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

Christian D. Mina
Philippine Institute for Development Studies (PIDS), the Philippines

&

Katsushi Imai
Economics, School of Social Sciences, University of Manchester, UK, & RIEB, Kobe University, Japan

First Draft: 7th April 2015
This Draft: 28th March 2016

Abstract

Using the panel data for the Philippines in 2003-2009, we estimate a three-level random coefficient model to measure household vulnerability and to decompose it into idiosyncratic and covariate components. We correct heterogeneity bias using Bell and Jones's (2015) 'within-between' formulation. A majority of the poor and 18 percent of the non-poor are found to be vulnerable to unobservable shocks, while both groups of households are more susceptible to idiosyncratic shocks than to covariate shocks. Adequate safety nets should be provided for vulnerable households that lack access to infrastructure, or are larger in size with more dependents and less-educated heads.

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

Corresponding Author:
Katsushi Imai (Dr)
Economics, School of Social Sciences,
University of Manchester,
Arthur Lewis Building, Oxford Road,
Manchester M13 9PL, UK;
Phone: +44-(0)161-275-4827 ; Fax: +44-(0)161-275-4928 ;
E-mail: Katsushi.Imai@manchester.ac.uk

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

1. Introduction

The Philippine economy showed remarkable performance during the period 2003-2006, which our study focuses on, in terms of gross domestic product (GDP). However, the growth decelerated from 2006 (5.2%) to 2009 (1.1%) (Table 1) and then recovered steadily in more recent years (3.7% in 2010 to 6.1% in 2014). The main growth driver during the period 2003-2006 was the services sector. In particular, exports of services spurred the growth in the services sector, particularly the business process outsourcing (BPO) industry. Agriculture and industry sectors, on the other hand, suffered negative growth rates in 2009. The gross national income (GNI) consistently increased from 2003 to 2009. The current account balance as a share of GDP went up significantly during this period, suggesting the improvement in the country's competitiveness. From 2003 to 2009, the Philippine peso appreciated while the net factor income from abroad almost doubled.

(TABLE 1 to be inserted)

An important question is how these macroeconomic conditions influenced Filipino households at micro levels. While peso appreciation lowered the value of international remittances, it also lowered import prices. This resulted 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 decelerated from 8.3 percent in 2008 to 4.2 percent in 2009. Apparently, effects of the global financial crisis did not persist. Meanwhile, the unemployment rate dropped from 11.4 percent in 2003 to 7.5 percent in 2009. However, the poverty headcount ratio did not significantly decline during the period 2003-2009. It rose from 20 percent in 2003 to 21.1 percent in 2006, and then remained almost same (20.9%) in 2009. The total number of poor households, on the other hand, grew from 3.3 million in 2003 to 3.9 million in 2009.[1] Poverty in the Philippines is also characterised by spatial disparity (Figure 1). The provinces with the highest poverty incidence from 2003 to 2009 are located in the south region, the poorest region of the country. On the other hand, several provinces in the central region had poverty rates higher than 30 percent while provinces in the north region had relatively lower poverty rates. The Gini coefficient at the national level remained high (48.7% in 2003 and 47.4% in 2009); higher than those in urban or rural areas (45.1% in 2003 and 44.6% in 2009 in urban areas and 42.9% in 2003 and 42.8% in 2009 in rural areas). The rural-urban disparity could have resulted in greater inequality at the national level than in urban or rural areas.

(FIGURE 1 to be inserted)

Earlier studies on poverty argued that a large component of the Philippine poverty is transient poverty, which is characterised by high vulnerability to shocks (Reyes et al., 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 et al., 2009, 2013; Reyes and Mina, 2013). Thus, in analysing further the underlying causes of persistence of poverty, it is necessary to take into account the effect of macro and micro shocks on household welfare. The 2010 Philippine Millennium Development Goals Progress Report noted that the combined impacts of economic, natural and other shocks could have contributed to the persistence of poverty in the country. During the past decade, the Philippines has faced many challenges including the aftermath of the 2007/08 global financial crisis, and exorbitant and unpredictable rice and fuel prices, and a series of extreme weather events, among others. 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 occurred between 2003 and 2009. These brought an increased frequency 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.

Bearing in mind these broad regional and economic contexts, this study aims to estimate vulnerability to poverty using a three-level linear random coefficient model applied to a Philippine household-level panel dataset covering three waves (2003, 2006 and 2009). We draw upon the growing literature of quantitative studies of vulnerability as an *ex ante* measure of poverty (Pritchett et al., 2000; Chaudhuri et al., 2002; Zhang and Wan, 2006). Specifically, we will 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 three-level longitudinal model, or random coefficient (RC) model to capture the effects of factors in different levels (i.e., time, household, and province). Heterogeneity bias in the RC model is corrected by using Bell and Jones's (2015) 'within-between' formulation to explicitly model both time-series (or 'within') variations in means of household- and province-level variables and cross-sectional (or 'between') variations across different households and provinces. While Bell and Jones argue that this method overcomes the limitation of the RC model (e.g., the possible correlation between covariates and residuals) and is preferable to the fixed-effects (FE) model, both RC and FE models are estimated in this study. In all cases, the attrition bias was corrected by the method of Fitzgerald et al. (1998).

The advantage of our approach includes: (i) decomposing the *ex ante* vulnerability estimate[2] into idiosyncratic and covariate components; (ii) reducing the possible bias in vulnerability estimates by using a multilevel model (for instance, controlling for possible downward bias of localized/aggregate shocks on the estimated mean of household's welfare measure (Günther and 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 2 provides a brief summary of the empirical literature on vulnerability in developing countries. Data and variables are discussed in Section 3. Section 4 describes the methodologies for multilevel analysis, estimation of vulnerability to poverty, and vulnerability assessment. Section 5 provides estimation results and vulnerability profile of the panel households. The final section concludes and provides some policy implications.

2. Empirical Literature

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 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 vulnerable while 22 percent are classified as poor.[3]

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 (2013). These studies utilized cross-sectional data and developed a two-level model. Günther and Harttgen (2009) estimated a random intercept model while Échevin (2013) estimated a RC model by including shock variables in the set of explanatory variables. As an extension, this study proposes the use of a three-level linear RC model as well as a FE model using panel data.

3. Data and Variables

We used the three-wave household-level panel data generated from the 2003, 2006 and 2009 rounds of the Family Income and Expenditure Survey (FIES) in the Philippines. After excluding all other ineligible households and/or housing units and taking into account nonresponses, the final set of FIES panel households reached 5,986 in each round. The panel of households was maintained by the then National Statistics Office - now the Philippine Statistics Authority (PSA) - only in 2003-2010 due to budgetary constraints. The 2000 Census of Population and Housing served as the sampling frame for nationally representative household-based surveys, including the FIES, Annual Poverty Indicators Survey (APIS) and Labour Force Survey (LFS). Households were tracked if at least one of the members remained in all of the three rounds. The original cohort in 2003 was composed of 9,344 households. In 2006, the number of sample households that remained in the panel was 7,201; that is, 2,143 households (22.9%) were dropped. In 2009, among those 7,201 sample households, 1,215 (16.9%) were dropped. As a result, a total of 5,986 households comprised the 2003-2006-2009 panel of Filipino households. According to the PSA, the main reasons for attrition include the following: household units were destroyed by natural calamities such as strong typhoon, landslide, earthquake, volcanic eruption; residential area was converted to an industrial area; the entire household migrated to other places because the head found a new job in another place; among others. Given that vulnerable households tend to be dropped from the surveys, our vulnerability measures are likely to be underestimated. While this is admittedly a major limitation of the study, our use of the panel data in deriving vulnerability estimates would offer rich policy implications as the majority of the existing empirical works on vulnerability used cross-sectional data. We used inverse probability weights as our approach for addressing attrition based on the method of Fitzgerald et al. (1998) that used observable characteristics in correcting for attrition bias.

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 by information on labour force, employment and educational attainment of household members generated from the relevant rounds of the

LFS, namely: July 2003, January 2004, July 2006, January 2007, July 2009, and January 2010.[4] 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 PSA based on the results of the triennial FIES. A Filipino household is considered poor if its per capita income is below the official (provincial) poverty threshold.[5] 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 a 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 (Tabunda, 2001) (Refer to Table 2 for the definition and summary statistics of these variables). These variables include household size, dependency ratio, and household head attributes (i.e., sex, age, education, and employment). We also considered regional dummies as well as aggregate-level variables, namely: transportation infrastructure index, economic and social infrastructure index, irrigation development index, agriculture index, and utilities index. The indices were generated using the Principal Component Analysis (PCA) mainly because some of the component variables of those indices are strongly correlated. Except for squares of household size and age of head, all main effect variables included in the model are not strongly correlated.[6] While the average real per capita household income increased over the years, most of the variables on household characteristics were stable in 2003-2009. The quality of infrastructure (e.g., paved roads; number of ports and airports; telephone density) improved while the total area planted and/or average use of fertiliser declined.

