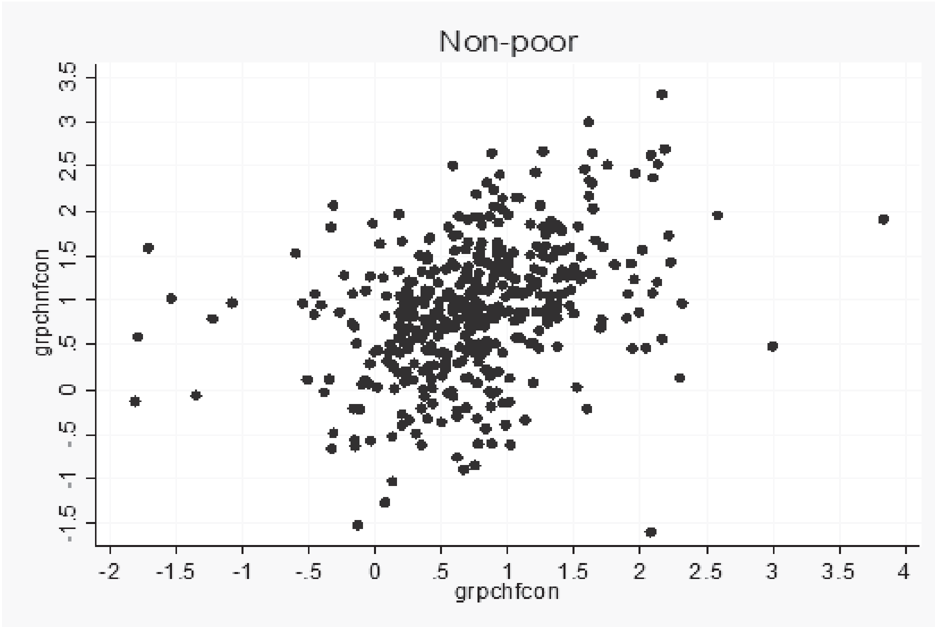


Figure 2: Growth Rate of Per Capita Food vs. Non-food Consumption, 1994–2004

in order to analyze the relative vulnerability of households in food consumption as food expenditure comprises over 65% of overall households' expenditure in our sample. The relative vulnerability is measured in terms of the coefficient of the interaction between growth rate of per capita income and one of the characteristics of the households we just mentioned; and also the coefficient of the interaction between growth rate of village per capita consumption and one of the characteristics of the households. In order to account for the violent conflict, a specific environment, of Nepal, we include the interaction term of village per capita consumption and violence. We estimate the following equation:

$$\Delta \ln C_{ht} = \alpha_0 + \alpha_1 \Delta \ln C_t^A + \alpha_2 \Delta \ln Y_{ht} + \alpha_3 Z_{ht} + \alpha_4 (\Delta \ln Y_{ht} \times Z_{ht}) + \alpha_5 (\Delta \ln C_t^A \times Z_{ht}) + \alpha_6 (\Delta \ln C_t^A \times V) + \alpha_7 \Delta X_{ht} + u_{ht} \qquad (6)$$

where Z_{ht} = 1 if {*LOW-CASTE, LOW-EDU, POOR*}, 0 otherwise. In this setting, the coefficient of the interaction term (α_4) measures the relative vulnerability (if $\alpha_4 > 0$ and significant) of households with chosen characteristics, Z_{ht} while controlling for other variables. In order to avoid multi-colinearity, we use one characteristic at a time when estimating equation (6) as these characteristics are correlated with each other.[20] The rest of the variables used in (6) are already defined in (5).

households with low education level since less than three years of schooling is below the primary level education, and we assume that less than primary level education is equivalent to no education at all. We use two-thirds of the national average income in order to identify the relatively poor households, but our results remain robust to the change in the cut-off income for relatively poor households.

[20] The correlation between low-caste and poor is 0.28; it is 0.22 between low-caste and low-education, and 0.27 between poor and low-education.

Table 5a presents the continuously updated GMM estimates for equation (6). The consumption growth of socially disadvantaged low-caste ethnic group is relatively smaller than the other group, but difference is not significantly different from zero. The coefficient of the interaction term,(*LOW-CASTE*GRPCHINC*), in Model-C1 is negative and significant (α_4 = –0.234) also indicating that the level of food-consumption vulnerability for the low caste/ethnic households is not significantly different from the reference group. The coefficient of the interaction term LOW-CASTE* GRVPCCON is positive and significant, indicating that food consumption is relatively better ensured compared to the reference category.

