Discussion Paper Series

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Kobe University

DP2015-16

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April 7, 2015

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This Draft: 7th April 2015

Abstract

This study estimates household vulnerability in the Philippines using a three-level and longitudinal linear random-coefficient model whereby vulnerability is decomposed into idiosyncratic and covariate components. Our three-wave panel data covering the period 2003-2009 allow us to analyse poverty situations in both vulnerability and poverty persistence dimensions. A majority of the poor and a third of the non-poor are found to be vulnerable to unobservable shocks, while more susceptible to unobservable idiosyncratic shocks than to covariate shocks. Adequate safety nets should be provided for vulnerable households with less-educated and agriculturally-engaged or jobless heads, rural dwellers, or with more members and/or dependents.

The JEL codes: C23, I32, O15
Key Words: Vulnerability, Poverty, Multilevel Model, Panel Data, the Philippines

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Estimation of Vulnerability to Poverty using a Multilevel Longitudinal Model: Evidence from the Philippines

I. Introduction

During the past decade, the Philippines has faced a lot of challenges including a series of extreme weather events, aftermath of the 2007/08 global financial crisis, and exorbitant and unpredictable rice and fuel prices, among others. The combined impacts of economic and natural shocks could have largely contributed to the slow rate of progress in poverty reduction in the country (NEDA and UNDP, 2010). Earlier studies on poverty argued that a large component of the Philippine poverty is transient poverty, which is characterized by high vulnerability to shocks (Reyes, et al., 2011; 2013). Among the key reasons why many Filipino households do not have the capacity to autonomously mitigate the adverse impacts of shocks include the lack of gainful employment, less access to credit and good-quality health facilities, and lack of institutional support, among others (Reyes and Mina, 2013; Reyes et al., 2009, 2013).

There has been a growing number of studies that emphasized the importance of looking beyond the *ex post* measure of poverty. Assessing the *ex ante* measure of poverty, referred to as vulnerability, and identifying determinants of vulnerability could provide essential inputs to policymakers in addressing the issue of poverty (e.g. Chaudhuri et al., 2002; Pritchett et al., 2000; Zhang and Wan, 2006). In the Philippines, however, only a handful of studies have estimated the vulnerability to poverty of households (Albert, Elloso and Ramos, 2008; Albert, Ramos and del Prado, 2013). Thus far, no study yet has developed an econometric panel data model in estimating Filipino households' vulnerability to poverty.

This study primarily aims to estimate vulnerability to poverty using a three-level and longitudinal linear random-coefficient model applied to a household-level panel data covering recent three waves (2003, 2006 and 2009) in the Philippines. Specifically, it aims to address the following three research questions: (1) Who are vulnerable to poverty in the Philippines?; (2) Which has a greater share in explaining the vulnerability to poverty, idiosyncratic shocks and covariate shocks; and (3) What are the main characteristics of vulnerable households. To our knowledge, this is the first study to estimate the vulnerability to poverty using a multilevel longitudinal model. The advantage of our approach includes (i) decomposing the "ex-ante" vulnerability estimate[1] into idiosyncratic and covariate components, (ii) reducing the possible bias in vulnerability estimates by using a multilevel model (e.g. controlling for possible downward bias of localized/aggregate shocks on the estimated mean of household's welfare measure (Güntherand Harttgen, 2009)) and (iii) characterising household poverty situations in both vulnerability and poverty persistence dimensions by utilising the panel data. Our study thus contributes to the growing but still scarce literature on vulnerability estimation and assessment of impacts of shocks on households' vulnerability. The findings from this study can also serve as critical inputs in crafting more specific policies and programs on poverty reduction.

The structure of the paper is as follows. Section II provides background of the study by reviewing macro economy, major shocks and poverty situation in the Philippines during the period 2003-2009. Section III then surveys the literature on conceptual frameworks of vulnerability as well as on their applications. Data and variables are discussed in Section IV. Section V describes the methodologies for multilevel analysis, estimation of vulnerability to poverty, and vulnerability assessment. Section VI provides estimation results and vulnerability profile of the panel households. Section VII concludes and provides some policy implications.

[1] Ligon and Schechter (2003) decomposed the vulnerability into idiosyncratic and aggregate components using the Bulgarian panel data, but this is essentially an ex-post measure based on the utility function approach.

II. Background

The 2010 Philippine Millennium Development Goals Progress Report noted that the combined impacts of economic, natural and other shocks could have contributed in the slowdown of economic growth and the persistence of poverty in the country. During the past decade, the Philippines have experienced a number of economic, natural and other shocks. One of the most notable shocks is the global financial crisis, which originated in the United States in July 2007. The Philippines felt the impact of the crisis from the second half of 2008 until the end of 2009. Economic analysts argued that workers in the manufactured exports sector, particularly those in electronics and garments sub-sectors, as well as the overseas Filipino workers (OFWs) had borne the brunt of the crisis. During the same period, the country also faced significant rice and fuel price increases. Domestic rice prices had dramatically increased up to 40 percent during the latter part of 2007 until the first half of 2008 due to upsurge in global foodgrain prices.

Aside from economic shocks, the Philippines have also been frequently visited by typhoons and other extreme weather events. Based on historical records of the National Oceanic and Atmospheric Administration, four El Niño and three La Niña episodes had occurred between 2003 and 2009. These had brought an incessant occurrence of destructive typhoons, excessive flooding and even prolonged droughts to the country. Official statistics show that these natural shocks have been getting more frequent and more intensified.

Despite these negative shocks, the Philippine economy had shown remarkable performance during the period 2003-2007 in terms of gross domestic product (GDP) (4.8-6.7%), but the growth decelerated from 2008 (4.2%) to 2009 (1.1%). The main growth driver during the period 2003-2006 had been the services sector, specifically the information and communications technology (ICT)-based tradable services. During the period 2006-2009, however, agriculture and industry sectors had suffered negative growth. The damages caused by a number of devastating typhoons during the same period largely contributed to significant losses in agriculture. The global financial crisis, on the other hand, adversely affected the industry sector, particularly manufacturing (Reyes *et al.*, 2013).

From 2003 to 2009, the Philippine peso appreciated while the net factor income from abroad almost doubled. In general, these trends could have been beneficial to Filipino households. Although peso appreciation lowers the value of remittances received by families of overseas contract workers, it also lowers import prices. This results in cheaper domestic rice, oil products and other basic commodities. Thus, although inflation was not maintained below 3.0 percent after 2003, the growth in prices managed to decelerate from 8.3 percent in 2008 to 4.2 percent in 2009. Apparently, effects of the global financial crisis did not persist. Meanwhile, unemployment rate dropped to 7.5 percent in 2009, from 11.4 percent in 2003.

The poverty situation in the Philippines had not improved significantly during the period 2003-2009. The poverty incidence among households rose by 1.1 percent from 2003 to 2006 (20.0 to 21.1 percent), and then barely changed from 2006 to 2009 (20.9 percent). The magnitude of poor households, on the other hand, grew from 3.3 million in 2003, 3.7 million in 2006, to 3.9 million in 2009. Poverty has been a non-negligible issue that needs to be addressed in the Philippines. However, no studies have characterised the country's poverty situations taking into account the effect of both macro and micro-level shocks in a dynamic context.

III. Literature

Concepts of Vulnerability

Different definitions of vulnerability to poverty have been introduced in the literature. Some definitions highlighted the significant roles that risks and shocks play in explaining the concept of vulnerability. Unlike the *ex post* poverty measure, vulnerability has been described as a forward-looking concept (e.g. Glewwe and Hall, 1998). Pritchett, Suryahadi and Sumarto (2000, p. 2) among others defined vulnerability to poverty as the "risk a household will fall into poverty in the future", involving the comparison between predicted welfare level and a particular poverty threshold.[2] The 2000/01 World Development Report presents a slightly different definition, which is stated as: "the likelihood that a shock will result in a decline in well-being" (World Bank, 2001).[3] Vulnerability to poverty has also been described as a "dynamic concept, involving a sequence of events after a [macroeconomic] shock" (Glewwe and Hall, 1998, p. 182). Glewwe and Hall (1998) used rate of change in household consumption" to measure vulnerability to poverty. Following this definition, Corbacho, Garcia-Escribano and Inchauste (2007, p. 95) characterized vulnerable households as "those that experience larger than average declines in socioeconomic status." Meanwhile, Gallardo (2013, p. 416) defined vulnerability to poverty as "the state of helplessness linked to two types of situations, [namely:] expected poverty [and] downside risk of falling into poverty."[4] Despite the many definitions or concepts of vulnerability to poverty being presented in the literature, researchers have not yet reached a consensus on the most preferred concept. Our definition thus follows the most widely used one, that is, the probability that a household will fall into poverty in the future.

Empirical literature

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[2] This definition and its variants were adopted by many studies, such as, McCulloch and Calandrino (2003), Günther and Harttgen (2009), Chaudhuri, Jalan and Suryahadi (2002), Christiaensen and Subbarao (2005), and Échevin (2013b).

[3] In line of this, some studies have highlighted the causal effect of a shock on a welfare measure in defining vulnerability (e.g. Alem and Söderbom; 2012; Kühl, 2003; Zhang and Wan, 2006). For instance, Kühl (2003) defined vulnerability as the propensity of a household to suffering a significant shock which brings its welfare below a socially accepted level.

[4] Other concepts have been proposed, for instance, by Ligon and Schechter (2003) based on utility function approach; Deng (2008) focusing on the exposure to risk and the capacity to resist downward movements, and Calvo (2008) covering multidimensional aspects.

The literature on vulnerability to poverty has been growing since the early 2000s. Various studies have adopted different measures of vulnerability and approaches on vulnerability estimation. There are also studies that identified the determinants of vulnerability, assessed the impact of different types of shocks on vulnerability, and decomposed poverty into structural and risk-induced, among others. For instance, Pritchett et al. (2000) used the vulnerability as expected poverty (VEP) approach in measuring vulnerability to poverty of Indonesian households. The study found that around 30-50 percent of Indonesian population are vulnerable to poverty, given a 20-percent poverty rate. Chaudhuri et al. (2002) estimated Indonesian households' vulnerability through calculation of the expected value of poverty based on a set of household characteristics. The study found that 45 percent of the Indonesian population are considered as vulnerable, while 22 percent are classified as poor.[5] Calvo (2008) applied multidimensional approach to the 1998-2002 panel data from Peru and found that rural households are more vulnerable to consumption poverty, but less vulnerable to leisure-poverty.

