THE ECONOMIC JOURNAL OF NEPAL, Vol. 43, No. 3 & 4, July - December, 2020, (Issue No. 154) © Cedecon-TU
DOI: https://doi.org/10.3126/ejon.v43i3-4.48035

Estimating Households' Vulnerability to Poverty from an Idiosyncratic Shock: Evidence from Nepal

Naveen Adhikari[1]
Pushpa Raj Shahi[2]
Shreezal GC[3]

Abstract

This paper estimates the vulnerability to the poverty level of the households in Nepal for an idiosyncratic shock using the third round of Nepal Living Standard Survey data. A feasible generalized least square technique is employed to calculate the vulnerability score, further disaggregated between rural-urban areas, provinces, and major caste/ethnic groups. The findings reveal that thirty-two percent of households are highly vulnerable, indicating that they have higher chances of falling below the poverty line due to death, illness, unemployment, and other household-specific shocks. The paper also finds that Karnali and Sudur Paschim Provinces have higher vulnerability than other provinces. Likewise, Dalits and Muslims have higher vulnerability scores compared to other castes / ethnic groups. The estimation suggests that the poverty incidence and vulnerability scores largely overlap, yet the vulnerability scores are consistently higher among all groups indicating a high risk of households falling into poverty. Therefore, it is desirable that major groups' vulnerability profile, in addition to poverty profile, should be constructed and aligns the pro-poor policies to the vulnerable groups to mitigate the risks of pushing such vulnerable households below the poverty line.

Keywords: *Consumption, Poverty, Vulnerability, Idiosyncratic shocks, Nepal*

Introduction

Measuring poverty and knowing its determinants has enticed considerable interest from policymakers and academics in the last four decades. The core to such interest

1 **Mr. Adhikari** is a Lecturer and Ph.D. scholar at the Central Department of Economics, Tribhuvan University. Email: naveen.adhikari@cdec.tu.edu.np.

2 **Mr. Shahi** is Joint Secretary at the Ministry of Industry, Commerce and Supplies, Government of Nepal. Email:pushparajshahi@gmail.com.

3 **Mr. G.C.** (Corresponding author) is a research fellow at Shodhashala-Center for Research and Policy Studies, Baluwatar, Kathmandu, Nepal. Email: shreezalgc@gmail.com

is to prepare the poverty profile, which provides poverty incidence across the social, economic, and geographical groups (Chen & Ravallion, 2010; Ravallion, 2016). Poverty indicators are taken to design anti-poverty programs and help to implement the targeted programs for a pro-poor reach. Despite the utmost importance of poverty indicators, such estimates have limitations on assessing household vulnerability. Since poverty indicators are the ex-post measures of a household's economic status, such indicators do not provide a prior assessment about a household's risk of falling poor in the future for the various kind of adversaries (Chaudhuri, 2003; Chaudhuri et al., 2002; Jalan & Ravallion, 1999).

On the other hand, a household's vulnerability to poverty provides a measure of a household's risks that may result in welfare losses in the future (Chaudhuri, 2003; Moret, 2014; Pritchett et al., 2000). Vulnerability to poverty is defined as a probability that a household may experience a state of poverty in the future. It inherits the inter-temporal nature of the problem and is a forward-looking measure of a household's wellbeing (Chaudhuri et al., 2002; Pritchett et al., 2000). That means a household that is currently non-poor may experience poverty in the future, or a poor household will continue to be poor in the future. The vulnerability to poverty, therefore, measures such likelihoods.

It is expected that household may face different kind of adversaries that results in welfare losses. Based on the magnitude of effect and scope due to a shock, such risks are classified as idiosyncratic and covariate risks (Calvo & Dercon, 2005; Dercon, 2001; Gaiha & Imai, 2014; Philip & Rayhan, 2004). The idiosyncratic shocks affect the individual households, and impacts are unrelated to neighboring households. Example of idiosyncratic shocks includes household-level shocks such as death, injury or unemployment. On the other hand, the widespread covariate shocks are of larger magnitude and affect many households in a locality exposed to similar shocks. Natural disasters, drought, crop failures, and epidemics are examples of such shocks.

Estimating vulnerability to poverty is vital as interventions can be placed in advance to avoid possible welfare loss of the households. Households with higher exposure to adversaries have implications for the choice of income-generating activities, may under-invest in education and health, and tend to take more conventional employment choices (Ajay & Rana, 2005; Morduch, 1999). Therefore, knowing the vulnerability level will help design and implement ex-ante policies such as social protection and insurance schemes to households with higher exposure to risks (Beegle et al., 2018).

Despite such importance, the literature remains scant in the Nepali context. The available literature in Nepal has focused primarily on understanding the drivers and determinants of poverty in Nepal (Acharya & Leon-gonzalez, 2012; Dev Bhatta & Sharma, 2012; Lokshin et al., 2007; Uematsu et al., 2016; Wagle & Devkota, 2018). Recent literature has paid attention to poverty dynamics- a measure that assesses the movement of the household in and out of poverty over time (Adhikari, 2011; Khanal, 2015; Wagle, 2017). However, literature is mainly missing in exploring the household's vulnerability to poverty in Nepal.

In this context, this paper aims to estimate the household's vulnerability level for household-specific shocks in Nepal. The motivation to write this paper is twofold. First, it will compute the vulnerability scores for the households which remain limited in our context. Second, it will compare the vulnerability scores with poverty incidence, examining how poverty and vulnerability complement or contradict each other. Knowing later is essential as most of the targeted programs use the poverty indicator. In contrast, the ex-ante risks of households may appear differently than poverty requiring a different mechanism and set of interventions to mitigate those risks.