In order to see if these socially disadvantaged groups are vulnerable to food consumption, we test the hypotheses that LOW-CASTE* GRVPCCON + GRVPCOON = 1 and *LOW-CASTE*GRPHINC +GRPHINC = 0.* The joint significance test statistics (see Table 5a) is for the low-caste groups is highly insignificant indicating that food consumption of this group is better insured compared to low-educated groups and the poor. As shown in Table 5b, the non-food consumption is less vulnerable in all three groups considered here.

Consumption Insurance for Low Caste/Ethnic Households

The evidence so far indicates that low caste/ethnic households, poor households, and households with low level of education are not relatively vulnerable than the other households in terms of food consumption. At first, it may seem contrary to the general expectation as the low caste/ethnic households are socially disadvantaged and discriminated in society in terms of access to resources, education and employment. We further test the consumption insurance hypothesis for the low caste/ethnic households. Given their low social status, those households may have stronger social networks in a given village and may help each other out in times of need. Such type of social insurance through caste/ethnicity-based social networks is observed in India (Munshi and Rosenzweig 2005). If this is the case, then the low caste/ethnic households might have better consumption insurance through their own social networks in a given village.

Table 6 presents the results from CU-GMM estimates for the sub-sample of low caste/ethnic households where the dependent variable is the growth rate of household per capita food consumption. Here, we estimate three models for the sub-sample. As surmised, the coefficients of all variables but aggregate consumption growth are insignificant across all models, and the coefficient is up to 1.28 indicating that a 10% increase in the village level average consumption growth leads to increase per capita consumption growth of low-caste/ethnic group by 12.8%, a very close association between these two variables compared to all other cases. The joint hypothesis of full consumption insurance is not rejected at 5% level, indicating that consumption insurance for low caste/ethnic group is fully insured. This result is somehow similar to Alvi and Dendir (2009) where they observe partial insurance in the case of the most vulnerable social groups in urban Ethiopia.

The results that support full consumption insurance hypothesis in the case of low caste/ethnic households may be due to the fact that those households may have relatively good social networks, and help each other out given their disadvantaged position in Nepalese

Table 5a: Continuously Updated Fixed Effect GMM Estimates for Comparing Vulnerability of Households under Different Characteristics (Dep. Var.: Food Exp.)

Variables	**Model-C1**	**Model-C2**	**Model-C3**
grpchinc	0.309***	0.254***	0.313***
	(0.094)	(0.090)	(0.121)
lMtotkill	–0.174***	–0.182***	–0.174**
	(0.065)	(0.067)	(0.069)
grvpcon	0.524***	0.573***	0.438***
	(0.066)	(0.072)	(0.092)
lowcaste	–0.106		
	(0.082)		
*GRPCHINC*lowcaste*	–0.234***		
	(0.088)		
*GRvpcON*lowcaste*	0.473***		
	(0.094)		
dHHsize	–0.056***	–0.053***	–0.053***
	(0.009)	(0.009)	(0.009)
dHHage	0.009***	0.013***	0.013***
	(0.003)	(0.002)	(0.002)
dHHmale	–0.147	–0.029	0.091
	(0.137)	(0.122)	(0.130)
LOWedu		–0.144*	
		(0.078)	
*GRPCINC*Lowedu*		–0.180**	
		(0.085)	
*grvpcon*lowedu*		0.400***	
		(0.085)	
poor			–0.146
			(0.108)
*grpchinc*poor*			–0.224*
			(0.121)
*grvpcon*poor*			0.462***
			(0.103)
Constant	0.172***	0.139**	0.153
	(0.062)	(0.066)	(0.106)
[a]*White-Koenker* nR^2	38.16**	38.93**	48.77
[b]*Kleibergen-Paap LM Test*	52.63***	35.73***	29.39**
[c]*Hansen J-Stat.* (χ^2_{15})	15.03	16.34	18.99
[d]$\chi^2_{(k)}$ [H0: $\Sigma\beta_{\Delta \ln C_t^A} = 1$ & $\Sigma\beta = 0$]	3.92	8.17**	20.90***
No of Clusters	92	92	92
Observations	922	922	922
R-squared	0.537	0.582	0.561

Notes: [a, b,] and [c] see Table 2 footnotes. Joint hypothesis of full consumption insurance is tested as: GRVPCON + GRVPCON*LOWCAST = 1 & GRPCHINC + GRPCHINC*LOWCAST = 0. Cluster-robust standard errors are within parentheses; ***, **, and * refer to significant at 1%, 5% and 10% level, respectively.