In the context of the Philippines, Chaudhuri (2003) used the 1997/98 data from the Philippines. The findings confirmed that vulnerable households outnumber those who are currently poor. Applying Chaudhuri's (2003) methodology, Albert et al. (2008) estimated Filipino households' vulnerability to poverty using the 1997 cross-sectional data. The estimated proportion of vulnerable households is 54 percent, which is almost twice that of household poverty incidence (28%). Households in rural areas, with unemployed heads, and with large size are those with higher vulnerability to poverty. Following the approach adopted in this study, Albert et al. (2013) evaluated the vulnerability of households before and amidst the global financial crisis using both cross-sectional and panel data. The study

[5] Similar applications include McCulloch and Calandrino (2003) and Zhang and Wan (2006) for China, and Imai, Gaiha and Kang (2011) for Vietnam.

noted that vulnerable households are found to have high opportunity costs in sending children to school and tend to be agricultural.[6]

The literature on vulnerability presents a wide range of methodologies; most common of which are the fixed effects and generalized least squares (GLS) random effects regressions. Only recently, Günther and Harttgen (2009) introduced multilevel modelling in vulnerability estimation, which is later adopted by Échevin (2013a). These studies utilized cross-sectional data and developed a two-level model. The first two studies estimated a random intercept model while the latter estimated a random coefficient model. In addition, Échevin (2013a) included shock variables in the set of observable covariates in the model while the first two studies only included covariates. No study yet has estimated a three- or a higher-level linear random coefficient model using panel data. The present study attempts to fill the gap.

IV. Data and Variables

The household-level panel data utilized in this study is the most recent three-wave panel data generated from the 2003, 2006 and 2009 rounds of the Family Income and Expenditure Survey (FIES) data. After excluding all other ineligible households and/or housing units and taking into account non-responses, the final set of FIES panel households reached around 5,977. The data contain annual information on households' socioeconomic characteristics including income, expenditure, household head profile, and other household characteristics, among others. The FIES data are supplemented with information on labour force, employment and educational attainment of household members generated from the relevant rounds of the Labor Force Survey (LFS), namely: July 2003, January 2004, July 2006,

[6] Other empirical studies on household vulnerability outside the Philippines include Échevin (2013b), Gallardo (2013), Kochar (1995), Glewwe and Hall (1998), Dercon and Krishnan (2000), Christiaensen and Subbarao (2005), Corbacho et al. (2007), Günther and Harttgen (2009), and Alem and Söderbom (2012).

January 2007, July 2009, and January 2010.[7] Since the FIES dataset contains only household-level information, data on aggregate-level characteristics and shocks are sourced from the official statistics released by various government offices.

The official poverty statistics in the Philippines are generated regularly by the National Statistical Coordination Board (NSCB) based on the results of the triennial FIES conducted by the NSO. A Filipino household is considered poor if its per capita income is below the official (provincial) poverty threshold.[8] Since per capita income is the welfare measure used in the generation of official poverty statistics in the country, (log of) per capita income was used as the dependent variable in the empirical model.

The set of covariates considered in this study are selected based on the covariates used in the previous poverty studies on the Philippines (Albert et al., 2008; Tabunda, 2001). Appendix Table 1 reports the definition and summary statistics of the variables we have used. They include household size, dependency ratio, and household head attributes (e.g. sex, age, education, and employment). We also use regional dummies as well as transportation infrastructure index economic and social infrastructure index, and agriculture and utilities index which have been generated using the Principal Component Analysis (PCA) because of strong correlations between some of the variables (see Appendix Table 1 for details). Except for squares of household size and age of head, all main effect variables included in the model are not strongly correlated.[9]

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[7] The set of information provided by the LFS July (January) round matches that of the first (second) round of the FIES.

[8] The official poverty thresholds, both at the regional and provincial level, are estimated by the NSCB using the cost-of-basic needs approach. Per capita national poverty thresholds in 2003, 2006 and 2009 are PhP10,976, PhP13,357 and PhP16,871, corresponding to US$1.543, US$1.682, and US$1.735 per capita per day in 2005 PPP, which range between the two international poverty lines based on US$1.25 and US$2.

[9] There is no pairwise correlation coefficient greater than or equal to 0.60.

The idiosyncratic shocks considered in this study are labour market shocks generated from the LFS[10] (Table 1). It is hypothesized that changes in the labour force structure within a household have a significant impact on household income. In particular, more jobless members could mean lower earning potentials of the household. Similarly, more vulnerable workers[11], more non-permanent wage/salary workers[12] or fewer overseas contract workers (OCWs) could mean lower and/or reduced income. These labour market indicators are mutually exclusive[13]. Pairwise correlations also suggest that none among them are strongly correlated with any covariates or aggregate-level shock variables.[14] The covariate shocks, on the other hand, that are considered in this study are rainfall and price (rice and fuel) shocks. These covariate shocks can have both idiosyncratic and covariate components since their impacts vary across households. Rainfall shocks, specifically heavy rainfall and drought, can have substantial impact on household welfare. This is particularly true in the Philippines where a large proportion of households are engaged in agriculture - the sector that is quite vulnerable to climate-related risks.

(Table 1 to be inserted)

The rice and fuel price shocks are hypothesized to have direct impact on household income and indirect impact on wage and employment. Consider an increase in both rice and fuel prices. Since the bulk of the rice being sold in the market is imported and most of the locally produced rice is for subsistence, the rice price increase might not be felt by local rice farmers. On the other hand, fuel price hike can substantially increase the cost of bringing

[10] Only the primary occupation is considered

[11] "[Based on ILO's (2009) definition,] vulnerable workers [are] those who are self-employed workers (without paid employees) and contributing family workers since they usually have relatively higher risk of getting zero or negative income in the face of economic, natural, and other types of shocks. These workers are also said to have informal work arrangements and less likely to have access to employment benefits or social protection programs." (Reyes and Mina, 2013, pp. 2-3)

[12] Non-permanent wage/salary workers are considered to be informally employed since they have no formal contracts and/or not entitled to employment benefits (Cuevas *et al.*, 2009).

[13] Self-employed and unpaid family members are classified as non-wage/salary workers. This classification of workers is only applied to domestic workers. Thus, OCWs cannot be part of either group.

[14] There is no pairwise correlation coefficient greater than or equal to 0.50

agricultural commodities to the market. It may be the case that the increase in transaction costs due to the fuel price hike might exceed the benefit from increased demand for rice. Another case is that a rice price hike might have an effect on income derived from entrepreneurial activities that use rice as an intermediate input, e.g., rice cakes, rice flour, among others. Decrease in income of households engaged in entrepreneurial activities might have a negative impact on wages and employment of labourers.

V. Methodology

The methodology proposed in Günther and Harttgen (2009) is extended in this study by applying it to short panel data with hierarchical structure and by taking into account observable shocks in income prediction. This section discusses this modified estimation methodology and presents the vulnerability assessment approach that extends Suryahadi and Sumarto (2003).

Multilevel analysis

Multilevel modelling is an appropriate approach if one wants to analyse "hierarchically structured data, with variables defined at all levels of the hierarchy" (Hox, 2000; p. 15). When data contain variables measured at different levels, nesting of lower-level units within higher-level ones produces additional sources of variation that violate the independence and homoskedasticity assumptions. This is also true with panel data, where random fluctuations can occur at repeated measurements leading to serially correlated errors (Gibbons, Hedeker and DuToit, 2010). Traditional regression models are considered not robust against violations of the aforementioned assumptions (Hox, 2000). One of the consequences of not taking into account the hierarchical structure of the data is the misestimation of standard errors, resulting in incorrect conclusions (Dupont and Martensen, 2007).

Unlike traditional regression models, "multilevel models are designed to analyse the relationship between variables that are measured at different hierarchical levels [with lower-levels nested within higher-levels]" (Günther and Harttgen, 2009, p.1225). Multilevel modelling is particularly appropriate if the study aims to assess the impact of idiosyncratic and covariate shocks (Échevin, 2013a). Aside from the fact that a multilevel model can contain explanatory variables defined at different hierarchical levels[15] without violating the independence assumption, it also gives correct standard errors and statistical results (Goldstein, 1999; Günther and Harttgen, 2009). A multilevel model also has the "ability to control for possible downward bias of localized shocks" on the estimated mean of household's welfare measure (*ibid.,* 2009, p.1225). Another advantage is to decompose the relative impacts of household-specific and community-specific [or aggregate-specific] shocks on households' vulnerability (*ibid.,* 2009). A multilevel model can also handle missing observations and/or irregularly spaced measurements in panel data (Gibbons, Hedeker and DuToit, 2010; Günther and Harttgen, 2009).

Three-level linear random coefficient mode

The empirical model estimated in this study is based on the formulation of a "three-level [multilevel] model for change" by Singer and Willett (2003). Let $\ln y_{tij}$ be the log of per capita income of household *i* in province[16] *j* at time *t*, where: level-1 units are the measurement occasions[17] indexed by $t = 1, 2, 3$; level-2 units are the households indexed by $i = 1, \ldots, n_i$; and, level-3 units are the provinces indexed by $j = 1, \ldots, n_j$. The three-level linear random coefficient model for $\ln y_{tij}$ can be written as follows:

[15] The model can also contain both time-varying and time-invariant variables.
[16] Province is the largest unit in the political structure of the Philippines, consisting of municipalities and, in some cases, of component cities (NSCB, 2014).
[17] Under fixed occasion design; wherein all households are measured at the same, regularly spaced time points (Snijders and Bosker, 2012)

$$\ln y_{tij} = \mathbf{x}^T_{(1)tij}\boldsymbol{\beta}_{(1)} + \mathbf{x}^T_{(2)ij}\boldsymbol{\beta}_{(2)} + \mathbf{x}^T_{(3)j}\boldsymbol{\beta}_{(3)} + \mathbf{x}^T_{(1)tij}\boldsymbol{\beta}_{(1)}\boldsymbol{\beta}^{'}_{(2)}\mathbf{x}^{T'}_{(2)ij} + \mathbf{x}^T_{(1)tij}\boldsymbol{\beta}_{(1)}\boldsymbol{\beta}^{'}_{(3)}\mathbf{x}^{T'}_{(3)j}$$

$$+ \mathbf{x}^T_{(2)ij}\boldsymbol{\beta}_{(2)}\boldsymbol{\beta}^{'}_{(3)}\mathbf{x}^{T'}_{(3)j} + \mathbf{Z}^T_{tij}\mathbf{v}_j + \mathbf{Z}^T_{tij}\mathbf{u}_{ij} + e_{tij}\,. \qquad (1)$$