(TABLE 2 to be inserted)

The rice and fuel price shocks are hypothesized to have direct impact on household income. 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 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.

4. Methodology

The methodology proposed in Günther and Harttgen (2009) is extended in this study by applying it to panel data with hierarchical structure and by taking into account observable shocks in income prediction. We propose to use the three-level model to decompose the *ex ante* vulnerability measure into covariate (aggregate) and idiosyncratic components. We also employ fixed-effects model to derive the vulnerability estimate without decomposing it into covariate and idiosyncratic components, and to see how different methods yield different vulnerability estimates.

4.1 Multilevel Modelling

Multilevel model is used to analyse "hierarchically structured data, with variables defined at all levels of the hierarchy" (Hox, 2000: 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 et al., 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: 1225). Multilevel modelling is particularly appropriate if the study aims to assess the impact of idiosyncratic and covariate shocks (Échevin, 2013). Aside from the fact that a multilevel model can contain explanatory variables defined at different hierarchical levels[7] 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 (Günther and Harttgen, 2009: 1225). Another advantage is that a multilevel model can be used to decompose the relative impacts of household-specific and community-specific [or aggregate-specific] shocks on households' vulnerability to poverty (Günther and Harttgen, 2009). Meanwhile, 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).

4.2 Three-level linear random coefficient model with a 'within-between' formulation

The empirical model estimated in this study is based on the formulation of a "three-level [multilevel] model for change" or "random coefficient (RC) model" by Singer and Willett (2003). To take into account the unobservable heterogeneity specific to households and provinces as a way to overcome the limitation of the RC model, we used the 'within-between' formulation put forward by Bell and Jones (2015) who follows Mundlak (1978). Bell and Jones argue that the said formulation would be particularly recommended when some of the covariates are likely to be endogenous.

Let $\ln y_{tij}$ be the log of per capita income of household *i* in province[8] *j* at time *t*, where: level-1 units are the measurement occasions[9] 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:

$$\ln y_{tij} = \mathbf{x}^T_{(1)tij}\boldsymbol{\beta}_{(1)} + \mathbf{x}^T_{(2)ij}\boldsymbol{\beta}_{(2)} + \mathbf{x}^T_{(3)tj}\boldsymbol{\beta}_{(3)} + \mathbf{Z}^T_{tij}\mathbf{v}_j + \mathbf{Z}^T_{tij}\mathbf{u}_{ij} + e_{tij} \tag{1}$$

The vector of all household-level and aggregate-level (or province-level) explanatory variables, $\mathbf{x}_{tij}^{T} = \left(\mathbf{x}_{(1)tij}^{T}, \mathbf{x}_{(2)ij}^{T}, \mathbf{x}_{(3)tj}^{T}\right)$, includes the following: time-varying (level-1) covariates, $\mathbf{x}_{(1)tij}^{T}$; time-invariant (level-2) covariates, $\mathbf{x}_{(2)ij}^{T}$; aggregate-level (level-3) covariates, $\mathbf{x}_{(3)tj}^{T}$. The vector $\mathbf{x}_{(1)tij}^{T}$ also contains a variable representing time (Frees, 2004). Associated with vector $\mathbf{x}_{tij}^{T}$ is $\boldsymbol{\beta}^{T} = \left(\boldsymbol{\beta}_{(1)}^{T}, \boldsymbol{\beta}_{(2)}^{T}, \boldsymbol{\beta}_{(3)}^{T}\right)$, which is a vector of fixed regression coefficients. The first three terms in equation (1) comprise the fixed part of the model. This is a baseline specification and we have also tried the specification with interaction terms within/across different levels.

The last three terms in equation (1) comprise the random part. '$\mathbf{Z}_{tij}^{T}\mathbf{v}_{j} + \mathbf{Z}_{tij}^{T}\mathbf{u}_{ij}$' captures the unobservable effects at province level *j* and household level *i*. $\mathbf{v}_{j}$, an unobservable random effect at the province level, captures, for instance, cultural or institutional factor at the provincial level. It includes the random intercept v_{0j} and the random coefficient v_{1j}, and is assumed as $\mathbf{v}_{j} \sim N\left(\mathbf{0}, \boldsymbol{\Sigma}_{v}\right)$. The random intercept is interpreted as the initial status of the unobservable random effect while the random coefficient for the time variable is interpreted as the rate of growth of the random effect. On the other hand, $\mathbf{u}_{ij}$ captures an unobservable household random effect such as psychological factor or risk-aversion. The random effect at the household level $\mathbf{u}_{ij}$ also includes the random intercept u_{1ij} and the random coefficient u_{0ij}, and is assumed as follows: $\mathbf{u}_{ij} \sim N\left(\mathbf{0}, \boldsymbol{\Sigma}_{u}\right)$. The matrix $\mathbf{Z}_{tij}^{T}$ contains the vectors of 1's for the random intercept and the time variable *z* for the random coefficient. 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: $e_{tij} \sim N(0, \sigma_{e}^{2})$.

The level-1 residual e_{tij} represents the unexplained variance in households' income and contains the impacts of idiosyncratic shocks as well as measurement errors and non-stochastic heterogeneity in the income-generating process, which was not captured by our model. We assume here that our flexible way of modelling the province-level effect by multilevel modelling has minimised the effect of measurement errors and non-stochastic heterogeneity (see the subsection 4.1). However, this is an empirical question and we cannot deny the possibility that we have overestimated the vulnerability, which is a major limitation of our study. Thus, we also adopted the 'within-between' formulation in the RC model and estimated a standard FE model. The level-2 residuals, $\mathbf{Z}_{tij}^{T}\mathbf{u}_{ij}$, represent the unexplained variances across households and also capture the impacts of idiosyncratic shocks. The level-3 residuals, $\mathbf{Z}_{tij}^{T}\mathbf{v}_{j}$, 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: 1226).

For identification purposes, the covariates $\mathbf{x}_{tij}^{T}$ are assumed to be exogenous, with $E\left(e_{tij} \mid \mathbf{x}_{tij}^{T}\right) = 0$, $E\left(\mathbf{u}_{ij} \mid \mathbf{x}_{tij}^{T}\right) = 0$ and $E\left(\mathbf{v}_{j} \mid \mathbf{x}_{tij}^{T}\right) = 0$ and residuals in levels 1, 2 and 3 are uncorrelated. Moreover, the model in equation (1) allows for heteroscedasticity 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 higher-level residuals in each of the composite residuals also allows for autocorrelation (Graham et al., 2008), although independence of the level-1 residuals can be imposed on the covariance structure.

To overcome the RC model's limitation due to potential correlations between covariates and an unobservable term at the household or province level, $\mathbf{u}_{ij}$ or $\mathbf{v}_{j}$, or the heterogeneity bias, we adopted the 'within-between' formulation (Bell and Jones, 2015) as in equation (1′), which explicitly takes into account the 'within variation' by having a vector of demeaned terms of time-varying covariates in levels 1 and 3 (time-varying covariates minus time-series mean of time-varying covariates: $\mathbf{x}_{(1)tij}^{T} - \overline{\mathbf{x}_{(1)ij}^{T}}$ and $\mathbf{x}_{(3)tj}^{T} - \overline{\mathbf{x}_{(3)j}^{T}}$) and the 'between variation' by having a vector of time-series means of time-varying covariates, $\overline{\mathbf{x}_{(1)ij}^{T}}$ and $\overline{\mathbf{x}_{(3)j}^{T}}$. This is a baseline specification and we have also tried the specification with interaction terms within/across different levels.

$$\ln y_{tij} = \left(\mathbf{x}_{(1)tij}^{T} - \overline{\mathbf{x}_{(1)ij}^{T}}\right)\boldsymbol{\beta}_{(1)} + \overline{\mathbf{x}_{(1)ij}^{T}}\boldsymbol{\beta}_{(2)} + \mathbf{x}_{(2)ij}^{T}\boldsymbol{\beta}_{(3)} + \left(\mathbf{x}_{(3)tj}^{T} - \overline{\mathbf{x}_{(3)j}^{T}}\right)\boldsymbol{\beta}_{(4)} + \overline{\mathbf{x}_{(3)j}^{T}}\boldsymbol{\beta}_{(5)} + \mathbf{Z}_{tij}^{T}\mathbf{v}_{j} + \mathbf{Z}_{tij}^{T}\mathbf{u}_{ij} + e_{tij} \qquad (1')$$

Among various advantages, this formulation would enable us to capture the within- or fixed-effect at household and province levels through $\boldsymbol{\beta}_{(1)}$ and $\boldsymbol{\beta}_{(4)}$ as well as the between-effect at household and province levels through $\boldsymbol{\beta}_{(2)}$ and $\boldsymbol{\beta}_{(5)}$. This 'within-between' formulation can overcome the main criticism of RE that covariates and unobservable terms are correlated.[10]

4.3 Estimation method

The restricted (or residual) maximum likelihood (REML) is used in the estimation of the multilevel model in this study for the following reasons. First, "REML is preferable with respect to the estimation of the variance parameters" (Snijders and Bosker, 2012: 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: 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.