Review of Literature

Although some of the determinants of poverty and vulnerability to poverty often overlap, the determinants attributable only to the vulnerability helps to identify the target groups before hand during policy-making. With this merit, the literature on vulnerability has been growing over the years. Such literature has evolved in methodological refinements, data considerations, and coverage (Chaudhuri et al., 2002; Dercon, 2001; Moret, 2014). The literature on vulnerability to poverty can be broadly categorized in terms of theoretical/conceptual measurement of risks (such as welfarist versus expected poverty), data requirements for estimation (cross-sectional vs. panel data), and magnitude of shocks that households may face (idiosyncratic vs. covariate shocks).

The empirical literature has recently surged in estimating the vulnerability to poverty. Several socio-economic covariates are found to determine the household's vulnerability status. For example, Dereje (2013) analyzed the vulnerability to poverty in Ethiopia, where most of the population is dependent on agriculture. About 47.66 percent of the total sample households and 17.93 percent of non-poor were highly vulnerable. The determinants of vulnerability were the large family size and the illiteracy of household heads. They also found that the determinants of ex-ante and ex-post poverty measures were similar in the Ethiopian economy.

In contrast, determinants such as locations and ethnic groups explained vulnerability but not poverty in Vietnam (Imai et al., 2011). Such factors facilitate policymakers in designing interventions targeting specific groups to mitigate the risks of vulnerabilities to poverty. In the context of Nigeria, the rural areas were found to be more vulnerable towards poverty on average, and covariate factors such as harvest failure and changes in prices of output and input were found to push households into poverty. The vulnerability was also explained by idiosyncratic factors such as livestock death, income earners' illness, and harvest failure (Mba et al., 2021).

The vulnerability in poverty is also often analyzed in developing countries concerning the covariate shocks since these shocks tend to affect a large group of households. For instance, the health problems in the Congo Region, such as malaria and HIV, have been prevalent for a long time now. Ouadika (2020) found that health shocks such as severe illness and malaria are significant determinants of vulnerability to poverty in Congo, and the majority of vulnerable households belonged to rural areas. Another form of covariate shock is natural calamities that can push people below the poverty line. A study in Bangladesh showed that climatic shocks have a negative effect on consumption expenditure, arguing that such shocks increase the vulnerability of households towards poverty (Barua & Banerjee, 2020).

Similarly, the vulnerability to poverty was higher (58 % of the population) in the drought-prone lowlands than other Ethiopia regions. Moreover, poverty-induced and risk-induced vulnerability was higher in rural areas than in their urban counterparts. Skoufias et al., (2021) and Nkrumah (2021) estimated the effect of social expenditures in Ghana using four rounds of the Ghana Living Standard Survey and found that the vulnerability to poverty concerning the social spending of the households increased from 38.43 percent in 1999 to 63.81 percent in 2017. Therefore, such covariate shocks that are risk-induced tend to make households vulnerable to poverty.

While the studies focused on measuring monetary poverty in the past, the recent literature uses multidimensional poverty that goes beyond the monetary measures of poverty and is considered a more accurate measure of poverty. Azeem et al., (2018) analyzed various ex-ante and ex-post poverty measures in Pakistan, such as monetary poverty, multidimensional poverty, and their respective vulnerabilities. They found that the ex-ante measures such as vulnerability to monetary poverty (VMP) and vulnerability to multidimensional poverty (VMDP) provide consistent vulnerability results. However, the ex-post measures such as monetary poverty (MP) and multidimensional poverty (MDP) identified different households which fall below the poverty line. The study identified about three-fifth of the households as the vulnerable groups. Households belonging to rural areas and those involved in agriculture were found to be vulnerable to poverty. Likewise, in Latin America, vulnerability to multidimensional poverty was measured using the data from three years 2005/06, 2012, 2017. They found the risk-induced vulnerability to be of more importance than poverty-induced vulnerability. They found the VMP gap decreasing over the three points of time (Prieto, 2018).

Many of the literature provide empirical evidence showing that poverty can be dynamic, i.e., the households that are not poor can be vulnerable, and the vulnerable households may not be poor in the future. Similarly, Schotte et al., (2017) explained how social stratification could be empirically measured and poverty dynamics can be assessed. They used four waves of National Income Dynamics Study (NIDS) data and classified households into five social class groups to explain the poverty dynamics. They found race as the strongest predictor of poverty, where Africans have the highest risk of chronic poverty. Only 20 percent of the South Africans were found to be stably in the middle-class group. About 7.3 percent of individuals classified as poor or vulnerable were pushed to the middle class in 2 years, and it was attributed to the increase in the number of working adults.

The literature found that most of the population vulnerable to poverty belongs to the rural areas. Apart from demographic and socioeconomic characteristics, various idiosyncratic and covariate shocks were found to induce vulnerability to poverty in developing countries. Therefore, the literature suggests that assessing the ex-ante measures of poverty is necessary to identify the vulnerable groups of the population towards poverty beforehand for better policy-making to reduce the incidence of poverty in the future. The shocks can be anticipated through ex-ante measures rather than the ex-post measures so as to minimize the probability of facing poverty in the future.

Methodology

Measurement of Vulnerability

The empirical literatures are growing in estimating the vulnerability to poverty, so is the advancement in the methodology. The improvement has been in terms of data requirements, estimation strategies and theoretical framework over the years. As vulnerability profiles of a household varies across time and space, a panel data structure remains suitable choice (Dercon, 2001). This will help to derive a robust estimate of vulnerability scores and give idea about the inter-temporal nature of the scores (Chaudhuri et al., 2002). However, the availability of high frequency household level data is scarce, especially in developing countries. Even if panel data are available, their coverage is often limited to useful national-level statistics (Pritchett et al., 2000).