The vector of all household-level and aggregate level (or province level) explanatory variables, $\mathbf{x}^T_{tij} = \left(\mathbf{x}^T_{(1)tij}, \mathbf{x}^T_{(2)ij}, \mathbf{x}^T_{(3)j}\right)$, includes the following: time-varying (level-1) covariates, $\mathbf{x}^T_{(1)tij}$, and their [same-level] interactions; time-invariant (level-2) covariates, $\mathbf{x}^T_{(2)ij}$, and their [same-level] interactions; aggregate-level (level-3) covariates, $\mathbf{x}^T_{(3)j}$, and their [same-level] interactions; and, cross-level interaction terms - the fourth, fifth and sixth terms in equation (1). The vector $\mathbf{x}^T_{(1)tij}$ also contains a variable representing time (Frees, 2004). Associated with vector $\mathbf{x}^T_{tij}$ is $\boldsymbol{\beta}^{\mathrm{T}} = \left(\boldsymbol{\beta}^{\mathrm{T}}_{(1)}, \boldsymbol{\beta}^{\mathrm{T}}_{(2)}, \boldsymbol{\beta}^{\mathrm{T}}_{(3)}\right)$, which is a vector of fixed regression coefficients. The first six terms in equation (1) comprise the fixed part of the model. The last three terms in equation (1) comprise the random part. The seventh and eighth terms involve the matrix $\mathbf{Z}^{\mathrm{T}}_{\mathrm{tij}}$ and the associated vectors of random effects at the household and provincial levels, $\mathbf{u}_{\mathrm{ij}}$ and $\mathbf{v}_j$, respectively where $\mathbf{Z}^{\mathrm{T}}_{\mathrm{tij}} = \begin{bmatrix} 1 & \mathrm{z}_1 \\ 1 & \mathrm{z}_2 \\ 1 & \mathrm{z}_3 \end{bmatrix}$, $\mathbf{u}_{ij} = \begin{bmatrix} u_{0ij} \\ u_{1ij} \end{bmatrix}$, and $\mathbf{v}_j = \begin{bmatrix} v_{0j} \\ v_{1j} \end{bmatrix}$. The matrix $\mathbf{Z}^{\mathrm{T}}_{\mathrm{tij}}$ contains the vectors of 1's for the random intercept and the time variable *z* for the random coefficient. The random effect at the household level $\mathbf{u}_{\mathrm{ij}}$ includes the random intercept u_{1ij} and the random coefficient u_{0ij}, and is assumed as follows: $\mathbf{u}_{\mathrm{ij}} \sim \mathrm{N}\left(\mathbf{0}, \boldsymbol{\Sigma}_{\mathrm{u}}\right)$, where $\boldsymbol{\Sigma}_{\mathrm{u}} = \begin{bmatrix} \sigma^2_{\mathrm{u0}} & \sigma_{\mathrm{u01}} \\ \sigma_{\mathrm{u01}} & \sigma^2_{\mathrm{u1}} \end{bmatrix}$. The random effect at the provincial level $\mathbf{v}_{\mathrm{j}}$ includes the random intercept v_{0j} and the random coefficient v_{1j}, and is assumed as follows: $\mathbf{v}_j \sim \mathrm{N}(\mathbf{0}, \mathbf{\Sigma}_v)$, where $\mathbf{\Sigma}_v = \begin{bmatrix} \sigma^2_{v0} & \sigma_{v01} \\ \sigma_{v01} & \sigma^2_{v1} \end{bmatrix}$. The random intercept is interpreted as the initial status while the random coefficient for the time variable is interpreted as the rate of growth. In this study, only the time variable was allowed to vary both at household and provincial levels. Thus, the model in equation (1) only has the random coefficient for the time variable. Meanwhile, the last term e_{tij} is the level-1 residual and is assumed as follows: $e_{tij} \sim \mathrm{N}(0, \sigma^2_e)$. The composite residual is then defined as: $r_{tij} = \mathbf{Z}^T_{tij}\mathbf{v}_j + \mathbf{Z}^T_{tij}\mathbf{u}_{ij} + e_{tij}$. The corresponding variance-covariance matrix have the following diagonal and off-diagonal elements: diagonal = $\mathbf{Z}^T_{tij}\mathbf{\Sigma}_v\mathbf{Z}_{tij} + \mathbf{Z}^T_{tij}\mathbf{\Sigma}_u\mathbf{Z}_{tij} + \sigma^2_e$; off-diagonal = $\mathbf{Z}^T_{tij}\mathbf{\Sigma}_v\mathbf{Z}_{t'ij} + \mathbf{Z}^T_{tij}\mathbf{\Sigma}_u\mathbf{Z}_{t'ij}$ $\forall t \neq t'$.

The level-1 residual e_{tij} represents the unexplained variance in households' income and captures the impacts of idiosyncratic shocks. The level-2 residuals, $\mathbf{Z}^T_{tij}\mathbf{u}_{ij}$, represent the unexplained variances across households and also capture the impacts of idiosyncratic shocks. The level-3 residuals, $\mathbf{Z}^T_{tij}\mathbf{v}_j$, represent the unexplained variances across provinces and capture the impacts of covariate shocks. It is assumed that "mainly economic variance [are captured by these residuals;] only to a lesser extent measurement error in [income]" (Günther and Harttgen, 2009, p. 1226).

For identification purposes, the covariates $\mathbf{x}^T_{tij}$ are assumed exogenous, with $\mathrm{E}(e_{tij} \mid \mathbf{x}^T_{tij}) = 0$, $\mathrm{E}(\mathbf{u}_{ij} \mid \mathbf{x}^T_{tij}) = 0$ and $\mathrm{E}(\mathbf{v}_j \mid \mathbf{x}^T_{tij}) = 0$. Moreover, the model in equation (1) allows for heteroskedasticity by introducing interactions between the time variable and higher-level residuals. This particular feature of the model is suitable to vulnerability analysis, where variances are usually assumed to be correlated with observable covariates. The presence of time-invariant higher-level residuals in each of the composite residuals also allows for autocorrelation (Graham, Singer and Willett, 2008), although independence of the level-1 residuals can be imposed on the covariance structure (StataCorp, 2011, p. 26).

Estimation method

The restricted (or residual) maximum likelihood (REML) is used in the estimation of the multilevel model in this study for the reasons that follow. First, "REML is preferable with respect to the estimation of the variance parameters" (Snijders and Bosker, 2012, p. 60). This is important because one of the objectives of the study is to assess the impacts of shocks. Second, Maximum Likelihood (ML) estimates fails to comply with consistency and asymptotic unbiasedness as the number of higher-level units becomes smaller (Raudenbush and Bryk, 2002). Third, "REML estimates the variance components while taking into account the loss of degrees of freedom resulting from the estimation of the regression parameters, while ML does not" (Snijders and Bosker, 2012, p. 60). The number of explanatory variables considered in this study, including the interaction terms, at different levels is large enough that can eat up a lot of degrees of freedom. Fourth, REML estimates are more reliable when dealing with unbalanced data, i.e., uneven distribution of lower-level observations nested within higher-level units. The data used in this study is considered unbalanced since the distribution of households nested within provinces is largely uneven.[18]

This study follows the approach outlined in Miller and Hollist (2007) in detecting and correcting attrition bias. Logistic regression is employed on 'stayers' using information from the first wave of panel data. The results of logistic regression indicate the presence of attrition in panel data. Following the proposed two-step procedure by Heckman (1979), we estimate the probit regression model of 'stayers' and compute the inverse Mills ratio (IMR).

[18] We use the xtmixed program in Stata with the independence of level-1 residuals maintained and with heteroskedasticity with respect to the time variable. Because of the unavailability of weights in the panel data used in this study and the fact that "[w]eighted estimation, whether frequency or sampling, is not supported under [REML]," the models estimated in this study were unweighted (StataCorp, 2011, p. 305).

IMR is then included as an independent variable in the multilevel model to account for attrition bias.

Estimation of vulnerability to poverty

The proposed methodology of estimating vulnerability to poverty is an extension of Günter and Harttgen (2009) based on Chaudhuri's (2003) method which involves estimation of expected mean and variance in household's welfare measure using cross-sectional data. In our study, this is further extended by applying it to short panel data with hierarchical structure, and by taking into account observable shocks in the prediction of log of per capita income (Échevin, 2013a).

Following Chaudhuri (2003), it is assumed that the variance of income both at household and aggregate levels, or the impact of idiosyncratic and covariate shocks, depends on a set of household-level and aggregate-level characteristics. Thus, using the linear functional form in equation (1), the squared residuals at different levels are regressed on the aforementioned covariates (excluding the shock variables)[19], as in the following:

$$\mathrm{e}^2_{\mathrm{tij}} = \mathbf{x}^{\mathrm{T}}_{(1)\mathrm{tij}}\boldsymbol{\alpha}_{(1)} + \mathbf{x}^{\mathrm{T}}_{(2)\mathrm{ij}}\boldsymbol{\alpha}_{(2)} + \mathbf{x}^{\mathrm{T}}_{(3)\mathrm{j}}\boldsymbol{\alpha}_{(3)} + \mathbf{x}^{\mathrm{T}}_{(1)\mathrm{tij}}\boldsymbol{\alpha}_{(1)}\boldsymbol{\alpha}'_{(2)}\mathbf{x}^{\mathrm{T}'}_{(2)\mathrm{ij}} + \mathbf{x}^{\mathrm{T}}_{(1)\mathrm{tij}}\boldsymbol{\alpha}_{(1)}\boldsymbol{\alpha}'_{(3)}\mathbf{x}^{\mathrm{T}'}_{(3)\mathrm{j}} + \mathbf{x}^{\mathrm{T}}_{(2)\mathrm{ij}}\boldsymbol{\alpha}_{(2)}\boldsymbol{\alpha}'_{(3)}\mathbf{x}^{\mathrm{T}'}_{(3)\mathrm{j}}; \quad (2)$$

$$\mathrm{u}^2_{0\mathrm{ij}} = \mathbf{x}^{\mathrm{T}}_{(2)\mathrm{ij}}\boldsymbol{\delta}_{(2)} + \mathbf{x}^{\mathrm{T}}_{(3)\mathrm{j}}\boldsymbol{\delta}_{(3)} + \mathbf{x}^{\mathrm{T}}_{(2)\mathrm{ij}}\boldsymbol{\delta}_{(2)}\boldsymbol{\delta}'_{(3)}\mathbf{x}^{\mathrm{T}'}_{(3)\mathrm{j}}; \quad (3)$$

$$v^2_{0j} = \mathbf{x}^{T}_{(3)j}\boldsymbol{\gamma}_{(3)}; \quad (4)$$

$$\mathrm{s}^2_{\mathrm{tij}} = \mathbf{x}^{\mathrm{T}}_{(1)\mathrm{tij}}\boldsymbol{\theta}_{(1)} + \mathbf{x}^{\mathrm{T}}_{(2)\mathrm{ij}}\boldsymbol{\theta}_{(2)} + \mathbf{x}^{\mathrm{T}}_{(3)\mathrm{j}}\boldsymbol{\theta}_{(3)} + \mathbf{x}^{\mathrm{T}}_{(1)\mathrm{tij}}\boldsymbol{\theta}_{(1)}\boldsymbol{\theta}'_{(2)}\mathbf{x}^{\mathrm{T}'}_{(2)\mathrm{ij}} + \mathbf{x}^{\mathrm{T}}_{(1)\mathrm{tij}}\boldsymbol{\theta}_{(1)}\boldsymbol{\theta}'_{(3)}\mathbf{x}^{\mathrm{T}'}_{(3)\mathrm{j}} + \mathbf{x}^{\mathrm{T}}_{(2)\mathrm{ij}}\boldsymbol{\theta}_{(2)}\boldsymbol{\theta}'_{(3)}\mathbf{x}^{\mathrm{T}'}_{(3)\mathrm{j}}; \quad (5)$$