As some of the assumptions for multilevel models are not testable, we apply the same model (equation (1)) to the first-differenced panel data as in equation (2). That is, we take the first difference of the dependent variable and the time-varying explanatory variables at both province and household levels and then apply the multilevel model by dropping all time-invariant variables and their interactions. Using the same notations, this can be expressed as follows:

$$\Delta \ln y_{tij} = \Delta \mathbf{x}^{T}_{(1)tij}\boldsymbol{\beta}_{(1)} + \Delta \mathbf{x}^{T}_{(3)tj}\boldsymbol{\beta}_{(3)} + \mathbf{Z}^{T}_{tij}\mathbf{v}_{j} + \mathbf{Z}^{T}_{tij}\mathbf{u}_{ij} + e_{tij} \qquad (2)$$

where: $\Delta \ln y_{tij}$ is income growth while $\Delta \mathbf{x}^{T}_{(1)tij}$ and $\Delta \mathbf{x}^{T}_{(3)tj}$ are the first differences of household- and province-level (time-varying) covariates. This is a baseline specification and we have also tried the specification with interaction terms within/across different levels. Using the same notation for presentational convenience, the random part, $\mathbf{Z}^{T}_{tij}\mathbf{v}_{j} + \mathbf{Z}^{T}_{tij}\mathbf{u}_{ij}$, is estimated in the same way using the panel data for two rounds. It should be noted that Chaudhuri et al.'s (2002) method for deriving a vulnerability estimate cannot be applied to the first-differenced estimate as it assumes the use of level of income under the assumption that it is normally distributed.

We have also applied the FE model to the panel data (in level) by introducing μ_{ij}, the unobservable fixed-effect at the household level, as in equation (3).

$$\ln y_{tij} = \mathbf{x}^{T}_{(1)tij}\boldsymbol{\beta}_{(1)} + \mathbf{x}^{T}_{(3)tj}\boldsymbol{\beta}_{(3)} + \mu_{ij} + e_{tij} \qquad (3)$$

Again, this is a baseline specification and we have also tried the specification with interaction terms. An advantage of the FE model is that we do not have to assume that μ_{ij} is correlated with a set of covariates. The disadvantages of the FE model, on the other hand, include the following: (i) it ignores the effects of all time-invariant province- and household-level variables; (ii) it also ignores the hierarchical structure of the data and thus the coefficient estimates could be biased (Goldstein, 1999); and, (iii) the relative impacts of household-specific and community-specific factors cannot be identified. Hence, our preferred model is the three-level RC model.

4.4. Attrition

Following Fitzgerald et al. (1998), this study tests for randomness of attrition, or whether attrition has a significant effect on the model estimates by estimating Fitzgerald et al.'s unrestricted attrition probit model and performing the Becketti et al.'s (1988) pooling test for attrition. The results of these models are reported in Online Appendix Tables 1 and 2. The results suggest that the following variables can be considered as significant predictors of attrition: household head profile (i.e., sex, age and square of it, educational attainment particularly elementary- and secondary-level education, employment[11]), household size and square of it, urban/rural, and labour market shocks and attrition rate within the province[12]. The results of the post-estimation Wald test and F-test for attrition[13], following the two aforementioned tests, revealed that attrition in the household-level panel data used in this study was non-random, suggesting the use of inverse probability weights in the analysis to take into account the attrition bias due to selection on observables. Inverse probability weights were calculated as the ratio of predicted probabilities from the unrestricted attrition probit to predicted probabilities from the restricted attrition probit (without the auxiliary variables)[14]. In all estimations in this paper, these inverse probability (or attrition) weights are used to assign more weight to households who remained in the panel.

4.5 Estimation of vulnerability to poverty

Our methodology of estimating vulnerability to poverty is an extension of Günter and Harttgen (2009) based on Chaudhuri et al.'s (2002) method which involves estimation of expected mean and variance in household's welfare measure using cross-sectional data. In our study, this is extended by applying it to the short panel data with hierarchical structure and by taking into account observable shocks in the prediction of log of per capita income (Échevin, 2013). Following Chaudhuri et al., we assume 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)[15], as in the following:

$$e_{tij}^2 = \mathbf{x}_{(1)tij}^T \boldsymbol{\alpha}_{(1)} + \mathbf{x}_{(2)ij}^T \boldsymbol{\alpha}_{(2)} + \mathbf{x}_{(3)tj}^T \boldsymbol{\alpha}_{(3)} \quad (4)$$

$$u_{0ij}^2 = \mathbf{x}_{(2)ij}^T \boldsymbol{\delta}_{(2)} + \mathbf{x}_{(3)tj}^T \boldsymbol{\delta}_{(3)} \quad (5)$$

$$v_{0j}^2 = \mathbf{x}_{(3)tj}^T \boldsymbol{\gamma}_{(3)} \quad (6)$$

$$s_{tij}^2 = \mathbf{x}_{(1)tij}^T \boldsymbol{\theta}_{(1)} + \mathbf{x}_{(2)ij}^T \boldsymbol{\theta}_{(2)} + \mathbf{x}_{(3)tj}^T \boldsymbol{\theta}_{(3)} \quad (7)$$

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

Interactions within/across different levels are included in equations (4), (5) and (7) while interactions among level-3 covariates are included in equation (6) in cases where equation (1) or (1)′ is estimated with interactions. Using the estimated coefficients from these regressions, the following expected variances are estimated: unobservable idiosyncratic variances $\hat{\sigma}_{e_{tij}}^2$

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 et al. (2002). The conditional probability of being poor, or vulnerability to poverty, of household *i* in province *j* at time *t* is estimated as follows:

$$\hat{V}_{tij} = \hat{P}\left(\ln y_{tij} < \ln \bar{y} \mid \mathbf{x}^T_{tij}\right) = \Phi\left(\frac{\ln \bar{y} - \ln \hat{y}_{tij}}{\sqrt{\hat{\sigma}^2_{tij}}}\right) \qquad (8)$$

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 $\hat{\sigma}^2_{v_{0j}}$. In the case where the FE model is estimated, only the total vulnerability estimate is derived because the variance cannot be decomposed into idiosyncratic and aggregate components.

While this *ex ante* vulnerability measure is widely used in the literature, limitations should be noted in interpreting it. First, error term e_{tij} contains not only stochastic innovation (i.e., risk or shock) in the income-generating process, but also non-stochastic heterogeneity in the income-generating process as well as measurement errors. In one sense, our flexible way of modelling the income-generating process through a RC model with interactions between the time variable and higher-level residuals addresses heteroscedasticity. While we use the RC model with 'within-between' formulation and the FE model to derive the total vulnerability, the estimates may suffer from the same problems. The major limitation of this study is being unable to disentangle the error term, but we believe that our proposed method of deriving vulnerability estimates based on the RC model with ‘within-between’ formulation (Bell and Jones, 2015) for panel data is a major improvement over the previous ones that are based on cross-sectional data (i.e., Chaudhuri et al.’s (2002); Günter and Harttgen’s (2009)).

4.6 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:

$$V^*_{t+k,ij} = 1 - \left[P\left(\ln y_{tij} > \ln \bar{y}\right)\right]^k \qquad (9)$$

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; $P(\ln y_{tij} > \ln \bar{y})$ is the probability of having an income above the poverty threshold in any given year. The vulnerability threshold of 0.5, the most commonly used threshold in the empirical literature (Pritchett et al., 2000; Kühl, 2003; Zhang and Wan, 2006), 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 (9), 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. The *chronic poor* are referred to as households that are persistently poor from 2003 to 2009. The *transitory poor* are households that became poor once or twice during the period 2003-2009. This group is further disaggregated into two sub-groups: the households which were in poverty in 2003 but escaped from poverty in 2006 or later ('*moving up'*) and those not in poverty in 2003 but slipped down into poverty in 2006 or later ('*slipping down*'). The *never poor* are referred to as the households which were consistently non-poor throughout the period.