In consideration of both non-availability of nationally representative panel data, this paper too employs a method developed by Chaudhuri et al., (2002) and discussed widely in Chaudhuri (2003); Chaudhuri et al., (2002); and Jalan et al., (2002) which relies on a cross-sectional data analysis technique to estimate the household's vulnerability to poverty. This measurement uses the expected poverty approach in estimating the vulnerability scores. In this framework, a household's vulnerability to poverty is defined as the ex-ante risk that will push the household down to the poverty line in the event of shocks. If a household is not currently poor but has a probability of being poor with some shocks, the household is termed as vulnerable.

In order to operationalize the household's vulnerability to poverty, it is necessary to construct a measure of poverty itself. The poverty status of the household can be defined as

$$p_{it} = \frac{u(z)-u(c_{it})}{|u(z)|} \text{ …….. (1)}$$

Here, P_{it} is the poverty status of the i^{th} household in t^{th} period, Z is the pre-specified poverty line, C_{it} is the consumption level of household *h* at time *t*. The function u (.) is assumed to be increasing. If the function u (.) is specified as:

$$\mathrm{u(c)} = \mathrm{z}^{\alpha} - (\max\{0, \mathrm{z} - \mathrm{c}\})^{\alpha} \text{ ……(2)}$$

With, the poverty index corresponds to Fosteret et al. (2010) the FGT class of decomposable poverty measures was introduced in Foster, Greer, and Thorbecke (Econometrica 52:761-776, 1984's measure of poverty defined as:

$$p_{\alpha,it} = \left(\max\left\{0, \frac{z-c_{ht}}{z}\right\}\right)^{\alpha} \text{ ……. (3).}$$

Here, if , the poverty measures reflect the headcount ratio.

Now the vulnerability level (V) of the i^{th} household in t^{th} time period can be defined as the probability that the household will fall below the poverty line at time $t+1$. i.e.

$$V_{it} = \Pr\,(lnc_{it,t+j} < lnz) \;\ldots\ldots\; (4)$$

Where V_{it} is the vulnerability level of i^{th} household in t^{th} period, pr is the probability, $\ln C_{it}$ is the log of consumption of i^{th} household in t^{th} time period, ln Z is the log of poverty line and t+j future time period. Substituting the definition of poverty defined in (3), the vulnerability status of the household is derived as:

$$v_{\alpha,it} = E[p_{\alpha,i,t+1}(c_{h,t+1})|F(c_{h,t+1})]\ldots\ldots (5)$$

$$= \int \left(\max\left\{0, \frac{z-c_{h,t+1}}{z}\right\}\right)^{\alpha} d\,F(c_{h,t+1})$$

$$= F(z)\int_{\underline{c}}^{z} \left(\frac{z-c_{h,t+1}}{z}\right)^{\alpha} \frac{f(c_{h,t+1})}{F(z)}\, \mathrm{d}f(c_{h,t+1})$$

Where, $F(c_{h,t+1})$ is the cumulative density function of the density function e. i. $c_{h,t+1}$.

This derivation suggests that a household's vulnerability depends upon stochastic properties of the inter-temporal consumption flow, which in turn is expected to explain by the observed household characteristics. The consumption prospects are conditional to prevailing characteristics of the household. As suggested in equation (5), the key to estimating parameters is to compute a probability distribution that will show the extent of vulnerability of the household in the future. This is further elaborated in the empirical strategy section.

Empirical Strategy

The core of estimation strategy lies in computing the probability that a household finds itself poor in the future period, depending on the mean consumption and the volatility (e.g. variance) on its consumption stream. Chaudhuri (2003) identifies three steps for the estimation: first, identify the data generation process; second; estimate the relevant parameters regression coefficients from the household survey data; and third, derive future consumption based on the probability distribution of the estimates.

In order to estimate the future consumption prospects, the first step is to link consumption with a set of observable household characteristics. Deaton (1992) and Browning & Lusardi (1996) provide an in-depth review of such determinants in a cross-sectional data setting. These reviews indicate that household consumption level depends on its current wealth and income, expectations about future income and uncertainties about the future, and several other household covariates such as education, caste/ethnic background, geography, and location. Table 1 presents the variables used in this study.

Let us suppose that this relationship is given by equation (1)

$$c_{it} = c(X_i, \alpha i, e_{it}) \ldots\ldots \text{ (6)}$$

Here, Ci is the per capita consumption expenditure. Xi represents a set of observable characteristics,αirepresents the unobserved time-invariant household level effect, and it captures the idiosyncratic shocks that contribute to differential welfare outcomes. The substitution of equation (6) into expression (5) gives a vulnerability level of a household as

$$v_{ht} = E\big(p_{\alpha,i,t+1}(c_{i,t+1})\big|F(c_{i,t+1}|X_i, \alpha i, e_{it}) \ \ldots\ldots \text{ (7)}$$

Equation (7) suggests that the vulnerability level of the household originates from a stochastic process of inter-temporal consumption flow, which in turn is dependent on observed household variables. The future consumption stream of the household, therefore, is conditional to current or existing household characteristics. The key to estimating process is ei, representing a mean zero disturbance term that captures the shocks that contribute to different per capita consumption levels for households that are otherwise observationally equivalent. The data generating process can be estimated as:

$$lnc_i = X_i\beta + e_i \ \ldots\ldots\ldots\ldots \text{ (8)}$$

Here, *ln*ci is the log of per capita income, *Xi* are the set of household characteristics described above (the variables used in the study are presented in Table 1), and he is the stochastic term. Given large variations in consumption expenditure, the log is taken. The relationship between *ei* and set of observed household characteristics then is given by -

$$\sigma_{e,i}^2 = X_i\theta \ \ldots\ldots \text{ (9)}$$

However, the variance is unknown. Due to the absence of the true variance, the parameters β & θ are estimated using a three-step feasible generalized least squares (FGLS) suggested byAmemiya (1977) and widely used in literature. To obtain FGLS estimates, we first run the OLS in equation (8). The predicted values of the residual are then obtained. This is given as:

$$\hat{e}_i^2 = X_i\theta + \varphi_i \ \ldots\ldots \text{ (10)}$$

The predicted values from equation (10) say μˆare used to transform this equation as:

$$\frac{\hat{e}_i^2}{\hat{\mu}} = (\frac{X_i}{\hat{\mu}})\theta + \frac{\varphi_i}{\hat{\mu}} \ \ldots\ldots \text{ (11)}$$