[19] Following Günter and Harttgen (2009) and Échevin (2013a), only random intercepts at levels 2 and 3 are used in equations (4) to (6). Also, similar to Échevin (2013a), only covariates are included; thus, excluding observable shocks as well as the IMR since these are already captured by the estimated residuals.

where: $s_{tij} = e_{tij} + u_{0ij} + v_{0j}$

Using the estimated coefficients from these regressions, the following expected variances are estimated: unobservable idiosyncratic variances $\hat{\sigma}^2_{e_{tij}}$ and $\hat{\sigma}^2_{u_{0ij}}$; covariate variance $\hat{\sigma}^2_{v_{0j}}$; and, total variance $\hat{\sigma}^2_{s_{tij}}$. These variance estimates are then used to assess the impact of idiosyncratic and covariate shocks on households' vulnerability by applying the measure of vulnerability to poverty proposed by Chaudhuri (2003). The conditional probability of being poor, or vulnerability to poverty, of household *i* in province *j* at time *t* is estimated as follows:

$$\hat{V}_{tij} = \hat{P}\left(\ln y_{tij} < \ln \bar{y} \mid \mathbf{x}^{T}_{tij}\right) = \Phi\left(\frac{\ln \bar{y} - \ln \hat{y}_{tij}}{\sqrt{\hat{\sigma}^2_{tij}}}\right) \qquad (6)$$

where: $\Phi(\cdot)$ denotes the cumulative density of the standard normal distribution; $\ln \bar{y}$ is the log of poverty threshold; $\ln \hat{y}_{tij}$ is the expected mean of log of per capita income of household estimated from equation (1); and, $\hat{\sigma}^2_{tij}$ is the expected total variance of unobservable shocks estimated from equation (5). Vulnerability estimation is also conducted separately for different components of variance in income, namely: idiosyncratic variances $\hat{\sigma}^2_{e_{tij}}$ and $\hat{\sigma}^2_{u_{0ij}}$, and covariate variance $\hat{\sigma}^2_{v_{0j}}$.

Vulnerability assessment

Operational assessment of vulnerability depends on the choice of vulnerability threshold ("minimum level of vulnerability above which all households are classified as vulnerable") and the time horizon over which vulnerability is to be assessed. The following equation, as presented in Günter and Harttgen (2009), is used for vulnerability assessment:

$$V^*_{t+k,ij} = 1 - \left[P\left(\ln y_{tij} > \ln \bar{y}\right)\right]^k, \qquad (7)$$

where: $V^*_{t+k,ij}$ is the vulnerability threshold at time *t* to fall below the poverty threshold (at least once) in the next *k* years; $P\left(\ln y_{tij} > \ln \bar{y}\right)$ is the probability of having an income above the poverty threshold in any given year. The vulnerability threshold of 0.5, which is the most commonly used threshold in the empirical literature (e.g., Échevin, 2013b; Zhang and Wan, 2006; Kühl, 2003; and, Pritchett, et al. 2000), is adopted in our study. On the other hand, a time horizon of 3 years is considered since the interval between the waves of the panel data used in this study is 3 years. Thus, given equation (7), the estimated vulnerability threshold at time *t* to fall below the poverty threshold (at least once) in the next 3 years is 0.2063.

The categorization of poverty and vulnerability to poverty of households adopted in this study slightly differs from that in Suryahadi and Sumarto (2003) as it takes into account the longitudinal structure of the data. The poverty status is identified based on the observed income of a household for the given period. A household is considered as poor (non-poor) if its per capita income is below (above) the poverty threshold. As shown in Table 2, the original eight categories are further grouped into four major categories, namely: *chronic poor, moderately poor*, *slightly poor,* and *never poor*. *The chronic poor* are referred to as households that are persistently poor from 2003 to 2009. *The moderately poor* are households that became poor twice during the period 2003-2009. *The slightly poor* are households that became poor only once during the period covered. *The moderately poor* and *the slightly poor* are moving in and out of poverty and can then be collectively known as the *'transient poor'*. Meanwhile, *the never poor* are referred to as households that are consistently non-poor throughout the period.

(Table 2 to be inserted)

The vulnerability status, however, is identified based on the estimated vulnerability to poverty of households. A household is considered as vulnerable (not vulnerable) if its estimated vulnerability to poverty is below (above) the vulnerability threshold. Similar to poverty groups, the major vulnerability groups of households (namely: highly vulnerable, moderately vulnerable, less vulnerable, and not vulnerable) are defined based on the number of times a household is classified as vulnerable. Moreover, the moderately vulnerable and less vulnerable households can be collectively known as 'relatively vulnerable'. Combining the poverty and vulnerability groups together, the following categories are used in generating the vulnerability profile of panel households: (1) chronic poor, highly vulnerable; (2) chronic poor, relatively vulnerable; (3) chronic poor, not vulnerable; (4) transient poor, highly vulnerable; (5) transient poor, relatively vulnerable; (6) transient poor, not vulnerable; (7) never poor, highly vulnerable; (8) never poor, relatively vulnerable; and, (9) never poor, not vulnerable.

VI. Empirical results

This section presents the results of estimation of the three-level linear random coefficient model as well as the vulnerability profile of panel of Filipino households. The results of the Mixed-effects REML regression are presented in Table 3. The estimated model (with random effects) is preferred to an OLS regression model (without random effects) based on the result of the likelihood ratio test. Likelihood ratio tests for additional random parameters also supported the inclusion of random coefficients for the time variable both at the household and provincial levels (Appendix Table 2). Moreover, given that random effects at all levels are included, the full model (containing all the main effect and interaction variables) presented in Table 3 is a big improvement from the intercept-only model in terms of capturing dependencies (particularly at higher levels) in the hierarchical data used in this study (Appendix Table 3). Meanwhile, use of logarithmic form of per capita income resulted in the satisfaction of the normality assumption of income and residuals at all levels (Appendix Figures 1-2). Scatter plots also indicate that outliers would not create a problem in the analysis.

(Table 3 to be inserted)

Some variables are initially significant but became insignificant when they are allowed to interact with other variables. This implies that the combined effects of these and other variables matter more in explaining the variation in income. Thus, main effect variables with significant interaction effects are retained in the model. Inclusion of the inverse Mills ratio is also justified by the significance of its coefficient.

Among the highly significant variables with large main effects are education and employment of household head, dependency ratio, and some regional dummies. Households with more-educated heads tend to have higher per capita income than those with less-educated heads. Less-educated people, in general, have lower employment opportunities and lower wage potential. In many Filipino families, the educational attainment of head (especially if either of the parents) gives an indication of the level of education of other members. Households with heads working in non-agriculture sector are also found to have higher income than those with heads engaged in agriculture or not employed. Reyes and Mina (2013) noted that the majority of the working poor are found in the agriculture sector. Apparently, the working poor have lower education level and thus, lower chance of getting higher-paying jobs. Dependency ratio is also considered as important predictor of household's well-being. The presence of more children in a household means lower proportion of labour force, which then limits the earning potentials of that household. Its negative relationship with income confirmed the findings in many poverty studies. Many of the regional dummies are also found significant. Signs of the coefficients of the regional dummies indicate that on average, incomes of households living in Caraga are among the lowest, if not the lowest. The majority of households living outside Caraga have relatively higher per capita income, except for a few regions, namely: Central Visayas, Northern Mindanao and Davao.

Other main effect variables that are found highly significant are as follows: time; household size and its square; age of head and its square; sex of head; and, some shock variables such as rainfall and fuel price shocks and decrease in the proportion of OCW members. The time variable indicates that, in general, the per capita income of households (in real terms) had increased over time. Signs of squares of household size and age of head and their squares confirm their quadratic relationships with income. Female-headed households are found to have relatively higher income than male-headed ones. Interestingly, many female-headed households in the Philippines are heavily dependent on cash receipts or support (either from abroad or domestic sources)[20]. Remittances (regardless of the source) are usually higher in value because, apparently, Filipinos are willing to leave their households only for better opportunities, e.g., higher-paying jobs.

Moreover, all highly significant shock variables have negative effects on income. Households residing in provinces that experienced rainfall and fuel price shocks tend to have relatively lower income. Because the majority of the working poor are engaged in agriculture (Reyes and Mina, 2013) and the agriculture sector is considered as highly vulnerable to climate-related disasters, frequent occurrence of extreme weather events is expected to reduce income. Many households are also negatively affected by fuel price shocks through a number of channels. For instance, large increases in fuel prices could lead to higher

[20] Based on the FIES data, cash receipts both from abroad and domestic sources comprised around 25 percent of the total income of female-headed households during the period 2003-2009. In contrast, cash receipts comprised only 3 to 5 percent of the total income of male-headed households.

transportation costs faced by entrepreneurs that regularly transport their produce to urban centres, or higher variable costs faced by employers that could mean reduction in workers' wages. Meanwhile, decrease in the proportion of OCW members could mean lower contribution to household income.