Table 5b: Continuously Updated Fixed Effect GMM Estimates for Comparing Vulnerability of Households under Different Characteristics (Dep. Var.: Non-food Exp.)

VARIABLES	mod510	mod520	mod530
grpchinc	0.118	0.163*	0.188*
	(0.087)	(0.090)	(0.112)
lMtotkill	–0.018	–0.038	–0.060
	(0.065)	(0.066)	(0.061)
grvpcon	0.496***	0.406***	0.461***
	(0.074)	(0.085)	(0.104)
lowcast	0.174*		
	(0.094)		
lowcastinc	–0.011		
	(0.094)		
vpcc_lowcast	–0.299***		
	(0.101)		
dHHsize	–0.067***	–0.063***	–0.063***
	(0.011)	(0.012)	(0.012)
dHHage	0.008***	0.008***	0.007***
	(0.003)	(0.003)	(0.003)
dHHmale	0.193*	0.161	0.176
	(0.115)	(0.119)	(0.115)
edu		0.077	
		(0.107)	
incedu		–0.004	
		(0.097)	
vpcc_edu		–0.085	
		(0.112)	
poor			0.074
			(0.112)
incpoor			–0.095
			(0.119)
vpcc_poor			–0.130
			(0.110)
Constant	0.343***	0.407***	0.370***
	(0.072)	(0.072)	(0.114)
[a]*White-Koenker* nR^2	46.53***	39.54**	44.79***
[b]*Kleibergen-Paap LM Test*	52.63***	37.73***	29.29**
[c]*Hansen J-Stat.* (χ^2_{15})	9.38	8.93	8.77
[d]$\chi 2_{(k)}$ [H0: $\Sigma \beta_{\Delta \ln C_t^A} = 1$ & $\Sigma\beta = 0$]	135.03***	95.15***	123.68***
No of Clusters	92	92	92
Observations	922	922	922
R-squared	0.545	0.535	0.535

Notes: *a*, *b*, and *c* see Table 2 footnotes. Joint hypothesis of full consumption insurance is tested as: GRVPCON+GRVPCON*LOWCAST = 1 & GRPCHINC+ GRPCHINC*LOWCAST=0. Cluster-robust standard errors are within parentheses; ***, **, and * refer to significant at 1%, 5% and 10% level, respectively.

Table 6: Continuously Updated GMM Estimates
(Dep. Var.: Food Exp. for Low Caste/Ethnic HHs)

VARIABLES	Model-D1	Model-D2	Model-D3
grvpcon	1.283***	1.270***	1.239***
	(0.120)	(0.130)	(0.116)
grpchinc	–0.200	–0.262	–0.121
	(0.128)	(0.167)	(0.147)
vpcc_mkill	–0.849	–0.822	–0.718
	(0.532)	(0.573)	(0.499)
inc_mkill	0.083	0.105	0.037
	(0.060)	(0.085)	(0.075)
lMkill	0.459	0.391	0.407
	(0.365)	(0.393)	(0.351)
edu		–0.237**	
		(0.104)	
poor			–0.087
			(0.102)
dHHsize	–0.082***	–0.087***	–0.082***
	(0.017)	(0.019)	(0.016)
dHHage	0.009	0.009*	0.007
	(0.005)	(0.005)	(0.005)
dHHmale	–0.277	–0.365*	–0.352*
	(0.205)	(0.215)	(0.194)
Constant	–0.117	0.017	-0.034
	(0.113)	(0.138)	(0.124)
[a]*White-Koenker* nR^2	29.13*	29.61*	23.22
[b]*Kleibergen-Paap LM Test*	28.64***	21.88**	19.24*
[c]*Hansen J-Stat.* ($\chi 2_{15}$)	5.33	5.46	6.07
$d\chi 2_{(k)}$ [H0: $\beta_{\Delta \ln C_t^A} = 1$ & $\beta = 0$]	5.82	5.29	4.24
No of Clusters	62	62	62
Observations	290	290	290
R-squared	0.515	0.488	0.564

Notes: *a*, *b*, *c*, and d see Table 2 footnotes. Joint hypothesis of full consumption insurance where $k = 2$ for all three models; Cluster-robust standard errors are within parentheses; ***, **, and * refer to significant at 1%, 5% and 10% level, respectively.

society. Another interesting feature of this low-caste group is that they provide services, such as, tailoring, and making households and agriculture tools (blacksmiths) for other households in the community. They provide such services and receive mostly in-kind annual fixed payment. This payment is a part of the household income of the low-caste group which does not change much from year to year. Such payments are not related to the agriculture production or household's income of those households who receive such services as they enter into the payment contract *ex-ante*, and receive the payment for the services after the harvest. This may be the reason why the food consumption of this low-caste group is better insured compared to others.