The OLS procedure is repeated for estimating (11), and the predicted value of equation (11) provides an efficient FGLS estimate, say ωˆ of σ_(e,i)^2. This is typically given as:

$$\hat{\sigma}_{e,i} = \sqrt{\hat{\omega}} \ \ldots\ldots\ldots \text{ (12)}$$

The consumption function presented in equation (8) then is transferred to derive the expected mean, variances and vulnerability index. The estimation procedure is to estimate the equation as:

$$\frac{lnc_i}{\hat{\sigma}_{e,i}} = \left(\frac{X_i}{\hat{\sigma}_{e,i}}\right)\beta + \frac{e_i}{\hat{\sigma}_{e,i}} \text{ .... } (13)$$

The expected mean and variance of log of consumption are respectively given by -

$$\hat{E}(lnc_i|X_i) = X_i\hat{\beta} \text{ .... (14), and}$$

$$\hat{V}((lnc_i|X_i) = X_i\hat{\theta} \text{ ....(15).}$$

If the consumption is log normally distributed, the vulnerability index, measured as probability, is given by the cumulative density function of standard normal density as:

$$\hat{v}_i = \Pr(lnc_\iota < \widehat{lnz|X_\iota}) = \emptyset[(lnz - X_i\hat{\beta})/\sqrt{\omega})] \text{ .... (16).}$$

Note that equation (16) yields some level of vulnerability to every household ranging from 0 to 1. Therefore, it is crucial to consider a threshold for categorizing the degree of vulnerability. By this token, every household is vulnerable if the vulnerable threshold is taken to be zero. In contrast, none of the households will be vulnerable if the threshold is assumed to be 1. Two thresholds are often in practice. First, the threshold is taken to be observed the poverty rate. That is, a household is termed vulnerable if the vulnerability index is more than the observed poverty rate. Under this criterion, a household is vulnerable if the vulnerability index is greater than 25 percent - the observed poverty rate for Nepal. Conversely, a household with a vulnerability score of less than 25 percent will be termed non-vulnerable. The second classification considers a threshold of 0.5, implying that a household with a vulnerability index of more than 0.5 will be highly vulnerable. In this study, a mix of both of these classifications is used to classify the vulnerability level. We classify a household with a high vulnerability level if the score is more than 0.5. A household will be identified as relatively vulnerable if the score is between 0.5 and observed poverty rate (0.25 in our case), and low vulnerable if such score is less than 0.25.

Sources of Data

This study uses the third round of the Nepal Standard Living Survey (NLSS - III). This data was collected by the Central Bureau of Statistics (CBS) in 2010 following an internationally accepted living measurement survey adopted by the World Bank. NLSS - III is nationally representative data comprising 5988 households spread across Nepal. Stratification was done covering 75 districts and urban and rural areas to represent the six strata, namely mountains, urban areas of Kathmandu Valley, other urban areas in the Hills, rural his, urban Hills, urban Terai, and urban, rural Terai. These strata were further grouped in 14 strata called the analytical domain comprising mountains, urban areas of the Kathmandu Valley, other urban areas in the Hills, rural eastern Hills, rural central Hills, rural western Hills, rural mid-western Hills, rural far-western Hills, urban Tarai, rural eastern Tarai, rural central Tarai, rural western Tarai, rural mid-western Tarai, and rural far-western Tarai. A probability proportion to size was applied to select the PSUs in the first state. In the second stage, 500 PSUs were selected, covering the 14 sub-strata. In the third stage, 12 households were selected with equal probability in each PSU using computerized household listings. The details of the survey design are discussed in CBS (2011).

The data set provides comprehensive coverage of variables under the study. The information in consumption, household demographic, social and economic characteristics, and access-related information are well captured in the questionnaire. Section-1 captures the household demographic information. Section -2 and Section -3 contain the housing and access to facilities-related information. Section -4 contains migration-related information. These sets provide the information for control covariates of the model employed in this paper. The outcome variable of the study- consumption is illustrated in a detailed way in Section - 5 (food expenses and home production) and section 6 (non-food expenditure). The analysis is carried out at the household level. NLSS - III provides information on 5988 households.

Results and Discussion

Table 1 summarizes the descriptive statistics of the variables used in this study. The average annual per capita consumption is NPR 45738.46, with a high variation among the household as suggested by the standard derivation. A majority of the household heads are male. The average age of household heads is 46, with the minimum and maximum ages being 11 and 95. The average household size is 4.76 out of which about 2.24 members depend on other family members for living on an average. Only 10 percent of household heads were found to be literate. About 65 percent of the households belong to rural areas, whereas 35 percent belong to urban. Most households belong to hilly and Terai areas, whereas only 7 percent of the households belong to the mountains. A majority of the households are found to be concentrated on CDR, i.e., 38 percent and the remaining belong to other development regions. The average distance of households to the paved road is 12.39 km, with a high variation of 28.31 km.