The vulnerability status is identified based on the estimated vulnerability to poverty of households. A household is considered vulnerable (not vulnerable) if its estimated vulnerability to poverty is below (above) the vulnerability threshold. 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 the less vulnerable households can be collectively known as 'relatively vulnerable'.

5. 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.

5.1 The results of the three-level linear random coefficient model

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 household and provincial levels (Online Appendix Table 3). 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 an improvement over the intercept-only model in terms of capturing dependencies (particularly at higher levels) in the hierarchical data used in this study. Meanwhile, the use of logarithmic form of per capita income resulted in satisfaction of the normality assumption of income and residuals at all levels (Online Appendix Figures 1-2). Scatter plots also indicate that outliers would not create a problem in the analysis.

(TABLE 3 to be inserted)

The first two columns of Table 3 show the results of Models 1 and 2, RC model without and with interaction terms, based on ‘within-between’ formulation (Bell and Jones, 2015), while the next two columns provide those of Models 3 and 4, FE models without and with interaction terms (e.g., household characteristics and time-varying province-level variables). The final column presents the result of Model 5, RC model applied to the first-differenced data. Attrition bias is corrected in all cases in Table 3 by using the method of Fitzgerald et al. (1998). The key results are reported selectively below.

Among the highly significant variables with large main effects are education of household head (positive), household size (negative) and its square (positive), dependency ratio (negative in Models 1, 3 and 5; an interaction with household size is highly significant and negative for Models 4 and 5), and some regional dummies. Households with more educated heads tend to have higher per capita income than those with less-educated heads (Models 1, 2, 4, and 5). A larger household tends to have a lower per capita household income with some non-linear effect, while dependency ratio is also considered as an important predictor of household’s well-being. The presence of more children in a household implies a lower share of adult members in employment, which limits the earning potentials of that household.

On other results, female-headed households are found to have relatively higher income than male-headed ones (Models 1 and 2). Interestingly, many female-headed households in the Philippines are heavily dependent on cash receipts or support (either from abroad or domestic sources, but chiefly remittances from abroad)[16]. Miralao (1992) compared male- and female-headed households and found that the latter, on average, have higher annual income, are smaller in size, have older heads, and have higher share of property and rental income than the former, while a male head is more likely to be in the labour market. Our data suggest that 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. However, as pointed by Miralao (1992), female-headed households are highly heterogeneous and there exist very poor female-headed households that should be supported by public policies.

Households residing in provinces that experienced rainfall and fuel price shocks tend to have relatively lower income. Because a majority of the working poor are engaged in agriculture (Reyes and Mina, 2013) and the agriculture sector is considered 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 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 overseas contact workers (OCW) members could mean lower contribution to household income.

A number of interaction variables have significant effects on income (Models 2 and 4). The income disparity between female- and male-headed households, in favour of the former, is observed in certain regions. This income disparity, however, does not hold when the head is highly educated (Model 2). 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. Most of other interaction terms are statistically significant.[17]

5.2 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 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 (displayed in Table 4, based on Model 2) show that 37.7 percent of panel households are classified as vulnerable at least once in any of the periods covered, i.e., 2003, 2006 and 2009 (sum of 'highly vulnerable' and 'relatively vulnerable' households). Around 15.9 percent of panel households are classified as vulnerable to unobservable covariate shocks while around 34.5 percent are vulnerable to unobservable idiosyncratic shocks. This finding implies that households have a 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, 85.9 percent of the chronic poor and 54.4 percent of the transitory poor are classified as vulnerable to unobservable idiosyncratic shocks in at least one of the periods covered. However, 62.3 percent of the chronic poor and 24.6 percent of the transitory poor are found to be vulnerable to unobservable covariate shocks. Notably, more chronic and transitory poor households are vulnerable to unobservable idiosyncratic shocks than to unobservable covariate shocks. On the other hand, a majority of the never poor are not classified as vulnerable in any of the periods covered. Only 17.5 of the never poor are considered as vulnerable.

If we use the FE model (Model 4) in deriving vulnerable estimates, however, almost all the households (99.8%) are classified as vulnerable, while all the chronic and transitory poor households are classified as vulnerable. It can then be inferred that the FE model cannot take account of time-invariant covariates (e.g., regional dummy variables) and unobservable heterogeneous effects (or random coefficients and intercepts) at the aggregate or province level. These factors are likely to be contained in the error terms and thus variances of the FE models are estimated to be higher than those of the RC models.

It is generally difficult to determine whether the RC (or RE) model or the FE model should be selected, but a few recent studies have questioned the validity of the FE model under certain circumstances. For instance, Gibbons et al. (2016) have replicated recent influential papers published in *American Economic Review* and found that, in the presence of heterogeneous treatment effects, the FE model tends to produce an inconsistent estimator of the sample-weighted average treatment effect (SWE). The RC model offers a way to incorporate the heterogeneous group effect. Clarke et al. (2015) carefully compared the FE model and the RE model (two-level hierarchical linear regression model) and concluded that "when the available data on higher-level units are rich, RE models can be built that adjust for higher-level selection" and "heterogeneous treatment effects are common and the SWE is often statistically and economically different from the FE estimate" (p.275). They also argued that "it is important to take a pragmatic view of what can reasonably be achieved by analysing data from observational studies, whichever approach is used.” The choice between FE and RE (or RC) models is essentially an empirical question (Rabe-Hesketh and Skrondal, 2012). Bell and Jones (2015) showed by Monte-Carlo simulations that “the RE approach is, in fact, nearly always preferable” (p.149) if the ‘within-between’ formulation is used. They argue that:

> *understanding the role of context (households, individuals, neighborhoods, countries, etc.) that defines the higher level, is usually of profound importance to a given research question - one must model it explicitly - and requires the use of an RE model that analyzes and separates both the within and between components of an effect explicitly, and assesses how those effects vary over time and space rather than assuming heterogeneity away from FE (Bell and Jones, 2015, p.149).*

In this regard, while we show the results of both FE and RC models, we will use the RC model as our preferred model to derive the vulnerability estimates.

5.3 Characteristics of vulnerable and poor households

In order to characterise vulnerability in comparison with poverty, we have derived the predicted value of vulnerability, $\hat{V}^{*}_{t+3,ij}$ in the equation (9), a probability of the household falling into poverty in the next three years for each household in 2009 (i.e., future vulnerability) and estimated it by initial conditions, that is, covariates at household and province levels in 2003 to avoid the issue of endogeneity using Ordinary Least Squares (OLS) with heteroscedasticity-consistent standard errors. The result is shown in the first column of Table 5. To compare this with determinants of various categories of poverty, we have also estimated a (robust) probit model for each of the following four categories: ‘*Chronic poverty*’, ‘*Moving up’* (from poverty in 2003 to non-poverty in 2006 and/or 2009), ‘*Slipping down*’ (from non-poverty in 2003 to poverty in 2006 and/or 2009), and ‘*Never poor’* (the second to the fifth column in Table 5) using the same set of covariates.

(TABLE 5 to be inserted)

We have highlighted the results selectively. First, the determinants of vulnerability and chronic poverty are broadly similar, reflecting the fact that the chronically poor in the past are likely to be also vulnerable to poverty in the future. The factors which are correlated to household vulnerability and chronic poverty include: (i) having a younger and less educated head; (ii) larger household size (where vulnerability will increase acceleratedly as the household size increases as suggested by a positive and significant coefficient estimate of the square of the household size) with a higher dependency ratio; (iii) being located in rural areas; and, (iv) lack of access to irrigation. Second, the factors which are only significantly associated with vulnerability, but not with chronic poverty, include lack of access to major transport infrastructure and lack of job security. Third, while lack of economic and social infrastructure is - rather surprisingly - associated with the higher probability of 'moving up'; having members in vulnerable employment prevented them from 'moving up' from poverty to non-poverty. On the other hand, even if households were not initially poor, they tended to slip down into poverty if they did not have access to transport infrastructure and/or irrigation facilities, or have more members in vulnerable employment. Finally, not surprisingly, better education, a smaller household size and a lower dependency ratio, living in urban areas, having access to better infrastructure and/or better education are main determinants of being 'never poor'.

6. Concluding remarks

The vulnerability to poverty of Filipino households is estimated in this study using a three-level longitudinal model and three-wave household-level panel data in the Philippines. Chaudhuri et al.'s (2002) method of estimating households' vulnerability to poverty - which has been widely adopted in numerous empirical works on vulnerability based on cross-sectional data - has been further extended in our study by applying the multilevel longitudinal random coefficient model to the panel data. We have corrected heterogeneity bias using Bell and Jones's (2015) 'within-between' formulation. 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.