Coping Mechanisms

In the absence of formal insurance markets, households may smooth their consumption either using local informal institutions or sometimes they may participate in costly self-insurance activities, such as depleting their savings and selling assets in order to protect household consumption during bad times. In our sample, credit market is used to some extent for smoothing household consumption. The share of loans to total household consumption is about 30% for the entire sample of households, and this ratio is about 46% for the sub-sample where households actually borrowed money for several purposes. For those households who borrowed money for consumption purposes (over 35% of households), the average ratio of credit to total consumption is 22.2% (ranging from 0.2% to 206%). Other than borrowing, about 25% of households use self-employment as a coping mechanism, and about the same percentage of households use share-cropping as a measure of consumption smoothing.[21]

One may argue that share-cropping can't be ex-post risk coping strategy because a farmer and a landlord is unlikely to switch from leasehold contract to share contract after the violence. As the violence here is of cumulative of 1996–2004, while sharecropping is for the year 2004, there is enough time to change from leasehold contract to share-contract in our context. In the leasehold contract, a farmer has to pay the agreed upon amount regardless of the crop yields, while in the share-contract, it is not the case. It helps to reduce the risk from crop failure, or low yields.

In this sub-section, we investigate different coping strategies of Nepalese households. Using the panel aspect of the NLSS-II data, we identify three different coping strategies of Nepalese households and analyze how the households are coping with different shocks, such as food deficit, and illness. The NLSS survey directly asked households whether households borrow for consumption, whether they share-cropped, and whether they opted for self-employment. We run three logit regressions in which the dependent variable is the absence or presence of one of the coping strategies that we mention above. We use various shocks as explanatory variables along with, violence in the village, household characteristics, community characteristics, and ecological variable. For household characteristics, we use caste/ethnicity, gender, age, education, and landholdings status (land owner or landless); for community characteristic, we use the presence of various kinds of social networks, such as forest user groups, water user groups, women groups, farmer groups, and credit groups, a perception index of households about the adequacy of public facilities, such as drinking water, electricity, post-office, public-health, road, school, and telephone in the villages; and for ecological variable we use mountain or hills with flat plain as the base category.

As we can see from Table 7, the probabilities of share-cropping and borrowing go down with the presence of violence in the village. These results indicate that cost of enforcing informal contracts may increase due to the deadly violence, and it also indicate a breakdown of the social norms, and social values because of the prolonged violence.

[21] Jacoby and Skoufias (1997) find that during bad years, children from poor family leave schools, a tendency absent in our sample as only six households reported 'school drop-out' out of 960 households surveyed in the sample.

Table 7: Logit Estimates for Household Coping Strategies (Dep Var.: Coping Strategy)