Table 1: Description of Variables and Summary Statistics Used in Analysis (n = 5988)

Variables	Mean	Std. dev.	Min.	Max.
Annual per capita expenditure in NPR	45738.46	42471.25	4541.01	510733.13
Household head is male if 1	0.73	0.44	0	1
Age of household head	46	14.13	11	95
Household Head is literate if 1	0.10	0.29	0	1
Household head is married if 1	0.76	0.43	0	1
Household size	4.76	2.31	1	20
Numbers of dependent members	2.24	1.66	0	13
Household owns an equipment if 1	0.72	0.45	0	1
Household head is self-employed if 1	0.35	0.48	0	1

Household has outstanding loan if 1	0.62	0.49	0	1
Household receives remittance if 1	0.31	0.46	0	1
Landholding in hectare	0.47	0.94	0	24.4
Distance to health post in km	2.27	4	0	132
Distance to haat bazar in km	2.53	11.35	0	600
Distance to paved road in km	12.39	28.31	0	288
Distance to primary in km	0.77	10.69	0	800
Distance to market center in km	7.93	16.81	0	800
Household is from Hill Brahmin / Chhetri if 1	0.34	0.47	0	1
Household is from Hill Janajatis if 1	0.4	0.49	0	1
Household is from Hill Dalits if 1	0.12	0.32	0	1
Household is from Hill Madhesi if 1	0.11	0.31	0	1
Household is from Hill Muslims if 1	0.03	0.18	0	1
Household is from others if 1	0.01	0.09	0	1
Household is from Urban if 1	0.35	0.48	0	1
Household is from Rural if 1	0.65	0.48	0	1
Household is from Mountain if 1	0.07	0.25	0	1
Household is from Hill if 1	0.54	0.5	0	1
Household is from Terai if 1	0.4	0.49	0	1
Household is from EDR if 1	0.21	0.41	0	1
Household is from CDR if 1	0.38	0.49	0	1
Household is from WDR if 1	0.19	0.39	0	1
Household is from MWDR if 1	0.13	0.33	0	1
Household is from FWDR if 1	0.09	0.28	0	1

Source: Author's calculation from NLSS - III, CBS(2011).

As discussed in the methodology, the FGLS technique is used to estimate the vulnerability scores. The OLS and FGLS results are presented in Annex. Since the prime focus of the study is to estimate the vulnerability scores based on these regression results, we do not attempt to explain the regression results in detail. Nevertheless, the results show that household level, access, wealth, and income-related indicators are statistically significant in explaining household consumption expenditure. The sex, education, age, and marital status of the household head are statistically significant. Likewise, the household size and number of dependent members (members with less than 15 or more than 60 years) negatively affect household consumption. The wealth indicators such as landholding and roof type of the house positively affect the consumption, yet ownership of the durable household asset is negatively associated with consumption. The access indicators measured in terms of distance to the health post, primary school, haat bazaar, and nearest market centers are also statistically significant though of varying signs and magnitudes. International remittance is positively associated with consumption. However, there is no statistically significant relationship between consumption and household having a member with a permanent job. The ecological belts and development regions variables are also found statistically significant (Table A1, Annex).

Tables 2, 3, and 4 present the results disaggregated by rural-urban area, provinces, and caste/ethnic group. The mean vulnerability score for households in rural and urban areas are estimated to be 37.56 and 20.03 percent, respectively (Table 2). The observed poverty incidence in these areas is 27.42 and 15.46 percent, respectively. The average vulnerability score can be interpreted as the probability that a household, currently non-poor, might fall below the poverty line in the event of idiosyncratic shocks. As expected, a higher proportion of the households from the rural areas have high vulnerability.

The vulnerability classification further suggests that about 30 percent of the rural households are highly vulnerable compared to 9 percent highly vulnerable households from urban areas. Among the currently poor, 42 percent of rural and 25 percent of urban households will continue to be poor or will further move away from the poverty line in case of adversaries. Among currently non-poor, the highly vulnerable proportion consists of 25 percent of rural and 6 percent urban households. The proportion of relatively and low vulnerable rural households account for 34 percent and 36 percent, respectively. About 30 percent of rural poor are relatively vulnerable compared to 16 percent of the urban households. The figures show that a rural household, regardless of its poverty status, is highly vulnerable than a household of urban residence.

Table 2: Vulnerability Index for Rural & Urban Areas of Nepal (in %, n = 5988)

Indicators	Rural	Urban	Nepal
Observed poverty Incidence	27.43	15.46	25.16
Average Vulnerability score	37.56	20.03	37.01
Highly Vulnerable			
% of total population (a)	30.10	8.52	32.15
% of poor (b)	44.61	25.21	42.04
% of non-poor (c)	24.64	5.47	21.33
Relatively Vulnerable			
% of total population (a)	33.35	16.22	26.25
% of poor (b)	29.80	27.79	28.69
% of non-poor (c)	34.69	14.16	28.11
Low Vulnerable			
% of total population (a)	36.55	75.26	41.61
% of poor (b)	25.58	47.30	37.26
% of non-poor (c)	40.67	80.37	43.06

Source: Author's Calculation based on NLSS - III

Note: The sum of categories across highly vulnerable, relatively vulnerable, and low vulnerable equals 100 %

Table 3 reports the vulnerability status of the households by provinces. Due to a limited number of observations, the figures are reported for the total population only. As expected, the Sudur Paschim and Karnali Provinces have higher average vulnerability scores than other provinces. The average vulnerability scores for Sudur Paschim and Karnali are 54 percent and 47 percent, respectively, followed by Lumbini (35 %), Province - 2 (34 %), Province-1 (33 %), and Gandaki (30 %). The score for Bagmati Province stands at 24 province the lowest among the provinces in Nepal. In terms of vulnerability categories, about 60 province of households in Sudur Pachim are highly vulnerable, followed by 12 percent relatively vulnerable and 25 percent low vulnerable. The Karnali Province, too, witnesses about half of its household being highly vulnerable. For province - 1, Province - 2, and Lumbini Province, about one-third of its population are highly vulnerable. To be precise, such proportions are 35 percent, 34 percent, and 33 percent for Lumbini, Province - 2, and Province - 1, respectively. About one-fourth of the households in Gandaki Provinces are highly vulnerable, while such figures are as low as 14 percent of total households in the Bagmati Province.