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 (education, sex, and age), composition (household size and dependency ratio) and location (urban/rural and region) significantly explain the variation in household income. Observable covariate (fuel price and rainfall) and idiosyncratic (labour market) shocks also have significant (negative) impacts on household income.

Further interesting findings can be drawn from the empirical results on our vulnerability estimates based on the multilevel model. Around 37.7 percent of the panel households are classified as vulnerable at least once in any of the periods covered. Only 15.9 percent of the panel households are vulnerable to unobservable covariate shocks while 34.5 percent are vulnerable to unobservable idiosyncratic shocks. Decomposition of poverty and vulnerability to poverty revealed that the chronic and the transitory 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.

Among a number of policy implications derived by our 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. 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). This is confirmed by our results comparing the determinants of vulnerability, chronic poverty, transitory poverty and chronic non-poverty. Clearly, policies and programs aimed at human capital investment are very important government interventions, especially in developing countries like the Philippines. 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. Policies to improve transportation infrastructure and/or irrigation facilities are also deemed important for reducing vulnerability.

References

Baulch, B. and Quisumbing, A. (2011). Testing and adjusting for attrition in household panel data. CPRC Toolkit Note. London, United Kingdom: Chronic Poverty Research Centre.

Becketti, S., Gould, W. Lillard, L., and Welch, F. (1988). The Panel Study of Income Dynamics after Fourteen Years: An Evaluation. *Journal of Labor Economics*, 6, 472-92.

Bell, A., & Jones, K. (2015). Explaining Fixed Effects: Random Effects Modeling of Time-Series Cross-Sectional and Panel Data. *Political Science Research and Methods* 3, 133-153.

Chaudhuri, S., Jalan, J., & Suryahadi, A. (2002). *Assessing household vulnerability to poverty from cross-sectional data: a methodology and estimates from Indonesia*. (Columbia University Department of Economics Discussion Paper Series, 0102-52). Retrieved from: http://academiccommons.columbia.edu.

Christiaensen, L.J., & Subbarao, K. (2005). Towards an understanding of household vulnerability in rural Kenya. *Journal of African Economies*, 14(4), 520-558.

Clarke, P., Crawford, C., Steele, F., & Vignoles, A. (2015). Revisiting fixed- and random-effects models: some considerations for policy-relevant education research. Education Economics, 23(3), 259-277.

Dupont, E., & Martensen, H. (Eds.). (2007). 'Multilevel modelling and time series analysis in traffic research – methodology', *EU FP6 project SafetyNet – Deliverable D7.4*. Retrieved from: http://erso.swov.nl/safetynet/fixed/WP7/D7_4/D7.4.pdf.

Échevin, D. (2013). Characterizing vulnerability to poverty in rural Haiti: a multilevel decomposition approach. *Journal of Agricultural Economics*, 64(3), 1-21.

Fitzgerald, J., Gottschalk and Moffit, R. (1998). „An analysis of sample attrition in panel data". *Journal of Human Resources,* 33(2), 251-299.

Frees, E.W. (2004). *Longitudinal and panel data: analysis and applications in the social sciences.* New York: Cambridge University Press.

Gibbons, R.D., Hedeker, D., & DuToit, S. (2010). Advances in analysis of longitudinal data. *Annual Review of Clinical Psychology*, 6, 79-107.

Gibbons, C.E., Serrato, J.C.S., & Urbancic, M.B. (2016). 'Broken or Fixed Effects?', Draft, Duke University, NC, USA (February 15, 2016).

Glewwe, P., & Hall, G. (1998). Are some groups more vulnerable to macroeconomic shocks than others? Hypothesis tests based on panel data from Peru. *Journal of Development Economics*, 56, 181-206.

Goldstein, H. (1999). *Multilevel statistical models*. London, Arnold.

Graham, S.E., Singer, J.D., & Willett, J.B. (2008). An introduction to the multilevel model for change. In P. Alasuutari, L. Bickman, & J. Brannen (Eds.), *The SAGE Handbook of Social Research Methods* (pp.6-22). Hillsdale, New Jersey: Erlbaum.

Günther, I., & Harttgen, K. (2009). Estimating household vulnerability to idiosyncratic and covariate shocks: a novel method applied in Madagascar. *World Development,* 37(7), 1222-1234.

Hox, J.J. (2000). Multilevel analyses of grouped and longitudinal data. In T. D. Little, K. U. Schnabel, & J. Baumert (Eds.), *Modeling longitudinal and multiple group data: practical issues, applied approaches, and specific examples* (pp.6-22), Hillsdale, New Jersey: Erlbaum.

Imai, K., Gaiha, R., & Kang, W. (2011). Poverty Dynamics and Vulnerability in Vietnam. *Applied Economics*, 43(25), 3603-3618.

Kühl, J.J. (2003). *Disaggregating household vulnerability-analyzing fluctuations in consumption using a simulation approach*. Unpublished Manuscript, Copenhagen, Denmark: Institute of Economics, University of Copenhagen.

Ligon, E., & Schechter, L. (2003). Measuring vulnerability. *Economic Journal*, 113(486), 95-110.

Maluccio, J. A. (2004). Using Quality of Interview Information to Assess Nonrandom Attrition Bias in Developing-Country Panel Data. *Review of Development Economics*, 8(1), 91-109.

McCulloch, N., & Calandrino, M. (2003). Vulnerability and chronic poverty in rural Sichuan. *World Development*, 31(3), 611-628.

Miralao, V. A. (1992). Female-headed households in the Philippines. *Philippine Sociological Review*, 40 1/4,46-56.

Mundlak, Y. (1978). On the pooling of time series and cross section data. *Econometrica*, 46(1), 69-85.

NEDA (National Economic and Development Authority) and UNDP (United Nations *Development* Programme) (2010). *Philippines Progress Report on the Millennium Development Goals 2010.* Retrieved from http://www.undg.org/docs/12270/MDG-National-Report-2010.pdf.

Philippine Statistics Authority (PSA) (2014). 'Concepts and definitions: Local Government Units', *Philippine Standard Geographic Code (PSGC) Interactive*. Retrieved from: http://www.nscb.gov.ph/activestats/psgc/articles/con_lgu.asp.

Pritchett, L., Suryahadi, A., & Sumarto, S. (2000). *Quantifying vulnerability to poverty: a proposed measure, with application to Indonesia (*SMERU Working Paper, May 2000). Retrieved from:
http://www.smeru.or.id/report/workpaper/vulnerability/vulnerability.pdf

Rabe-Hesketh, S., and Skrondal, A. (2012). *Multilevel and longitudinal modeling using Stata Volume I: Continous Response.* Texas: STATA press.

Raudenbush, S. W., & Bryk, A.S. (2002). *Hierarchical linear models. 2nd edn*. Thousand Oaks, California: Sage.

Reyes, C. M., Domingo, S. N., Mina, C. D., & Gonzales, K. G. (2009). Policy options for rice and corn farmers in the face of seasonal climate variability. *Philippine Journal of Development*, 36(1), 133-157.

Reyes, C. M., & Mina, C.D. (2013). *Where are the poor employed? Profiling the working poor* (PIDS Policy Notes, 2013-04). Retrieved from: http://dirp4.pids.gov.ph/ris/pn/pidspn1304.pdf.

Reyes, C. M., Tabuga, A. D., Mina, C. D., & Asis, R. D. (2013). Promoting inclusive growth through the 4Ps (pp.84-129). In PIDS, *Economic Policy Monitor: Regional economic integration and inclusive growth – engaging nations, embracing people*, Retrieved from: http://dirp4.pids.gov.ph/ris/books/pidsepm2012.pdf.

Schultz, T. W. (1975). Human capital and disequilibrium. *Journal of Economic Literature,* 13(3), 827-846.

Singer, J. D., & Willett, J. B. (2003). *Applied longitudinal data analysis: modeling change and occurrence*. New York: Oxford University Press.

Snijders, T. A. B., & Bosker, R. J. (2012). *Multilevel analysis: an introduction to basic and advanced multilevel modeling. 2nd edn*. London: SAGE Publications Ltd.

Suryahadi, A., & Sumarto, A. (2003). Poverty and vulnerability in Indonesia before and after the economic crisis. *Asian Economic Journal*, 17(1), 45-64.

Tabunda, A. M. (2001). El Niño or El Peso? Crisis and poverty in the Philippines revisited. In The World Bank Institute, *Strengthening poverty data collection and analysis,* Bangkok: The World Bank Institute.