	Coping Strategies					
	Share-Cropping		Self-Employed		Borrowing for Consumption	
Ind. Var.	**Coeff.**	***dy/dx***	**Coeff.**	***dy/dx***	**Coeff.**	***dy/dx***
	–0.152*	–0.025*	–0.004	–0.001	–0.329***	–0.072***
VIOLENCE	(0.091)	(0.015)	(0.084)	(0.014)	(0.081)	(0.018)
	0.301	0.051	–0.803***	–0.122***	–0.040	–0.009
REMITTANCE	(0.190)	(0.033)	(0.217)	(0.030)	(0.173)	(0.038)
FOODDEFICIT	0.246	0.042	0.034	0.006	0.771***	0.177***
	(0.202)	(0.036)	(0.199)	(0.033)	(0.175)	(0.042)
	0.054	0.009	0.243	0.041	0.268	0.060
ILLNESS	(0.193)	(0.032)	(0.187)	(0.033)	(0.175)	(0.040)
	0.781***	0.148***	0.002	0.000	0.208	0.047
FLOOD	(0.242)	(0.051)	(0.277)	(0.046)	(0.229)	(0.053)
LOW CASTE	-0.216	-0.035	1.382***	0.258***	–0.212	–0.046
	(0.251)	(0.040)	(0.262)	(0.051)	90.217)	(0.046)
	0.153	0.026	0.221	0.037	–0.223	–0.048
MID CASTE	(0.219)	(0.488)	(0.229)	(0.039)	(0.194)	(0.042)
	1.030***	0.140***	0.619**	0.091**	–0.026	–0.006
MALE HEAD	(0.264)	(0.029)	(0.276)	(0.035)	(0.203)	90.045)
	–0.037***	-0.006***	–0.022***	–0.004***	–0.018***	–0.004***
HHAGE	(0.008)	(0.001)	(0.007)	(0.001)	(0.006)	(0.001)
	–0.082***	-0.013***	0.090***	0.015***	–0.066***	–0.015***
HHEDU	(0.025)	(0.004)	(0.023)	(0.004)	(0.021)	(0.005)
	0.010	0.002	0.521**	0.093**	–0.169	–0.037
LANDLESS	(0.260)	(0.043)	(0.226)	(0.043)	(0.213)	(0.045)
Wald (χ^2_{19})	102.95***		99.38***		124.37***	
$\hat{y} = \Pr(coping = j)$	0.208		0.207		0.326	
Pseudo R^2	0.103		0.128		0.118	
No of Observations	922		922		922	

Note: Other than various shocks and household characteristics, we also use community characteristics such as, presence of various kinds of social networks (forest user groups, water user groups, women groups and farmer groups), perception index of households about the adequacy of the public facilities (drinking water, electricity, post-office, public-health, road, school, and telephone) in the villages, ecological belts (mountain or hills with flat plain as a base category). Coefficients of these community characteristics as well as the constant term are not included in the table. Cluster-robust standard errors are within parentheses; ***, **, and * refer to significant at 1%, 5% and 10% level, respectively.

When the household members are more educated, they opt for self-employment or they get better jobs than sharing cropping. The probability of borrowing for consumption purposes goes up if the household experiences a food-deficit, since without such borrowing it is very likely that household members would starve. The probability of borrowing for consumption goes down if the household is living in a village where violence has broken out. This makes intuitive sense as violence increases the transaction costs of borrowing. Illness does not seem to have any significant effect on any of these coping strategies.

Instrument Sensitivity

The CUE estimates may be very sensitive to the instruments. Therefore, we re-estimate the different models presented in Tables 2 with a different sub-set of instruments to test the sensitivity of results with respect to the set of instruments. We do so by removing sub-sets of instruments from the original set. The instruments taken out are related to social network indices (farmer index, water index, forest index, and women index). The CUE estimates with the smaller set of instruments are reported in Table 8. We can compare the results from table 2 with Table 8. A closer look reveals that there is no

Table 8: Continuously Updated GMM Est. (Sub-set of Instruments, Dep. Var.: Non-Food Exp.)

VARIABLES	Model-E1	Model-E2	Model-E3	Model-E4	Model-E5
grpchinc	0.129	0.155*	0.124	0.149	0.242
	(0.089)	(0.091)	(0.089)	(0.091)	(0.202)
lMtotkill	0.007		0.008		–0.015
	(0.062)		(0.063)		(0.239)
grvpcon	0.368***	0.369***	0.348***	0.350***	0.311**
	(0.061)	(0.061)	(0.069)	(0.070)	(0.155)
dHHsize	–0.064***	–0.063***	–0.064***	–0.063***	–0.061***
	(0.011)	(0.012)	(0.011)	(0.012)	(0.013)
dHHage	0.008***	0.008***	0.008***	0.008***	0.007**
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
dHHmale	0.140	0.135	0.138	0.133	0.116
	(0.121)	(0.121)	(0.122)	(0.122)	(0.127)
ltotkill		–0.011		–0.010	
		(0.046)		(0.046)	
dflood			0.087	0.087	
			(0.112)	(0.112)	
inc_mkill					–0.078
					(0.095)
vpcc_mkill					0.116
					(0.287)
Constant	0.408***	0.415***	0.427***	0.433***	0.420***
	(0.046)	(0.048)	(0.054)	(0.055)	(0.094)
[a]*White-Koenker nR*^{2}	34.10***	33.22**	37.63***	36.92***	28.36**
[b]*Kleibergen-Paap Wald Stat.*	30.80***	34.18***	31.02***	34.43***	19.46**
[c]*Hansen J-Stat.* (χ^2_{15})	4.45	4.41	4.52	4.49	3.94
[d]$\chi^2_{(k)}$ [H0: $\beta_{\Delta \ln C_t^A} = 1$ & $\beta = 0$]	108.71***	106.98***	104.90***	102.83***	32.35***
No of Clusters	92	92	92	92	92
Observations	922	922	922	922	922
R-squared	0.541	0.539	0.543	0.540	0.528