A number of interaction variables have significant effects on income. The income disparity between female- and male-headed households, in favour of the former, is particularly true in certain regions like Ilocos and CALABARZON. This income disparity, however, does not hold when the head is highly educated. This finding suggests that more-educated heads have higher chance of getting high-paying occupations without the need to leave their households for better income opportunities.

The positive effect of education on income is more evident in Zamboanga Peninsula and Northern Mindanao. Households with more-educated heads are also not significantly affected by various employment shocks such as: increase in the proportion of working members who are non-permanent wage workers, self-employed or unpaid family workers; or, decrease in the proportion of members who are OCWs. More-educated individuals can easily find a good-paying secondary job, as a way of augmenting their household income, once their households face labour market shocks. In the Philippines, it is not unusual to find highly educated workers having more than one job. The positive effect of education, however, is weakened when interacted with household size. In fact, regardless of whether the head is more-educated or is engaged in a higher-paying sector, an additional member in a household reduces per capita income. The negative effects of household size and dependency ratio on income are evident in Bicol and Zamboanga Peninsula—the regions with high poverty incidence.

Households headed by workers in the non-agriculture sector in Davao region are particularly better-off than those living in Caraga region and those headed by agricultural workers or jobless individuals. Regardless of employment of head, however, households are adversely affected by rainfall shocks. Although an urban/rural dummy appears to have insignificant main effect, its interactions with a number of other variables are found significant. Households located in urban areas are found to have higher income than those living in rural areas. Infrastructure development, like that of irrigation, also strengthens the positive effect of urbanity on household income. Meanwhile, living in urban areas or in regions where poverty incidence is relatively lower and nearer to the country's capital (i.e., Central Luzon, CAR) somehow protects households from shocks like fuel price hike or reduction in the proportion of members who are OCWs.

Vulnerability profile

Estimates of vulnerability to poverty

Decomposition of poverty and vulnerability to poverty (by degree and by source), using the vulnerability estimates and the vulnerability threshold of 0.2063 (calculated using the vulnerability threshold of 0.5 and the time horizon of 3 years), is summarized in Table 4. It should be noted, however, that the estimated vulnerability of a household in this our study is interpreted as the household's probability of falling into poverty at least once in the next 3 years.

(Table 4 to be inserted)

The results show that more than half (57.6%) of panel households are classified as vulnerable at least once in any of the periods covered, i.e., 2003, 2006 and 2009. Around 40 percent of panel households are classified as vulnerable to unobservable covariate shocks while around 60 percent are vulnerable to unobservable idiosyncratic shocks. This finding implies that households have higher probability of falling into poverty when faced with idiosyncratic shocks than when faced with covariate shocks. That is, they are more vulnerable to idiosyncratic shocks probably because the impacts of these shocks are more direct and more specific. The impacts of covariate shocks, on the other hand, are indirect and vary across households. This could point to the poor functioning of the insurance mechanism within communities and the difficulty of anticipating idiosyncratic shocks.

Looking at the different poverty groups, it can be observed that a majority of poor households in the panel are also vulnerable to unobservable shocks. In fact, almost all (98.6%) of the chronic poor and 85 percent of the transient poor are classified as vulnerable in at least one of the periods covered. Only a small percentage of poor households (1.5% of the chronic poor; 13.7% of the transient poor) are not vulnerable. Many of these households have incomes that are not very far from the poverty threshold. On the other hand, a majority of the never poor are not classified as vulnerable in any of the periods covered. Only 37 percent of the never poor are vulnerable, and almost all of them are classified as vulnerable only once or twice.

Notably, more chronic and transient poor households are vulnerable to unobservable idiosyncratic shocks than to unobservable covariate shocks. While this is true, the proportion of chronic poor households that are vulnerable to unobservable idiosyncratic shocks (97.4%) does not largely differ from the proportion of those that are vulnerable to unobservable covariate shocks (90.5%). On the other hand, the difference between the proportions of the two groups of transient poor households (23.1%) is considered substantial. Around 80 percent of transient poor households are vulnerable to unobservable idiosyncratic shocks while only around 60 percent of the transient poor are vulnerable to unobservable covariate shocks. Meanwhile, there are also more never poor households that are vulnerable to unobservable idiosyncratic shocks than to unobservable covariate shocks.

Characteristics of poor and vulnerable households

In order to provide a better understanding of the vulnerability to poverty of Filipino households, a snapshot of the key characteristics of different groups of panel households is summarised in Table 5. The relationships between the household's degree of vulnerability to poverty and their key characteristics are consistently observed in all poverty groups, although negative (positive) characteristics[21] are more evident among the chronic (never) poor. A selective summary is given below.

(Table 5 to be inserted)

One of the most interesting patterns that can be drawn from the table is that household size and dependency ratio increase with the degree of vulnerability. As more members and/or dependents join a household, the estimated vulnerability to poverty of that household tends to increase. Age of head, however, appears to be negatively associated with the degree of vulnerability. This can be explained by the fact that older heads tend to have more stable source of income relative to younger ones. In terms of sex of head, it can be observed that the proportion of female-headed (male-headed) households decreases (increases) as the degree of vulnerability increases, and vice versa. As mentioned earlier, a large proportion of female-headed households are remittance-receiving.

Moreover, education of head is also observed to be negatively related to household's degree of vulnerability. As the degree of vulnerability increases, the proportion of households with less-educated heads increases while the proportion of those with more-educated heads decreases. This particular finding supports Schultz's (1975) hypothesis that more-educated individuals are assumed to be more adaptive to "new circumstances" and thus, have higher coping capability (Glewwe and Hall, 1998; Christiaensen and Subbarao, 2005).

[21] In this study, negative characteristics may include larger household size, higher dependency ratio, lower level of education, more engaged in agriculture, lower access to basic amenities, rural dweller, among others. The positive characteristics, on the other hand, are the opposites of the aforementioned characteristics.

The proportion of households with heads who are working in the non-agriculture sector decreases with the degree of vulnerability while the proportion of those with agriculturally-engaged or jobless heads increases with the degree of vulnerability. In the Philippines, a large proportion of workers in the agriculture sector have been considered as vulnerable, informally employed, or labourers/ unskilled - the “lowest paying occupational group”, (Reyes and Mina, 2013, p. 4). Apparently, many of the agricultural workers have lower level of education, relative to those absorbed in the non-agriculture sector such as industry and services.

In terms of access to basic amenities (i.e., electricity, safe water and sanitary toilet facility) and land ownership, the patterns are clearly observed among chronic and transient poor households. The proportion of households with access to basic amenities or that own a land decreases with the degree of vulnerability. Meanwhile, living in urban areas or in regions with lower poverty incidence is more associated with lower degree of vulnerability. The proportion of urban (rural) households is higher in the ‘not vulnerable’ (‘highly vulnerable’) group.

The results of the Multiple Correspondence Analysis (MCA)[22] embolden the above findings and the findings from those in developing countries. As shown by Quadrant 4 in Figure 1, households with young, less-educated, agriculturally-engaged or jobless heads and those that are living in rural areas are the most commonly associated characteristics of the majority of the poor and highly vulnerable households. In particular, these households are categorized under the following groups of households: chronic poor and vulnerable (either highly or relatively vulnerable); transient poor and relatively vulnerable; and, never poor but highly vulnerable. This finding confirms the agriculture-rural-poverty nexus in the context of

[22] Multiple Correspondence Analysis (MCA) is a descriptive statistical technique used in handling high-dimensional categorical data. It allows one to analyse the pattern of relationships of several nominal variables with several levels or categories. One of its outputs is an *n*-dimensional map that displays the multi-way association among the levels of the variables, i.e., proximity among levels of different nominal variables means that these levels tend to appear together in the observations (Greenacre and Blasius 2006).

the Philippines. Low level of education and lack of gainful employment, especially in rural areas where opportunities are generally limited, are also among the key factors that increase the household's risk of falling into poverty. Meanwhile, workers aged below 20 are not expected to have finished tertiary-level education. Those who are aged 21-24, although have college education, are just starting to build their career and might probably assume the lower-level positions in the organizations where they are working. Interestingly, these findings are consistent with those that can be drawn from Quadrant 2. Urban households and households with heads who are more-educated and/or engaged in non-agriculture employment are most probably the not vulnerable households, regardless of the poverty status.

(Figure 1 to be inserted)

Other households that are poor and, at the same time, vulnerable - i.e., transient poor and highly vulnerable - are commonly larger in size (more than 3 members), have higher dependency ratio (more than half of the members are aged below 15), male-headed, or headed by someone aged between 25 and 64. Quadrant 1 suggests that what makes a transient poor household highly vulnerable is that it might have higher number of members and/or dependents. This group of households in the panel is largely composed of those with male and/or prime-aged heads.

Meanwhile, Quadrant 3 suggests that the non-vulnerability of transient poor households, which are mainly composed of those with female and/or older heads, is that they may be insured by income from remittances and/or pension, respectively. This group of households can also be protected from falling into poverty by maintaining a low number of members, especially those below the working-age. The aforementioned characteristics, however, also describe the group that are never poor but relatively vulnerable. Many factors can be attributed to this finding. One possible explanation is that households with older heads are not always protected against income shocks, particularly those who are no longer working but are not entitled to pension. Another one is that female-headed households may not always be remittance-receiving households, or if remittance-receiving, the remittances are not received on a regular basis or are enough for the household.

VII. Concluding remarks

The vulnerability to poverty of Filipino households is estimated in this study using a three-level longitudinal model and the most recent three-wave household-level panel data in the Philippines. Chaudhuri's (2003) method of estimating households' vulnerability to poverty - which has been widely adopted in a numerous empirical works on vulnerability based on cross-sectional data - has been further extended in our study by applying the multilevel longitudinal model to the panel data. This leads to our specific methodological contributions to the empirical literature on vulnerability, such as, decomposing the "ex-ante" vulnerability estimate into idiosyncratic and covariate components; reducing the possible bias in vulnerability estimates by using a multilevel model; and characterising household poverty situations in both vulnerability and poverty persistence dimensions by utilising the panel data.[23]

Interestingly, the estimated multilevel model contains a set of significant and empirically sound predictors of household income. Consistent with the findings from local poverty studies, profile of heads (i.e., education, employment, sex, and age), composition (i.e., household size and dependency ratio) and location (i.e., urban/rural and region) significantly explain the variation in household income. Observable covariate (i.e., fuel price and rainfall) and idiosyncratic (i.e., labour market) shocks also have significant (negative) impact on household income.