World Bank (2001). *World Development Report 2000/2001: Attacking Poverty*. New York: Oxford University Press.

Zhang, Y. and Wan, G. (2006). 'An empirical analysis of household vulnerability in rural China', *Journal of the Asia Pacific Economy*, Vol. 11(2), pp. 196-212.

TABLE 1 Selected macroeconomic indicators, Philippines, 2003-2009

Indicator	2003	2004	2005	2006	2007	2008	2009
Gross Domestic Product (GDP) growth rate, %	5.0	6.7	4.8	5.2	6.6	4.2	1.1
Agriculture	4.7	4.3	2.2	3.6	4.7	3.2	-0.7
Industry	4.3	5.2	4.2	4.6	5.8	4.8	-1.9
Services	5.5	8.3	5.8	6.0	7.6	4.0	3.4
Gross National Income (GNI), at constant prices	4,913	5,262	5,630	5,911	6,276	6,590	6,989
Current account balance, % of GDP	0.3	1.8	1.9	4.4	4.8	2.1	5.6
Net factor income from abroad, at constant prices	904	985	1,149	1,195	1,248	1,353	1,692
Exchange rate (PhP/US$), average of period	54.20	56.04	55.09	51.31	46.15	44.32	47.68
Inflation, %	2.3	4.8	6.5	5.5	2.9	8.3	4.2
Population growth rate, %	2.0	1.9	1.9	1.9	1.8	1.8	1.8

Source: Key Indicators for Asia and the Pacific 2013, Asian Development Bank.

PhP = Philippine peso; US$ = US dollar

TABLE 2. Definition and summary statistics of variables

Variable	Definition	2003				2006				2009			
		Mean	**Std Dev**	**Min**	**Max**	**Mean**	**Std Dev**	**Min**	**Max**	**Mean**	**Std Dev**	**Min**	**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
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

[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.

TABLE 3. Results of the Random Coefficient Model (RC) and Fixed-effects (FE) Model (with correction of attrition based on Fitzgerald et al. (1998))

Dependent variable: Log of per capita income

Explanatory Variables	**RC Model: 'within-between' formulation**		**FE Model**		**RC Model: First-differenced**
	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**
Fixed part					
Time	**0.0595 (0.0032)*** **	**0.0605 (0.0026)*** **	**0.0652 (0.0016)*** **	**0.0672 (0.0018)*** **	**-0.0393 (0.0210)***
Household composition					
Household size [a)]	**-0.1970 (0.0093)*** **	**-0.2646 (0.0188)*** **	**-0.1998 (0.0106)*** **	**-0.3161 (0.0245)*** **	**-0.1987 (0.0090)*** **
Household size (between) [b)]	**-0.0989 (0.0151)*** **	**-**	**-**	**-**	**-**
Square of household size [a)]	**0.00887 (0.00073)*** **	**0.0266 (0.0032)*** **	**0.0091 (0.0008)*** **	**0.0322 (0.0039)*** **	**0.0090 (0.0007)*** **
Square of household size (between) [b)]	0.00179 (0.00073)	**-**	**-**	-	**-**
Dependency ratio [a)]	**-0.337 (0.0276)*** **	**0.1007 (0.0592)***	**-0.3355 (0.0284)*** **	0.0016 (0.0708)	**-0.3122 (0.0267)*** **
Dependency ratio (between) [b)]	**-0.850 (0.0499)*** **	**-**	**-**	-	**-**
Household head profile					
Sex	**-0.0506 (0.0140)*** **	**-0.1700 (0.0603)*** **	-0.0189 (0.0189)	-0.0635 (0.0709)	-0.0145 (0.0179)
Age [a)]	**0.00822 (0.0031)*** **	- [d)]	**0.0084 (0.0032)*** **	0.0054 (0.0036)	**0.0066 (0.0030)** **
Age (between) [b)]	**0.0138 (0.0039)*** **	- [d)]	**-**	-	**-**
Square of age [a)]	-0.00004 (0.00003)	0.00003 (0.00003)	**-0.0001 (<0.000)*** **	**-0.0001 (<0.000)** **	**-0.0001 (<0.000)** **
Square of age (between) [b)]	**-0.0001 (0.00003)*** **	**-0.00009 (0.00003)*** **			
Educational attainment [c)]					
At least elementary graduate	**0.141 (0.0119)*** **	**0.1820 (0.0246)*** **	0.0036 (0.0151)	**0.0547 (0.0256)** **	0.0121 (0.0144)
At least secondary graduate	**0.400 (0.0146)*** **	**0.5130 (0.0339)*** **	0.0158 (0.0216)	**0.0804 (0.0393)** **	0.0240 (0.0201)
At least college graduate	**0.889 (0.0226)*** **	**0.7830 (0.110)*** **	0.0003 (0.0383)	0.0664 (0.1577)	**0.4029 (0.1327)*** **
Location					
Urban/rural	**0.253 (0.0159)*** **	0.0623 (0.0396)	0.1899 (0.1375)	0.1105 (0.1905)	0.2103 (0.1519)
Regional Dummies	**Yes**	**Yes**	**No**	**No**	**No**
Aggregate-level variables					
Transportation infrastructure index [a)]	-0.0259 (0.0251)	- [d)]	**-0.0323 (0.0155)** **	**-0.0290 (0.0167)***	-0.0060 (0.0285)
Transportation infrastructure (between) [b)]	-0.00575 (0.0219)	- [d)]	**-**	**-**	-
Economic and social infrastructure index [a)]	**-0.0133* (0.0080)***	- [d)]	**0.0206 (0.0091)** **	**-0.0422 (0.0252)***	0.0134 (0.0158)
Economic and social infrastructure (between) [b)]	0.0492 (0.0318)	- [d)]	**-**	**-**	-
Irrigation development index [a)]	0.0013 (0.0015)	- [d)]	0.0002 (0.0010)	-0.0001 (0.0012)	0.0006 (0.0019)
Irrigation development index (between) [b)]	0.00167* (0.0009)	- [d)]	-	-	-
Agriculture index [a)]	-0.0135 (0.0305)	- [d)]	**-0.0223 (0.0080)*** **	-0.0043 (0.0100)	-0.0129 (0.0130)
Agriculture index (between) [b)]	-0.00575 (0.0219)	- [d)]	**-**	-	-
Utilities index [a)]	0.0103 (0.0114)	- [d)]	**0.0120 (0.0055)** **	0.0082 (0.0059)	-0.0046 (0.0102)
Utilities index (between) [b)]	0.0199 (0.0169)	- [d)]	**-**	-	-

Idiosyncratic shocks					
More jobless members	0.00807 (0.0086)	0.01191 (0.0087)	0.0057 (0.0091)	0.0099 (0.0092)	**0.0768 (0.0359)****
More members engaged in vulnerable employment	0.00102 (0.0086)	0.0168 (0.0105)	0.0031 (0.0085)	0.0187 (0.0107)*	-0.0087 (0.0092)
More members with non-permanent jobs	-0.00029 (0.00903)	0.0021 (0.0091)	**0.0147 (0.0089)***	**0.0181 (0.0089)****	0.0077 (0.0096)
Fewer overseas contract worker (OCW) members	**0.109 (0.0198)*****	**0.101 (0.0197)*****	-0.0147 (0.0221)	-0.0148 (0.0219)	-0.0064 (0.0206)
Covariate shocks					
Rainfall shock	**-0.0679 (0.0132)*****	-0.0425 (0.0169)**	-0.0708 (0.0119)***	-0.0547 (0.0155)***	-0.2938 (0.0878)***
Rice price shock	0.00762 (0.0819)	-0.0323 (0.07469	0.0007 (0.0548)	0.0020 (0.0536)	0.0308 (0.0981)
Fuel price shock	**-0.0374 (0.00661)*****	**-0.0363 (0.0075)*****	-0.0459 (0.0063)***	-0.0404 (0.0075)***	-0.0949 (0.0324)***

TABLE 3. (continued).