Notes: *a*, *b*, *c*, and *d* see Table 2 footnotes. Joint hypothesis of full consumption insurance where $k = 2$ for first two models and $k=3$ for the last two models; Cluster-robust standard errors are within parentheses; ***, **, and * refer to significant at 10%, 5% and 1%, respectively.

fundamental (qualitative or quantitative) differences between the new results and the ones presented in tables 2, indicating that our results are not sensitive to a particular sub-set of instruments. The stability of the coefficients and standard errors with the use of different sets of instruments also indicates that our CUE estimates do not suffer weak instrument or identification problems. If identification is weak, then estimated coefficients would be very sensitive to the different subset of instruments (Stock et al. 2002).

6. Conclusion

We analyze the implication of full consumption insurance hypotheses in the face of violent conflict using household surveys data from Nepal. While using traditional indirect measures of shocks, such as household income, we control for the level of violence in the given community, and additional shocks due to natural disasters. As the correlations between all these shocks are not high, we use all shocks simultaneously. In the presence of error heterogeneity and endogeneity of some of the key right hand side variables we use continuously updated GMM estimation that is robust to the weak instruments.

Our results indicate that households are better insured from income shocks in the case of non-food expenditures, but those households are relatively vulnerable in the case of food consumption. In our sample, food consumption absorbs the majority of the household total expenditure, and the presence of violence in the village seems lead to reduce the food consumption growth of households. But, when we interact the violence with the growth rate of per capita income and growth rate of village per capita consumption, the coefficient of the coefficient of the growth rate of per capita household income turns into insignificant and the overall consumption insurance hypothesis cannot be rejected at 10% level or better. This result supports the view that Maoist movement sustained in the rural areas of the Nepal for a decade and they fared well in the election to the Constitution Assembly because they adopted a policy of confiscating the land from absentee and large land holders and provided the land to the villagers (supporters) to farm the land under cooperatives. This arrangement may have helped to smooth the households' consumption in the villages that experience the violence. When analyzed the effect of household income growth on the food consumption growth with such interaction terms, all types of households are vulnerable, but we find that households with low education and with low income are not more vulnerable than the households with higher education level and with higher income level. When we divide the households based on the caste/ethnicity, a variable that is considered as the root cause of several ills in Nepalese society, the socially disadvantaged low caste/ethnicity does not appear to be more vulnerable than the reference caste/ethnicity. It may be the case that the low caste/ethnic households have strong social networks among themselves that may protect them from food consumption vulnerability. Though it is an interesting issue, we do not have the social network information for specific caste/ethnic households for further analysis, and we hope to pursue this issue further.

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APPENDIX A: MICRO-LEVEL ESTIMATION METHODOLOGY

The basic methodology of micro-level estimation (Elbers *et al* 2003) is a technique that links survey with census information and it resembles the small-area statistics of Ghosh and Rao (1994). In the recent years, the technique has been used in Ecuador, Brazil, South Africa, Panama, Madagascar and Nicaragua for mapping poverty. This section summarizes the basic idea of the micro-level estimates.

Assume that per-capita household expenditure, y_{ch}, depends on a vector of observable characteristics, X_{ch}, of the household that are present in both survey and census data sets. Then the linear approximation of the conditional distribution of y_{ch} is given by:

$$\ln y_h = E(\ln y_h \mid X_h) + u_h = X'_{ch}\beta + u_{ch} \qquad [A.1]$$

Where, c refers to the sample cluster (level of aggregation of survey and census data) and u as a vector of disturbances, $u \sim \Im(0, \Sigma)$. By nature, the survey data is just a sample of a total population, therefore, the residual of [A.1] must contain the location variance to allow for a within cluster correlation (spatial autocorrelation) in disturbances as $u_{ch} = \eta_c + \varepsilon_{ch}$, where η is the cluster component and ε is household components. They are independent of each other and uncorrelated with X_{ch}. Generalized least squares (GLS) or Weighted Least Squares (WLS) estimation of [A.1] using household survey data provides the estimates of the complex error structures, $\hat{u}_{ch}$, that can be decomposed as $\hat{u}_{ch} = \hat{\eta}_c + e_{ch}$. Following table provides the variables used for survey-to-census imputation and the first-stage results.