[23] Some of the limitations of the methodology, however, include non-testable assumptions in the estimation of the multilevel model; and unweighted analysis due to unavailability of sampling weights in the panel data.

Further interesting findings can be drawn from the empirical results on our vulnerability estimates. More than half of the panel households are classified as vulnerable at least once in any of the periods covered. Around 40 percent of the panel households are vulnerable to unobservable covariate shocks while around 60 percent are vulnerable to unobservable idiosyncratic shocks. Decomposition of poverty and vulnerability to poverty revealed that the chronic and the transient poor, and even the never poor, are more vulnerable to unobservable idiosyncratic shocks than to unobservable covariate shocks. Impacts of idiosyncratic shocks might have been more direct and more specific compared to those of covariate shocks.

The results of the tabulation and multiple correspondence analysis suggest that highly vulnerable households, regardless of the poverty status, are most commonly characterized by the following: less-educated, agriculturally-engaged or jobless, and very young heads; and, rural dwellers. Other relatively vulnerable households have higher number of members and of dependents.

A number of policy implications can be drawn from the empirical results. Education is an important determinant of both poverty and vulnerability. Highly educated individuals have higher probability of gaining more stable and/or better-paying jobs. Education also serves as an important investment and, at the same time, insurance tool against shocks. More-educated individuals are likely to be more adaptive to varying circumstances and have higher coping capability (Glewwe and Hall, 1998; Christiaensen and Subbarao, 2005). In addition, more-educated heads tend to keep their household size smaller because they better understand the implications of having a larger household. Clearly, policies and programs aimed at human capital investment are very important government interventions, especially in developing countries like the Philippines. Thus, the current plan of expanding the *Pantawid Pamilyang Pilipino* Program (4Ps), the Philippine version of the conditional cash transfer (CCT) program, to ensure that the current children-beneficiaries finish not only elementary but also high school is a good strategy. Extending the coverage to ensure college education and increasing the number of beneficiaries could bring more promising outcomes.

Employment of head is also an important determinant of poverty and vulnerability, and it is closely related to education. Since investment in human capital is more of a long-term strategy, increasing labour demand for less-educated workers is a good short-term strategy. One specific strategy is for the government to help improve the agriculture sector. Increasing agricultural productivity can lead to improved competitiveness, and thus, increased labour demand and/or higher wages. Another specific strategy that the government can adopt is to help increase productivity of non-agriculture industries (i.e., manufacturing industries that participate in the regional production networks) in order to increase their labour absorption.

Remittances and pension can also be considered as risk-mitigating tools. In particular, remittances are said to reflect some measure of diversification of earning sources and can thus insure households against shocks. In the same manner, pension is considered as a stable source of income and could serve as insurance against labour market and other shocks. Meanwhile, the government should provide adequate safety nets to poor and vulnerable households in order to protect them against various economic, natural and other shocks. These could include employment and skills training programs, which can be implemented on a regular basis and can be intensified in times of crisis.

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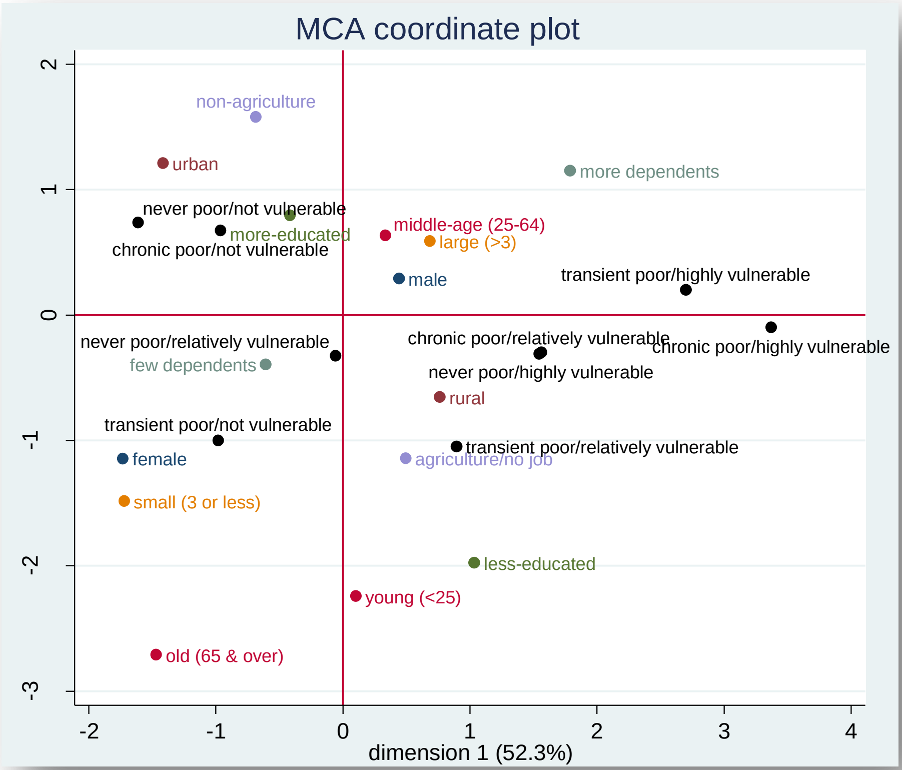
Figure 1. Multiple Correspondence Analysis two-dimensional map: poverty and vulnerability status of panel households



Source: Author's estimates using the 2003-2006-2009 FIES panel data.

TABLE 1
Definition of idiosyncratic and covariate shock variables

Shock variable	Definition
Idiosyncratic shocks	
More jobless	1 if the proportion of members who are either unemployed or not in the labor force increased during the year; 0 otherwise
More vulnerable workers	1 if the proportion of employed members who are either self-employed or unpaid family workers increased during the year; 0 otherwise
More non-permanent wage workers	1 if the proportion of employed members who are non-permanent wage/salary workers increased during the year; 0 otherwise
Fewer OCWs	1 if the proportion of members who are overseas contract workers decreased during the year; 0 otherwise
Covariate shocks	
Rainfall shock	1 if the percentage deviation from normal rainfall went beyond the 80-120% range more than 50 percent of the time during the year*; 0 otherwise
Rice price shock	1 if the annual average of rice inflation rate is 20% and above; 0 otherwise
Fuel price shock	1 if the annual average of fuel inflation rate is 20% and above; 0 otherwise

* 'Normal rainfall' is the average amount of rainfall for the period 1971-2000. Annual figures on percentage deviation could have been generated but it is not expected to capture the varying impacts of rainfall shocks throughout the year. An all-year round occurrence of slightly above-normal rainfall usually has more adverse impact on a rural agricultural area and a low-lying urban area than a half-year occurrence of highly above-normal rainfall.

TABLE 2

Categorization of poverty and vulnerability to poverty of households

Poverty status

Original category			Major Category	
PPP	-	Poor in 2003, 2006 and 2009	Chronic poor	
PPN	-	Poor in 2003 and 2006; Non-poor in 2009	Moderately poor	Transient poor
PNP	-	Poor in 2003 and 2009; Non-poor in 2006		
NPP	-	Non-poor in 2003; Poor in 2006 and 2009		
PNN	-	Poor in 2003; Non-poor in 2006 and 2009	Slightly poor	
NPN	-	Non-poor in 2003 and 2009; Poor in 2006		
NNP	-	Non-poor in 2003 and 2006; Poor in 2009		
NNN	-	Non-poor in 2003, 2006 and 2009	Never poor	

Vulnerability status

Original category			Major Category	
VVV	-	Vulnerable in 2003, 2006 and 2009	Highly vulnerable	
VVN	-	Vulnerable in 2003 and 2006; Not vulnerable in 2009	Moderately vulnerable	Relatively vulnerable
VNV	-	Vulnerable in 2003 and 2009; Not vulnerable in 2006		
NVV	-	Not vulnerable in 2003; Vulnerable in 2006 and 2009		
VNN	-	Vulnerable in 2003; Not vulnerable in 2006 and 2009	Less vulnerable	
NVN	-	Not vulnerable in 2003 and 2009; Vulnerable in 2006		
NNV	-	Not vulnerable in 2003 and 2006; Vulnerable in 2009		
NNN	-	Not vulnerable in 2003, 2006 and 2009	Not vulnerable	

TABLE 3
Results of the Mixed-effects REML regression

Dependent variable: Log of per capita income

Variable	Parameter
Fixed part	
Time	0.0530 (0.0043)***
Household composition	
Household size	-0.1651 (0.0081)***
Square of household size	0.0066 (0.0006)***
Dependency ratio	-0.4570 (0.0238)***
Household head profile	
Sex	-0.0587 (0.0157)***
Age	0.0141 (0.0023)***
Square of age	-0.0001 (0.0000)***
Educational attainment	
At least elementary graduate	0.1170 (0.0114)***
At least secondary graduate	0.2084 (0.0407)***
At least college graduate	0.9563 (0.0824)***
Employment	0.1637 (0.0308)***
Location	
Urban/rural	0.0284 (0.0426)
Region[a/]	
Ilocos	0.2860 (0.1184)*
Cagayan	0.3605 (0.1030)***
Central Luzon	0.1476 (0.1010)
CALABARZON	0.2989 (0.1108)**
MIMAROPA	0.0974 (0.0985)
Bicol	0.1934 (0.1058)
Western Visayas	0.0794 (0.0999)
Central Visayas	-0.1741 (0.1126)
Eastern Visayas	0.2769 (0.0980)**
Zamboanga Peninsula	0.0227 (0.1254)
Northern Mindanao	-0.0099 (0.1050)
Davao	-0.018 (0.1043)
SOCCSKSARGEN	0.1009 (0.1024)
Cordillera Administrative Region (CAR)	0.0489 (0.1452)
Autonomous Region in Muslim Mindanao (ARMM)	0.4305 (0.1406)**
Other aggregate-level variables	
Transportation infrastructure index	0.0245 (0.0157)
Economic and social infrastructure index	0.0084 (0.0082)
Irrigation development	0.0008 (0.0008)
Agriculture index	-0.0190 (0.0120)
Utilities index	0.0037 (0.0074)
Idiosyncratic shocks	
More jobless	0.0075 (0.0084)
More vulnerable workers	-0.0031 (0.0076)
More non-permanent wage workers	-0.0060 (0.0096)
Less OCWs	-0.1583 (0.0234)***

Figures in parentheses are standard errors; *** p<0.001, ** p<0.01, * p<0.05.