Table 3: Vulnerability Level by Provinces (in %, n = 5988)

Provinces	Poverty Incidence	Average Vulnerable Scores	Proportion of Population of Provinces (%)		
			Highly Vulnerable	Relatively Vulnerable	Low Vulnerable
Province - 1	16.74	35.09	30.92	22.48	46.60
Province - 2	26.69	38.53	32.87	33.68	33.45
Bagmati	20.59	26.39	13.79	30.82	55.38
Gandaki	21.46	31.30	23.79	31.30	44.91
Lumbini	24.25	38.24	36.07	24.88	39.05
Karnali	37.65	49.44	50.33	13.45	36.22
Sudur Paschim	45.61	56.31	63.11	12.33	24.57
Total	25.16	37.01	32.15	26.25	41.61

Source: Author's Calculation based on NLSS – III.

The vulnerability scores by major caste/ethnic groups are provided in Table 4. The households from Dalits community (44.25 %) are found to be highly vulnerable, followed by Madhesi others (36.09%) and Muslims (34.87). The *Madhesi* other categories include households other than Terai *Dalits* and *Janajatis.* Likewise, 32.16 percent of households belonging to Hill Brahmin, Chhetri, Thakuri and *Jogi / Sanyashi* are found to be highly vulnerable. The *Janajatis* are found to have a relatively low proportion (26.26) of vulnerable households.

Table 4: Vulnerability Status by Major Caste / Ethnic Groups (in %, n = 5988)

Major Caste / Ethnic Groups	Poverty Incidence	Average Vulnerable Scores	Proportion of Pop^{n} of Caste / Ethnic Groups (%)		
			Highly Vulnerable	Relatively Vulnerable	Low Vulnerable
Hill Brahmin/Chhetri	17.76	37.04	32.16	24.61	43.23
Janajatis	24.36	33.37	26.26	27.59	46.15
Dalits	41.31	43.64	44.25	21.44	34.30
Madhesi Others	28.87	39.89	36.09	29.51	34.39
Muslims	20.18	39.35	34.87	27.29	37.84
Others	12.34	25.16	10.30	36.33	53.36
Total	25.16	37.01	32.15	26.25	41.61

Source: Author's Calculation based on NLSS - III

The results presented Table 2, 3 and 4 offers some insights. First, the vulnerability and poverty estimate largely overlap in Nepal. That means the vulnerability score is high for those categories, where observed poverty is also high. For example, the vulnerability score is high in rural areas, Karnali, Sudurpachim, Province-2, Dalits, Madhesi others, Muslims communities. These are the groups where the population below the poverty line is also high. This can be explained in terms of the lack of economic resources such as land, access to market and service centers, and their high dependence on the agriculture sector. This suggests that disparities in household's economic condition and access have a bearing on vulnerability scores too.

Second, the proportions of highly vulnerable households are higher than the poverty incidence for most groups. For example, the observed poverty incidence for Nepal is 25.16 percent, while the proportion of highly vulnerable households stands at 32.15 percent. This is consistent for both poor and non-poor households, through the vulnerability level of the poor is higher than non-poor is high. That means that the chance of poor remaining poor in the future period is higher than a non-poor falling into poverty. Such chances are 42 percent for the poor compared to nearly half (20 %) for the non-poor. These figures underscore the importance of knowing vulnerable groups in advance to possibly mitigate the household risks for falling into poverty in the future.

Third, observed poverty incidence and vulnerability scores are different for certain groups despite the significant overlaps. For example, the Janajatis have higher poverty rates (24.36 %) compared to Hill Brahmin / Chhetri / Thakuri (17.76), yet the proportion of highly vulnerable *Janajati* households is low (26.26 %) compared to the latter group (32.16 %). Likewise, the proportion of highly vulnerable households are less than the observed poverty rate in the Bagmati Province. These figures suggest that vulnerability and poverty may behave differently, and therefore, different targeting mechanisms may be needed.

While this study is first, to authors' knowledge, of its kind; there are very limited literatures available to compare the findings and check the validity of the estimates. However, the findings largely complement other estimates such as derived from poverty dynamics. For example, Adhikari (2011) found 6 percent of non-poor moved into poor while 14 percent of poor moved out of poverty between 2003/04 - 2010/11. The findings further support a wide variation in transient poverty across the ecological region, development regions and major caste/group. Wagle & Devkota (2018) found that movement of households in and out of poverty is more frequent that otherwise implied by the comparison of poverty ratio over the time. These evidences suggest the poverty dynamics and vulnerability of household to poverty should be explored in greater detail rather than simply relying on the static measure of poverty ratios in designing the pro-poor policies.

Conclusion

This paper estimates the vulnerability score for Nepal. The results are further computed for rural-urban, provinces, and major caste/ethnic groups in Nepal. Using the NLSS - III of data, the only latest information available capturing details of household consumption and other socioeconomic covariates, this paper uses a three-stage feasible generalized least square technique to compute the vulnerability scores. The findings reveal that the overall vulnerability of Nepal is 33 percent implying that they have the probability of falling into poverty for household-level shocks. Such score is invariably high for rural areas (43 %) compared to an urban area (8 %). Such scores remain high for *Dalits* and Muslims compared to other castes/ethnic groups in Nepal. Likewise, Karnali and Sudu Paschim have a higher proportion of highly vulnerable households compared. It reiterates that vulnerability scores are different from the poverty scores implying a different set of targeting is required when it is looked at from an ex-ante assessment perspective.