Variable	**RC Model: 'within-between' formulation**		**FE Model**		**RC Model: First-differenced**
	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**
Interactions					
[Time × Region Dummies or Province Variables]	**No**	**Yes**	**No**	**Yes**	**Yes**
[Household Characteristics –cross-Interactions]	**No**	**Yes**	**No**	**No**	**No**
[Household Characteristics X Region Dummies]	**No**	**Yes**	**No**	**Yes**	**Yes**
[Household Characteristics X Province Variables]	**No**	**Yes**	**No**	**Yes**	**No**
[Region Dummies X Province Variables]	**No**	**Yes**	**No**	**Yes**	**No**
Selected results on interactions (excluding those on time, region or province dummies)					
Sex X Age [a)]	**-**	0.0019 (0.0017)	**-**	**0.0023 (0.0012)***	**-**
Sex X Age (between) [b)]	**-**	**0.0310 (0.0010)*****	**-**	**-**	**-**
Sex X Education, College	**-**	**0.163 (0.0417)*****	**-**	-0.0246 (0.0608)	**-**
Education, College X Age [a)]	**-**	**0.011 (0.0025)*****	**-**	0.0018 (0.0028)	**-**
Education, College X Age (between) [b)]	**-**	**0.00418 (0.00172)****	**-**	**-**	**-**
Education, Elementary X Rain	**-**	**-0.04839 (0.0235)****	**-**	**-0.0501 (0.0226)****	**-**
Education, Secondary X Household size [a)]	**-**	**-0.02229 (0.0073)*****	**-**	**-0.0120 (0.0060)****	**-**
Education, Secondary X Household size (between) [b)]	**-**	**-0.02416 (0.00738)*****	**-**	**-**	**-**
Education, College X Household size [a)]	**-**	**-0.02839 (0.01084)*****	**-**	**-0.0287 (0.0109)*****	**-**
Education, College X Household size (between) [b)]	**-**	**-0.03337 (0.01173)*****	**-**	-0.0177 (0.0272)	**-**
Education, College X Transport Infrastructure [a)]	**-**	**-0.18925 (0.05737)*****	**-**	-0.0177 (0.0272)	**-**
Education, College X Transport Infrastructure (between) [b)]	**-**	**-0.06311 (0.01876)*****	**-**	**-**	**-**
Household size [a)] X Dep. Ratio [a)]	**-**	**-0.08814*** (0.02992)**	**-**	**-0.0684 (0.0132)*****	**-**
Household size (between) [b)]X Dep. Ratio (between) [b)]	**-**	**-0.18906 (0.02084)*****	**-**	**-**	**-**
Irrigation [a)] X Utility Index [a)]	**-**	**-0.01126 (0.00347)*****	**-**	**0.0013 (0.0005)*****	**-**
Irrigation (between) [b)]X Utility Index (between) [b)]	**-**	**0.00110 (0.00045)*****	**-**	**-**	**-**
Fuel price shock X More members engaged in vulnerable employment	**-**	**-0.04435 (0.01684)*****	**-**	**-0.0437 (0.0170)****	**-**
Square of age × More members in vulnerable employment	**-**		**-**		<0.000 (<0.000)***
Square of age × More members with non-permanent jobs	**-**	**-**	**-**	**-**	<0.000 (<0.000)**

Square of hh size × Rainfall shock	-	-	-	-	-0.0010 (0.0004)**
Agriculture index × More jobless members	-	-	-	-	0.0325 (0.0122)***
Rainfall shock × More members in vulnerable employment	-	-	-	-	-0.0265 (0.0143)*
More jobless members × Fewer overseas contract worker (OCW) members	-	-	-	-	0.0915 (0.0304)***
Education of head (secondary) × More members in vulnerable employment	-	-	-	-	0.0542 (0.0247)**
Intercept	0.194 (0.135)	0.5219 (0.1068)***	1.0066 (0.1097)***	1.864 (0.2040)***	0.4825 (0.1577)***
Random part					
Province-level					
Variance (Random slope)	**0.0004 (0.0001)*** **	**0.0002 (0.00007)*** **	-	-	**0.0011 (0.0004)*** **
Variance (Random intercept)	**0.0265 (0.0081)*** **	**0.00716 (0.0034)** **	-	-	**0.0593 (0.0228)*** **
Covariance (Random slope, Random intercept)	**-0.0025 (0.0009)*** **	**-0.0008 (0.0004)* **	-	-	**-0.0079 (0.0031)*** **
Household-level:					
Variance (Random slope)	**0.0027 (0.0003)*** **	**0.0027 (0.0003)*** **	-	-	**0.0361 (0.0014)*** **
Variance (Random intercept)	**0.2973 (0.0155)*** **	**0.2859 (0.0152)*** **	-	-	**1.9943 (0.0862)*** **
Covariance (Random slope, Random intercept)	**-0.0164 (0.0020)*** **	**-0.0167 (0.0019)*** **	-	-	**-0.2682 (0.0107)*** **
Occasion-level:					
Time 0: Variance (Residual)	**0.0811 (0.0057)*** **	**0.0805 (0.0056)*** **	-	-	-
Time 3: Variance (Residual)	**0.1152 (0.0034)*** **	**0.1130 (0.0033)*** **	-	-	**0.1317 (0.0085)*** **
Time 6: Variance (Residual)	**0.0862 (0.0056)*** **	**0.0869 (0.0055)*** **	-	-	**0.1140 (0.0098)*** **

Figures in parentheses are standard errors; *** p<0.001, ** p<0.01, * p<0.05. Statistically significant coefficient estimates are shown in bold.

[a] Demeaned or 'within' term ($\mathbf{x}^{T}_{(1)tij} - \overline{\mathbf{x}^{T}_{(1)ij}}$ or $\mathbf{X}^{T}_{(3)tij} - \overline{\mathbf{X}^{T}_{(3)tj}}$)is shown for Model 1 and Model 2.

[b] 'Between' term or time-series average of time-varying variables ($\overline{\mathbf{x}^{T}_{(1)ij}}$ or $\overline{\mathbf{X}^{T}_{(3)tj}}$).

[c] Base category: At most elementary level.

[d] BA variable has been dropped due to the high correlations with interactions.

TABLE 4. Poverty and vulnerability status of panel households, by degree and by source

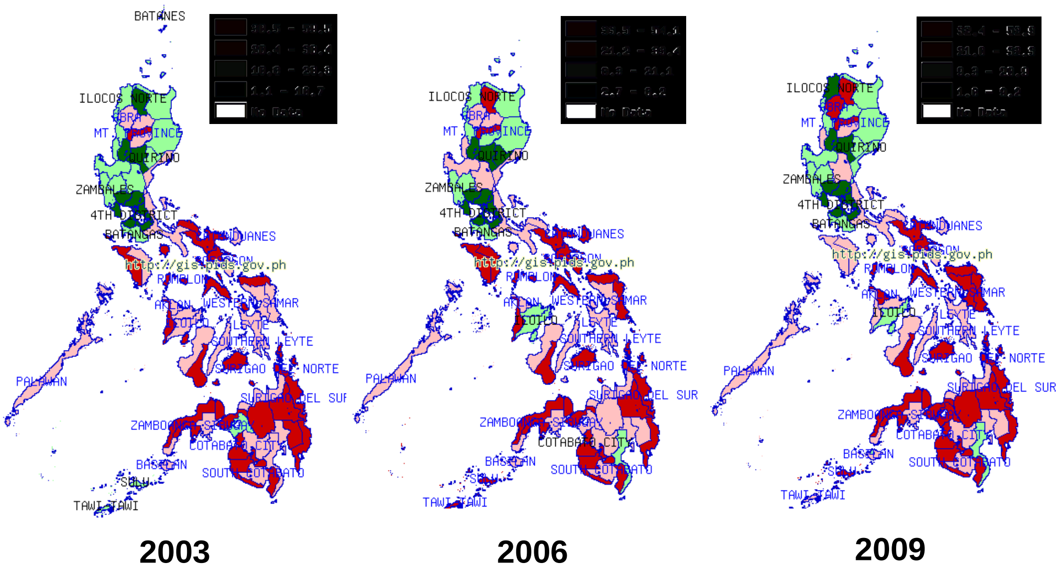
Vulnerability status	*Chronic poor*	*Transitory poor*	*Never poor*	All
Based on Random Coefficient Model				
Total vulnerability				
Highly vulnerable	56.3	19.9	2.4	13.9
Relatively vulnerable	32.1	38.9	15.1	23.8
Not vulnerable	11.6	41.2	82.5	62.4
Covariate vulnerability				
Highly vulnerable	58.7	20.6	2.5	13.9
Relatively vulnerable	3.6	4.0	0.8	2.0
Not vulnerable	37.8	75.4	96.7	84.1
Idiosyncratic vulnerability				
Highly vulnerable	56.3	19.9	2.4	13.9
Relatively vulnerable	29.6	34.5	12.4	20.6
Not vulnerable	14.1	45.6	85.2	65.6
Based on Fixed-Effects Model				
Highly vulnerable	11.1	5.4	2.8	4.5
Relatively vulnerable	88.9	94.6	96.9	95.3
Not vulnerable	0.0	0.0	0.3	0.2