TABLE 3
(continued)

Variable	Parameter
Covariate shocks	
Rainfall shock	-0.0565 (0.0161)***
Rice price shock	-0.0300 (0.0653)
Fuel price shock	-0.0761 (0.0114)***
Interactions	
Sex of head × Education of head (at least college graduate)	0.2025 (0.0412)***
Sex of head × Ilocos	-0.1391 (0.0438)**
Sex of head × CALABARZON	-0.1326 (0.0414)**
Education of head (at least secondary graduate) × More non-permanent wage workers	0.0581 (0.0187)**
Education of head (at least secondary graduate) × Less OCWs	0.1056 (0.0367)**
Education of head (at least college graduate) × Household size	-0.1283 (0.0278)***
Education of head (at least college graduate) × Square of household size	0.0099 (0.0024)***
Education of head (at least college graduate) × Zamboanga Peninsula	0.2722 (0.1057)*
Education of head (at least college graduate) × Northern Mindanao	0.2241 (0.0883)*
Education of head (at least college graduate) × More vulnerable workers	0.1151 (0.0303)***
Employment of head × Household size	-0.0114 (0.0038)**
Employment of head × Davao	0.1120 (0.0422)**
Employment of head × Rainfall shock	-0.0526 (0.0237)*
Household size × Bicol	-0.0277 (0.0081)**
Dependency ratio × Zamboanga Peninsula	-0.2605 (0.0939)**
Urban/rural × CALABARZON	0.1122 (0.0547)*
Urban/rural × Bicol	0.1513 (0.0582)**
Urban/rural × Western Visayas	0.1507 (0.0515)**
Urban/rural × Central Visayas	0.1041 (0.0530)*
Urban/rural × Zamboanga Peninsula	0.3492 (0.0736)***
Urban/rural × Davao	0.2344 (0.0713)**
Urban/rural × Irrigation development	0.0033 (0.0007)***
Urban/rural × Fuel price shock	0.0288 (0.0123)*
Central Luzon × Fuel price shock	0.0538 (0.0191)**
CAR × Less OCWs	0.2570 (0.1028)*
Inverse Mills Ratio (IMR)	-0.3023 (0.0502)***
Intercept	0.9174 (0.1187)
Random part	
Province-level	
Variance (Random slope)	0.0003 (0.0001)
Variance (Random intercept)	0.0211 (0.0057)
Covariance (Random slope, Random intercept)	-0.0012 (0.0006)
Household-level:	
Variance (Random slope)	0.0024 (0.0003)
Variance (Random intercept)	0.1989 (0.0074)
Covariance (Random slope, Random intercept)	-0.0061 (0.0012)
Occasion-level:	
Time 0: Variance (Residual)	0.0960 (0.0064)
Time 3: Variance (Residual)	0.1166 (0.0035)
Time 6: Variance (Residual)	0.0872 (0.0063)

TABLE 4

Poverty and vulnerability status of panel households, by degree and by source

Vulnerability status	Chronic poor	Transient poor	Never poor	All
Total vulnerability				
Highly vulnerable	57.5	23.5	3.0	15.4
Relatively vulnerable	41.1	62.7	34.0	42.2
Not vulnerable	1.5	13.7	63.0	42.4
Covariate vulnerability				
Highly vulnerable	25.6	5.9	0.4	5.1
Relatively vulnerable	64.9	53.2	17.9	33.5
Not vulnerable	9.5	40.9	81.7	61.4
Idiosyncratic vulnerability				
Highly vulnerable	47.3	17.7	2.6	12.4
Relatively vulnerable	50.1	64.5	36.1	45.8
Not vulnerable	2.6	17.8	61.3	41.8

Source: Author's estimates using the 2003-2006-2009 FIES panel data.

TABLE 5
Characteristics of different groups of panel households, 2009

Indicator	Chronic poor			Transient poor			Never poor			All households
	Highly vulnerable	Relatively vulnerable	Not vulnerable	Highly vulnerable	Relatively vulnerable	Not vulnerable	Highly vulnerable	Relatively vulnerable	Not vulnerable	
Mean household size	7.5	5.6	3.6	6.7	5.0	4.0	6.5	4.7	3.8	4.8
Mean dependency ratio	0.5	0.4	0.2	0.4	0.3	0.2	0.4	0.2	0.2	0.3
Mean age of head	44.8	49.3	55.6	45.8	51.7	54.3	52.9	53.7	54.7	52.4
Proportion of male-headed households	96.3	88.2	85.7	95.8	84.9	70.6	85.1	78.7	71.8	79.7
Proportion of households with heads who are at most elementary undergraduate	58.6	46.2	28.6	49.1	42.4	29.4	35.8	27.4	12.0	28.7
Proportion of households with heads who are at least elementary graduate	34.8	32.3	28.6	44.0	36.1	37.3	49.3	35.6	24.0	31.8
Proportion of households with heads who are at least secondary graduate	6.6	21.5	42.9	6.9	21.4	30.2	14.9	33.4	39.3	29.1
Proportion of households with heads who are at least college graduate	0.0	0.0	0.0	0.0	0.2	3.2	0.0	3.6	24.7	10.4
Proportion of households with heads who are engaged in non-agriculture	16.5	28.2	57.1	25.5	29.9	35.7	34.3	45.0	55.5	41.9
Proportion of households with access to electricity	46.2	62.1	71.4	70.4	77.4	78.6	91.0	94.0	95.7	84.6
Proportion of households with access to safe water	60.8	69.2	71.4	59.7	74.1	83.3	94.0	85.6	91.9	82.0
Proportion of households with access to sanitary toilet facility	56.0	70.8	85.7	67.6	75.0	80.2	91.0	91.3	95.4	84.7
Proportion of households that own a land	60.4	67.2	100.0	63.9	75.2	83.3	79.1	81.1	85.4	78.6
Proportion of urban households	5.5	20.5	57.1	6.9	17.9	49.2	7.5	25.7	59.1	35.0
Proportion of households living in Cagayan Valley	0.0	2.1	14.3	0.5	4.5	14.3	0.0	5.4	12.9	7.5
Proportion of households living in Central Luzon	0.7	5.1	0.0	0.0	7.8	18.3	3.0	13.2	16.5	11.4
Proportion of households living in CALABARZON	2.6	6.2	0.0	0.9	9.5	11.9	0.0	6.6	20.7	11.9
Proportion of households living in Bicol	13.9	9.2	14.3	11.6	7.6	7.9	6.0	5.8	5.8	7.3
Proportion of households living in Zamboanga Peninsula	16.8	5.6	0.0	12.0	3.5	2.4	11.9	2.9	1.6	4.4
Proportion of households living in Caraga	15.4	7.7	0.0	13.0	6.6	0.8	14.9	6.5	0.6	5.3

Note: Regions shown are those with the highest (CALABARZON, Central Luzon and Cagayan Valley) and lowest (Caraga, Bicol and Zamboanga Peninsula) poverty incidences during the period 2003-2009.
Source: Author's estimates using the 2003-2006-2009 FIES panel data.

Online Appendix
Appendix Table 1
Definition and summary statistics of variables

Variable	Definition	2003 Mean	2003 Std Dev	2003 Min	2003 Max	2006 Mean	2006 Std Dev	2006 Min	2006 Max	2009 Mean	2009 Std Dev	2009 Min	2009 Max
Log of per capita income	Log of per capita income (deflated by the 2003 provincial poverty threshold)	0.54	0.77	-1.69	4.73	0.72	0.77	-1.39	4.85	0.97	0.76	-1.51	5.19
Time	Number of years from the baseline (2003)	0	0	0	0	3	0	3	3	6	0	6	6
Household composition													
Household size	Average number of household members during the year	5.08	2.14	1	15	5.02	2.18	1	15	4.85	2.17	1	17
Square of household size	Square of household size	30.37	25.32	1	225	29.91	25.96	1	225	28.26	24.96	1	272
Dependency ratio	Proportion of household members aged below 15	0.33	0.24	0	1	0.30	0.24	0	1	0.27	0.23	0	1
Household head profile													
Sex	Sex of household head: 1 if male; 0 if female	0.85	0.86	0	0	0.84	0.37	0	1	0.81	0.39	0	1
Age	Age of household head, in years	47.51	47.44	14	17	49.92	13.45	13	94	52.10	13.37	11	98
Square of age	Square of age of household head	2448.11	2440.67	1420	289	2673.48	1435.52	169	8836	2892.73	1474.97	121	9604
Educational attainment	Education dummies:												
At most elementary level	1 if either elementary undergraduate or have no grade completed; 0 otherwise *(base category)*	0.30	0.46	0	1	0.30	0.46	0	1	0.30	0.46	0	1
At least elementary graduate	1 if either elementary graduate or secondary undergraduate; 0 otherwise	0.34	0.47	0	1	0.35	0.48	0	1	0.34	0.47	0	1
At least secondary graduate	1 if either secondary graduate or college undergraduate; 0 otherwise	0.28	0.45	0	1	0.28	0.45	0	1	0.29	0.45	0	1
At least college graduate	1 if either college graduate or postgraduate; 0 otherwise	0.08	0.27	0	1	0.08	0.27	0	1	0.08	0.27	0	1
Employment	1 if employed in non-agriculture sector; 0 if either employed in agriculture sector or not employed	0.42	0.49	0	1	0.41	0.49	0	1	0.40	0.49	0	1
Location													
Urban/rural	Urban/rural indicator: 1 if urban; 0 if rural	0.33	0.47	0	1	0.33	0.47	0	1	0.33	0.47	0	1
Region[a/]	Regional dummies:												
Ilocos	1 if a household resides in Ilocos; 0 otherwise	0.07	0.26	0	1	0.07	0.26	0	1	0.07	0.26	0	1
Cagayan	1 if a household resides in Cagayan Valley; 0 otherwise	0.06	0.24	0	1	0.06	0.24	0	1	0.06	0.24	0	1
Central Luzon	1 if a household resides in Central Luzon; 0 otherwise	0.09	0.29	0	1	0.09	0.29	0	1	0.09	0.29	0	1
CALABARZON	1 if a household resides in CALABARZON; 0 otherwise	0.10	0.30	0	1	0.10	0.30	0	1	0.10	0.30	0	1
MIMAROPA	1 if a household resides in MIMAROPA; 0 otherwise	0.04	0.20	0	1	0.04	0.20	0	1	0.04	0.20	0	1
Bicol	1 if a household resides in Bicol; 0 otherwise	0.07	0.25	0	1	0.07	0.25	0	1	0.07	0.25	0	1
Western Visayas	1 if a household resides in Western Visayas; 0 otherwise	0.09	0.28	0	1	0.09	0.28	0	1	0.09	0.28	0	1
Central Visayas	1 if a household resides in Central Visayas; 0 otherwise	0.08	0.27	0	1	0.08	0.27	0	1	0.08	0.27	0	1

[a/] NCR was not included in the analysis because it is the only region that is not composed of provinces. It is composed of four districts, which are composed of cities.