Table A: First Stage Regression Results for Micro-level Estimation

		1995/96		2003/04	
Variables	**Definition**	**Coefficient**	**SE**	**Coefficient**	**SE**
INTERCEPT		8.20***	0.096	8.68***	0.081
AGEHEAD	Age of HH Head	0.00*	0.001	0.00***	0.001
BAHUNCHHETRI	1 if upper caste (Bahun or Chhetri), else 0	0.07**	0.027	0.07***	0.023
CANWRITE	1 if HH head can write, else 0	–0.02	0.022	–0.05**	0.022
CENTRAL	1 if region is central, else 0	0.30***	0.052	0.02	0.041
DAKASA	1 if lower caste (Damai, Kami, or Sarki), else 0	–0.08**	0.036	-0.10***	0.031
EASTERN	1 if region is eastern, else 0	0.35***	0.053	-0.03	0.043
EDUCATION	HH head's years of schooling	0.02**	0.009	0.01**	0.003
FARMERH	1 if HH head is farmer, else 0	0	0.019	-0.04	0.033
FULEWOOD	1 if household uses fuelwood for energy, else 0	–0.03	0.027	–0.07***	0.021
FWESTERN	1 if region is far-western, else 0	–0.04	0.065	0.01	0.057
HHAGE	Average age of all household members	0.01***	0.001	0.01***	0.001
HHEDU	Household average year's of schooling	–0.01	0.009	0.01***	0.003

Variables	Definition	1995/96 Coefficient	1995/96 SE	2003/04 Coefficient	2003/04 SE
HHFARMER	% of household members employed in agriculture	–0.14***	0.047	–0.28***	0.065
HHMONTHWORK	Household's average months of employment	0.02***	0.003	0.03***	0.004
HHSIZE	Average household size	–0.05***	0.004	–0.03***	0.003
HHWRITE	% of all household member who can write	0.43***	0.043	0.43***	0.033
HINDU	1 if household religion is Hindu, else 0	–0.04	0.028	0.02	0.023
LIGHTELECTY	1 if household uses electricity, else 0	0.24***	0.034	0.17***	0.021
MALE	1 if household head is male, else 0	–0.01	0.025	–0.06***	0.02
MARRIED	1 if household head is married, else 0	–0.03	0.025	0.02	0.022
MOUNTAIN	1 if Mountain region, else 0	0.01	0.048	0.12***	0.042
NEWARI	1 if mother tongue is Newari, else 0	0.01	0.068	0.09**	0.042
OWNHOUSE	1 if household owns a house, else 0	–0.02	0.036	0.21***	0.031
OWNLAND	1 if the household owns land, else 0	0.13***	0.026	0.10***	0.022
PERMANENT-HOUSE	1 if the household owns a house with brick/concrete, else 0	0.34***	0.04	0.15***	0.03
RURAL	1 if rural area, else 0	–0.10*	0.06	–0.14***	0.034
SEMIPERMANENT	1 if household owns a house with semi-permanent structure, else 0	0.15***	0.03	–0.05**	0.024
TAMAGURALI	1 if Tamang, Magar, Gurung, Rai, or Limbu, else 0	0.01	0.031	–0.06**	0.027
TERAI	1 if Terai region, else 0	–0.09**	0.045	–0.02	0.033
TERAICASTE	1 if Low caste from Terai, else 0	0.08**	0.033	0.01	0.03
TOILETFLUSH	1 if the household owns flush toilet, else 0	0.22***	0.044	0.22***	0.025
TV	1 if the household owns a TV, else 0	0.19***	0.04	0.57***	0.032
WATERPIPED	1 if the household uses piped water, else 0	0.05**	0.025	0.10***	0.023
WATERWELL	1 if the household uses well-water, else 0	0.05	0.033	0.03	0.03
WESTERN	1 if western region, else 0	0.19***	0.055	0.06	0.044
[1]Adjusted R^2		0.502		0.642	
N		3373		3909	
Sample Clusters		274		326	

[1]The adjusted R^2 is reported from the OLS regression as GLS does not have such a measure.