The findings of the paper offer some policy implications. The vulnerability to the poverty profile of the major groups should be constructed periodic rather than simply relying on the static poverty ratio for a pro-poor policy design. Given that vulnerability scores are higher than the observed poverty incidence, there is a need to widen the scope of pro-poor policies to mitigate the risk of a household falling back to poverty. The social safety net programs could be aligned with the vulnerability profile of the households. Such scores will help in identifying the priority groups or regions to be covered under such programs.

Acknowledgments

The authors would like to acknowledge the use of NLSS - III data. The paper's lead author has purchased the data set as stated in the data use protocol by Central Bureau of Statistics. The authors would like to thank the anonymous reviewers for their feedback and comments to enrich the quality and content of the paper.

References

Acharya, C. P., & Leon-gonzalez, R. (2012). The impact of remittance on poverty and inequality: A micro-simulation study for Nepal. *GRIPS Discussion Paper 11-26*, *3*(9), 1–30. http://www.aessweb.com/journals/September2013/5004/2289

Adhikari, S. R. (2011). Poverty dynamics in Nepal between 2004 and 2011 : An analysis of hybrid dataset. *NRB Economic Review*, 27–40.

Ajay, T., & Rana, H. (2005). Conceptualising and measuring poverty as vulnerability: Does it make a difference?'. *ERD Policy Brief Series No. 41*.

Amemiya, T. (1977). The maximum likelihood and the non-linear three-stage least squares estimator in the general non-linear simultaneous equation model. *Econometrica*, *45*(4), 955. https://doi.org/10.2307/1912684

Azeem, M. M.; Mugera, A. W.; & Schilizzi, S. (2018). Vulnerability to multi-dimensional poverty: An empirical comparison of alternative measurement approaches. *Journal of Development Studies*, *54*(9), 1612–1636. https://doi.org/10.1080/00220388.2017.1344646

Barua, S., & Banerjee, A. (2020). Impact of climatic shocks on household well-being: evidence from rural Bangladesh. *Asia-Pacific Journal of Rural Development*, *30*(1–2), 89–112. https://doi.org/10.1177/1018529120977246

Beegle, K.; Honorati, M.; & Monsalve, E. (2018). Reaching the poor and vulnerable in Africa through social safety nets. *Realizing the full potential of social safety nets in Africa*, 49–86. https://doi.org/10.1596/978-1-4648-1164-7_ch1

Browning, M., & Lusardi, A. (1996). Household saving: Micro theories and micro facts. *American Economic Association*, *34*(4), 1797–1855.

Calvo, C., & Dercon, S. (2005). Measuring individual vulnerability. *University of Oxford Economics Discussion Paper Series*, *229*(229), 1–30. http://www.economics.ox.ac.uk/materials/working_papers/paper229.pdf%5Cnhttp://www.pik-potsdam.de/research/research-domains/transdisciplinary-concepts-and-methods/project-archive/favaia/workspace/documents/kavis-documents/calvo-dercon.pdf

CBS (Central Bureau of Statistics) (2011). *Nepal Living Standards Survey - 2010/11 (NLSS - III): Statistical report*, Central Bureau of Statistics, Kathmandu.

Chaudhuri, S. (2003). Assessing vulnerability to poverty : concepts , empirical methods vand illustrative examples. *Department of Economics*, *Columbia University, New York,* 56. http://info.worldbank.org/etools/docs/library/97185/keny_0304/ke_0304/vulnerability-assessment.pdf

Chaudhuri, S.; Jalan, J.; & Suryahadi, A. (2002). Assessing household vulnerability to poverty from cross-sectional data: A methodology and estimates from Indonesia. *World*, *0102–52*(April), 36. https://doi.org/10.13140/RG.2.1.2126.7360

Chen, S., & Ravallion, M. (2010). China is poorer than we thought, but no less successful in the fight against poverty. *Debates on the Measurement of Global Poverty*, *August*. https://doi.org/10.1093/acprof:oso/9780199558032.003.0015

Deaton, A. (1992). *Understanding consumption*. Oxford University Press.

Dercon, S. (2001). Assessing vulnerability. *chemical and engineering news*, *79*(47), 14. https://doi.org/10.1201/b18632-14

Dereje, F. D. (2013). Assessing households vulnerability to poverty in rural oromiya - Ethiopia. *Journal of Economics and Sustainable Development*, *4*(8), 110–117.

Dev Bhatta, S., & Sharma, S. K. (2012). The determinants and consequences of chronic and transient poverty in Nepal. In *SSRN Electronic Journal* (Issue September). https://doi.org/10.2139/ssrn.1753615

Foster, J.; Greer, J.; & Thorbecke, E. (2010). The foster-greer-thorbecke (FGT) poverty measures: 25 years later. *Journal of Economic Inequality*, *8*(4), 491–524. https://doi.org/10.1007/s10888-010-9136-1

Gaiha, R., & Imai, K. (2014). Measuring vulnerability and poverty: Estimates for rural India, Research Paper No . 2008 / 40. In *Measuring Vulnerability and Poverty Estimates for Rural India Raghav Gaiha 1 and Katsushi Imai 2* (Issue January 2008).