Appendix Table 1 (Cont.)

Variable	Definition	2003				2006				2009			
		Mean	Std Dev	Min	Max	Mean	Std Dev	Min	Max	Mean	Std Dev	Min	Max
Eastern Visayas	1 if a household resides in Eastern Visayas; 0 otherwise	0.06	0.23	0	1	0.06	0.23	0	1	0.06	0.23	0	1
Zamboanga Peninsula	1 if a household resides in Zamboanga Peninsula; 0 otherwise	0.05	0.22	0	1	0.05	0.22	0	1	0.05	0.22	0	1
Northern Mindanao	1 if a household resides in Northern Mindanao; 0 otherwise	0.05	0.22	0	1	0.05	0.22	0	1	0.05	0.22	0	1
Davao	1 if a household resides in Davao; 0 otherwise	0.06	0.23	0	1	0.06	0.23	0	1	0.06	0.23	0	1
SOCCSKSARGEN	1 if a household resides in SOCCSKSARGEN; 0 otherwise	0.06	0.23	0	1	0.06	0.23	0	1	0.06	0.23	0	1
Cordillera Administrative Region (CAR)	1 if a household resides in CAR; 0 otherwise	0.04	0.20	0	1	0.04	0.20	0	1	0.04	0.20	0	1
Autonomous Region in Muslim Mindanao (ARMM)	1 if a household resides in ARMM; 0 otherwise	0.04	0.20	0	1	0.04	0.20	0	1	0.04	0.20	0	1
Caraga	1 if a household resides in Caraga; 0 otherwise *(base category)*	0.04	0.21	0	1	0.04	0.21	0	1	0.04	0.21	0	1
Other aggregate-level variables													
Transportation infrastructure index	Principal Component Analysis (PCA) index of road density, paved road ratio, and number of ports and airports (domestic and international)	-0.53	1.18	-3.37	2.34	0.22	1.24	-3.11	4.03	0.34	1.20	-3.13	4.24
Economic and social infrastructure index	Principal Component Analysis (PCA) index of the following: ratio of rural banks to total *barangays*; ratio of elementary and secondary schools to total *barangays*; ratio of *barangay* health stations to total *barangays*	-0.03	1.35	-2.39	5.45	-0.03	1.28	-2.34	4.13	0.07	1.42	-2.26	5.73
Irrigation development	Ratio of total service area to estimated total irrigable area	50.91	23.09	6.46	155.98	52.72	23.86	6.56	160.52	55.64	23.57	7.50	161.80
Agriculture index	Principal Component Analysis (PCA) index of total area planted and average use of fertilizer	0.83	1.11	-1.73	4.19	-0.38	0.78	-1.73	2.38	-0.43	0.79	-1.56	2.35
Utilities index	Principal Component Analysis (PCA) index of telephone density and percentage of energization	-0.14	1.08	-3.21	1.97	0.03	0.91	-2.80	1.68	0.10	1.26	-5.57	3.83

Appendix Table 2

Results of Likelihood ratio tests for inclusion of random coefficients

Likelihood ratio test 1:
Model 1 (no random coefficient) vs. Model 2 (with random coefficient at level 2):
LR χ_2^2 = 78.00, Pr > χ^2 = 0.0000

Likelihood ratio test 2:
Model 2 (with random coefficient at level 2) vs. Model 3 (with random coefficients at levels 2 & 3):
LR χ_4^2 = 112.50, Pr > χ^2 = 0.0000

Note: Models 1 to 3 have identical fixed-effects specifications.

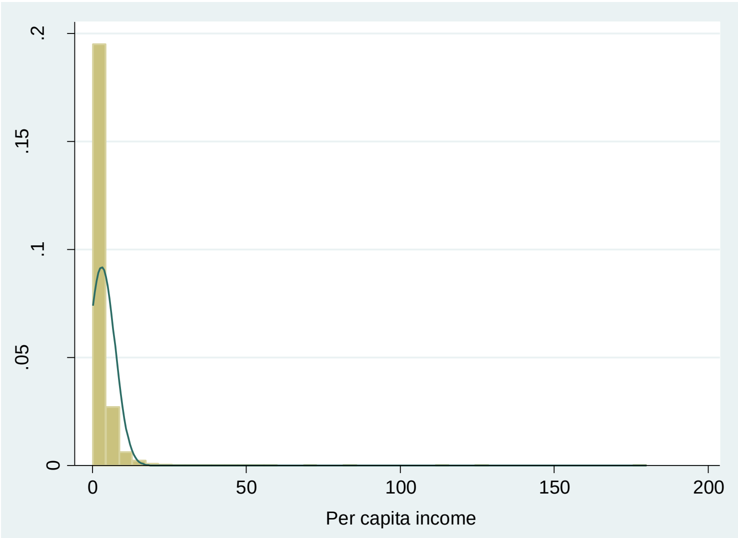
Appendix Table 3

Comparison between Intercept-only and Full models

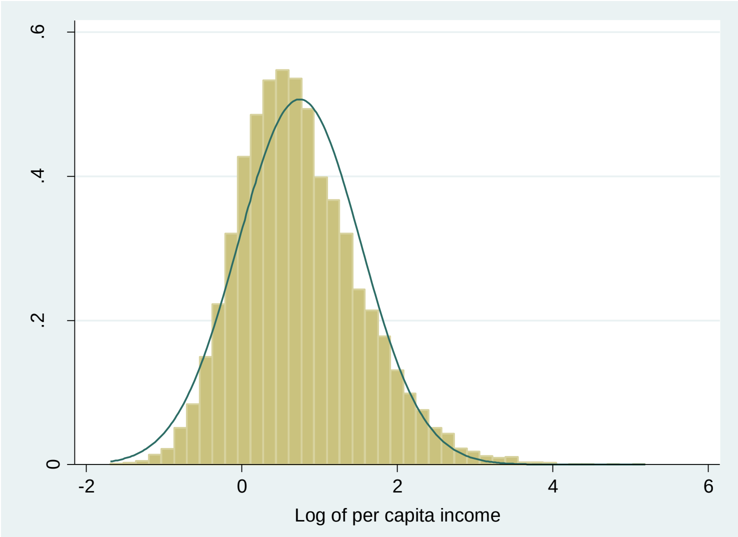
Random-effects Parameters	Intercept-only	Full
Province-level		
Variance (Random slope)	0.0053	0.0003
Variance (Random intercept)	0.2316	0.0211
Covariance (Random slope, Random intercept)	-0.0297	-0.0012
Household-level:		
Variance (Random slope)	0.0021	0.0024
Variance (Random intercept)	0.4237	0.1989
Covariance (Random slope, Random intercept)	-0.0063	-0.0061
Occasion-level:		
Variance (Residual)	0.1113	
Time 0: Variance (Residual)		0.0960
Time 3: Variance (Residual)		0.1166
Time 6: Variance (Residual)		0.0872

Note: Both models have random intercept and random slopes of time at all levels.
The Full model includes all the main effect and interaction variables.
Source: Author's estimates using the 2003-2006-2009 FIES panel data.

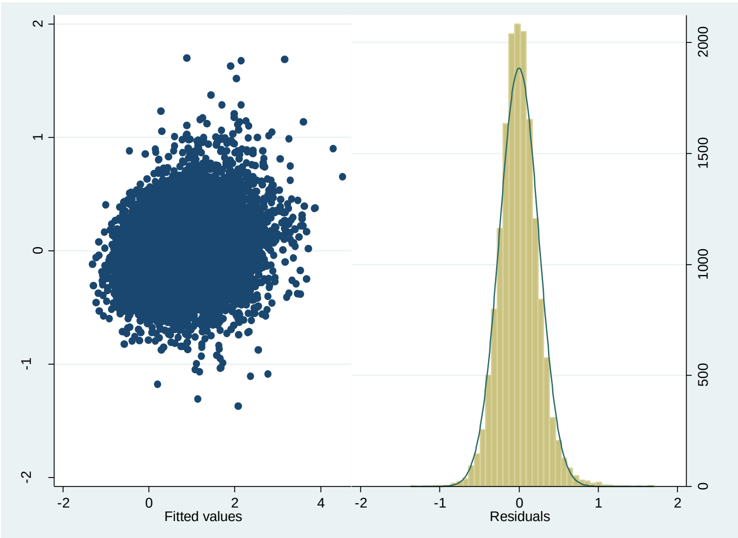
Appendix Figure 1a. Histogram (with normal-density plot) of per capita income



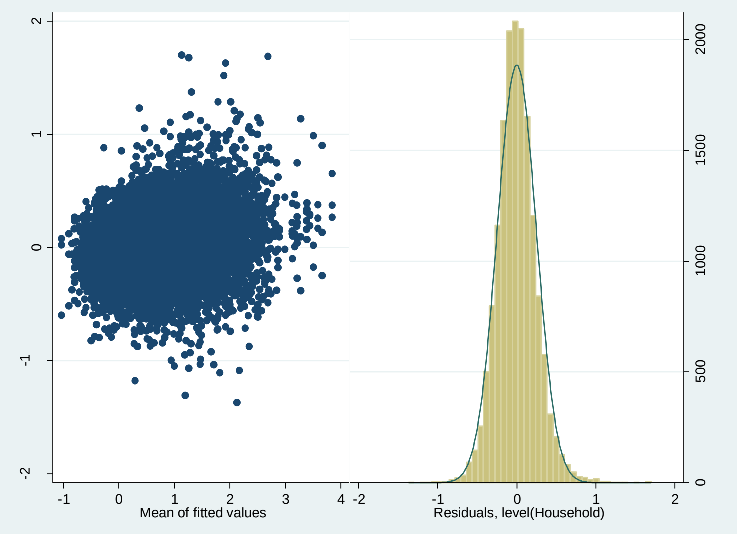
Appendix Figure 1b. Histogram (with normal-density plot) of log of per capita income



Appendix Figure 2a. Scatter plot and histograms of the fitted values and level-1 residuals



Appendix Figure 2b. Scatter plot and histograms of the household-level mean of fitted values and level-2 residuals



Appendix Figure 2c. Scatter plot and histograms of the provincial-level mean of fitted values and level-3 residuals