Imai, K. S.; Gaiha, R.; & Kang, W. (2011). Vulnerability and poverty dynamics in Vietnam. *Applied Economics*, *43*(25), 3603–3618. https://doi.org/10.1080/00036841003670754

Jalan, J., & Ravallion, M. (1999). Are the poor less well insured? Evidence on vulnerability to income risk in rural China. *Journal of Development Economics*, *58*(1), 61–81. https://doi.org/10.1016/S0304-3878(98) 00103-5

Khanal, P. (2015). The nature of chronic and transient poverty: analyzing poverty dynamics in Nepal. *Economic Journal of Development Issues*, *15*(1), 103–115. https://doi.org/10.3126/ejdi.v15i1-2.11870

Lokshin, M.; Bontch-Osmolovski, M.; & Glinskaya, E. (2007). Work-related migration and poverty reduction in Nepal. *Policy Research Working Paper*, *4231*, 1–59. https://openknowledge.worldbank.org/handle/10986/7123

Mba, P. N., Nwosu, E. O., & Orji, A. (2021). Effects of exposure to risks on household vulnerability in developing countries: A new evidence from urban and rural areas of Nigeria. *SAGE Open*, *11*(1). https://doi.org/10.1177/21582440211002214

Morduch, J. (1999). Between the state and the market: Can informal insurance patch the safety net? *World Bank Research Observer*, *14*(2), 187–207. https://doi.org/10.1093/wbro/14.2.187

Moret, W. (2014). Vulnerability assessment methodologies: A review of the literature. *Washington, DC: FHI, 360*.

Nkrumah, R. K.; Annim, S. K.; & Afful, B. (2021). Household social expenditure in Ghana: Examining the ex-post effects and vulnerability to poverty. *Social Sciences*, *10*(2), 1–15. https://doi.org/10.3390/socsci10020040

Ouadika, S. A. B. (2020). Health shocks and vulnerability to poverty in Congo. *Humanities and Social Sciences Communications*, *7*(1), 1–8. https://doi.org/10.1057/s41599-020-00674-w

Philip, D., & Rayhan, M. I. (2004). Vulnerability and poverty : What are the causes and how are they related. *ZEF Bonn, center for Development Research, University of Bonn.*

Prieto, J. (2018). Degrees of vulnerability to poverty : A low-income dynamic approach for Chile. *Journal of Economic Inequality*, *13*(2), 1–56.

Pritchett, L.; Suryahadi, A.; & Sumarto, S. (2000). Quantifying vulnerability to poverty. *Policy Research Working Paper*, *September*, 1–31. www.worldbank.org/research/workingpapers.

Ravallion, M. (2016). The economics of poverty: History, measurement, and policy. In *Oxford University Press*. https://doi.org/10.1016/j.soscij.2018.03.005

Schotte, S.; Zizzamia, R.; & Leibbrandt, M. (2017). Social stratification, life chances and vulnerability to poverty in South Africa (Issue 208).

Skoufias, E.; Vinha, K.; & Beyene, B. M. (2021). Quantifying vulnerability to poverty in the drought-prone lowlands of Ethiopia.

Uematsu, H.; Rizal, A.; & Tiwari, S. (2016). Trends and drivers of poverty reduction in Nepal: A historical perspective. *World Bank Policy Research Working Paper*, *7830*(September). https://openknowledge.worldbank.org/handle/10986/25146

Wagle, U. R. (2017). The caste / ethnic bases of poverty dynamics: A longitudinal analysis of chronic and structural poverty in Nepal. *Journal of Development Studies*, *53*(9), 1430–1451. https://doi.org/10.1080/00220388.2016.1224850

Wagle, U. R.; & Devkota, S. (2018). The impact of foreign remittances on poverty in Nepal: A panel study of household survey data, 1996–2011. *World Development*, *110*, 38–50. https://doi.org/10.1016/j.worlddev.2018.05.019.

Annex - A

Regression Results: OLS and FGSL Estimates

Dependent Variable: log of consumption	OLS	FGLS
Household head is male	-0.03* (0.02)	-0.15*** (0.01)
Age of household head	0.00*** (0.00)	0.01*** (0.00)
Household is literate	0.36*** (0.02)	0.48*** (0.01)
Household head is married	0.08*** (0.02)	0.10*** (0.01)
Household size	-0.02*** (0.00)	0.02*** (0.00)
Numbers of dependent members	-0.13*** (0.01)	-0.07*** (0.00)
Household owns an equipment	-0.33*** (0.02)	-0.45*** (0.01)
Land holding in hectare	0.09*** (0.01)	0.08*** (0.00)
Household has galvanized, cement or tiles roof	0.32*** (0.02)	0.30*** (0.01)
Distance to health post in km	-0.01*** (0.00)	0.03*** (0.00)
Distance to haat bazar in km	-0.00* (0.00)	-0.00*** (0.00)
Distance to paved road in km	-0.00*** (0.00)	-0.00*** (0.00)
Distance to primary in km	-0.00 (0.00)	-0.00*** (0.00)
Distance to market_cen in km	-0.00*** (0.00)	0.04*** (0.00)
Household head is self employed	0.13*** (0.01)	0.21*** (0.01)
Household has a member with permanent job	-0.02 (0.03)	-0.01 (0.01)

Household receives international remittance 1 if yes	0.23*** (0.04)	0.32*** (0.02)
Household is from Hill	-0.01 (0.03)	0.17*** (0.01)
Household is from Terai	-0.14*** (0.03)	0.23*** (0.01)
Household is from EDR	0.29*** (0.03)	0.26*** (0.01)
Household is from CDR	0.41*** (0.03)	0.51*** (0.01)
Household is from WDR	0.31*** (0.03)	0.36*** (0.01)
Household is from MWDR	0.23*** (0.03)	0.19*** (0.01)
Constant	10.31*** (0.05)	6.07*** (0.09)
Observations	5,988	5,988
R-squared	0.50	0.93

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