Source: Authors' estimates using the 2003-2006-2009 FIES panel data. Only sample households included in the estimation sample were included (n = 5,199)

TABLE 5. Determinants of Vulnerability, Chronic Poverty, "Moving Up", "Moving Down" and "Never Poor" (based on covariates in 2003)

Dependent Variable:	**Vulnerability**	**"Chronic Poverty"**	**"Moving Up"**	**"Slipping Down"**	**"Never Poor"**
Explanatory Variables Model	OLS	Probit	Probit	Probit	Probit
Household head profile					
Sex	**0.0161*** **	0.0898	0.11	0.0905	**-0.161** **
	(0.0056)	(0.111)	(0.0799)	(0.0727)	**(0.0686)**
Age	**-0.0146*** **	**-0.0532*** **	0.0157	**-0.0342*** **	**0.0412*** **
	(0.0011)	**(0.0135)**	(0.0118)	**(0.01000)**	**(0.00973)**
Square of age	**0.00012*** **	**0.000432*** **	-0.000127	**0.000293*** **	**-0.000323*** **
	(0.000010)	**(0.000132)**	(0.000113)	**(0.0000933)**	**(0.0000920)**
At least elementary graduate	**-0.0461*** **	**-0.427*** **	**-0.174*** **	-0.0691	**0.458*** **
	(0.0060)	**(0.0634)**	**(0.0555)**	(0.0536)	**(0.0517)**
At least secondary graduate	**-10.141*** **	**-0.948*** **	**-0.518*** **	**-0.361*** **	**1.131*** **
	(0.0062)	**(0.0798)**	**(0.0658)**	**(0.0621)**	**(0.0588)**
At least college graduate	**-0.213*** **	.	**-1.339*** **	**-1.533*** **	**2.472*** **
	(0.00831)	.	**(0.180)**	**(0.215)**	**(0.181)**
Household size	**-0.0115*** **	**0.175*** **	**0.291*** **	-0.0471	**-0.0758* **
	(0.00436)	**(0.0675)**	**(0.0518)**	(0.0431)	**(0.0436)**
Square of household size	**0.00274*** **	-0.00247	**-0.0173*** **	0.00162	-0.00347
	(0.000381)	(0.00479)	**(0.00412)**	(0.00345)	(0.00346)
Dependency ratio	**0.294*** **	**2.140*** **	**0.544*** **	**0.221* **	**-1.563*** **
	(0.0123)	**(0.182)**	**(0.138)**	**(0.132)**	**(0.123)**
Urban/rural	**-0.0828*** **	**-0.445*** **	**-0.299*** **	**-0.120** **	**0.460*** **
	(0.00447)	**(0.0743)**	**(0.0601)**	**(0.0546)**	**(0.0493)**
Economic and social infrastructure index	**-0.00973** **	0.0421	**-0.115*** **	-0.0236	**0.0988*** **
	(0.00415)	(0.0447)	**(0.0390)**	(0.0383)	**(0.0361)**
Utilities index	-0.00336	**-0.123*** **	**-0.0646** **	0.00446	**0.0676*** **
	(0.00205)	**(0.0344)**	**(0.0269)**	(0.0248)	**(0.0243)**
Agriculture index	0.00124	0.0148	0.00968	0.0374	-0.0401
	(0.00310)	(0.0422)	(0.0365)	(0.0347)	(0.0313)
Transportation infrastructure index	**-0.0216*** **	0.0368	0.0558	**-0.0652** **	-0.012
	(0.0426)	(0.0396)	(0.0357)	**(0.0329)**	(0.0307)
Irrigation development index	**-0.00659*** **	**-0.00335** **	0.000288	**-0.00309** **	**0.00376*** **
	(0.00134)	**(0.00170)**	(0.00140)	**(0.00135)**	**(0.00126)**
More jobless members	-0.00651	-0.0981	-0.0754	0.0598	0.0563
	(0.0052)	(0.0791)	(0.0630)	(0.0570)	(0.0548)
More members engaged in vulnerable employment	**-0.0163*** **	0.0386	**-0.133** **	**0.0941* **	-0.000652
	(0.0052)	(0.0688)	**(0.0597)**	**(0.0549)**	(0.0520)
More members with non-permanent jobs	**-0.0163*** **	0.00921	0.0138	0.0667	-0.0455
	(0.00544)	(0.0711)	(0.0598)	(0.0569)	(0.0530)
Fewer overseas contract worker (OCW) members	**-0.0269*** **	.	-0.25	**-0.494*** **	**0.737*** **
	(0.0103)	.	(0.161)	**(0.173)**	**(0.155)**
Regional Dummies	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
_cons	0.778	-0.399	-2.368	0.224	-1.124
	(0.398)	(0.396)	(0.351)	(0.299)	(0.288)
N	5096	4655	5199	5199	5199

Figures in parentheses are standard errors; *** p<0.001, ** p<0.01, * p<0.05. Statistically significant coefficient estimates are shown in bold. All regressions are based on the Huber-White robust estimators. Source: Authors' estimates using the 2003 FIES panel data.



Source: *GIS-based Socioeconomic Profile of the Philippines*, Philippine Institute for Development Studies

FIGURE 1. Poverty incidence and magnitude of poverty among households by province in the Phillipines

Online Appendices

Online Appendix Table 1. Fitzgerald et al.'s (1998) unrestricted attrition probit model

Dependent variable: Attrition dummy

Variable	Parameter
Intercept	0.8218 (0.2319)***
Log of per capita income	-0.0375 (0.0273)
Attrition dummy	-
Attrition rate within a province	0.0258 (0.0024)***
Household composition	
Household size	-0.2079 (0.0296)***
Square of household size	0.0125 (0.0024)***
Dependency ratio	0.0124 (0.0892)
Household head profile	
Sex	-0.1274 (0.0434)***
Age	-0.0367 (0.0065)***
Square of age	0.0003 (0.0001)***
Educational attainment[a/]	
At least elementary graduate	-0.1277 (0.0402)***
At least secondary graduate	-0.0859 (0.0460)*
At least college graduate	0.1070 (0.0697)
Employment	0.0819 (0.0347)**
Location	
Urban/rural	0.1841 (0.0357)***
Regional Dummies	**Yes**
Aggregate-level variables	
Transportation infrastructure index	-0.0143 (0.0243)
Economic and social infrastructure index	-0.0192 (0.0164)
Irrigation development index	-0.0009 (0.0010)
Agriculture index	0.0031 (0.0254)
Utilities index	0.0110 (0.0281)
Idiosyncratic shocks	
More jobless members	-0.1111 (0.0405)***
More members engaged in vulnerable employment	-0.5252 (0.0469)***
More members with non-permanent jobs	-0.5475 (0.0497)***
Fewer overseas contract worker (OCW) members	-0.4389 (0.1017)***
Covariate shocks[c/]	
Rainfall shock	-0.0604 (0.1051)
Fuel price shock	0.1345 (0.1834)

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

[a/] base category: At most elementary level

Online Appendix Table 2. Becketti, Gould, Lillard and Welch (BGLW) pooling test for attrition

Dependent variable: Log of per capita income

Variable	Parameter
Intercept	0.0249 (0.1258)
Log of per capita income	-
Attrition dummy	-0.0249 (0.1258)
Attrition rate within a province	0.0034 (0.0013)***
Household composition	
Household size	-0.1336 (0.0159)***
Square of household size	0.0045 (0.0012)***
Dependency ratio	-0.6821 (0.0451)***
Household head profile	
Sex	-0.0806 (0.0265)***
Age	0.0133 (0.0038)***
Square of age	-0.0001 (0.0000)*
Educational attainment[a/]	
At least elementary graduate	0.1907 (0.0187)***
At least secondary graduate	0.5209 (0.0225)***

At least college graduate	1.1751 (0.0378)***
Employment	0.2094 (0.0175)***
Location	
Urban/rural	0.1047 (0.0190)***
Region Dummies [b/]	**Yes**
Aggregate-level variables	
Transportation infrastructure index	-0.0090 (0.0120)
Economic and social infrastructure index	0.0210 (0.0084)**
Irrigation development index	0.0014 (0.0005)***
Agriculture index	-0.0398 (0.0131)***
Utilities index	0.0264 (0.0135)*
Idiosyncratic shocks	
More jobless members	0.0339 (0.0202)*
More members engaged in vulnerable employment	0.0298 (0.0199)
More members with non-permanent jobs	-0.0241 (0.0188)
Fewer overseas contract worker (OCW) members	0.2976 (0.0480)***
Covariate shocks[c/]	
Rainfall shock	-0.1261 (0.0520)**
Fuel price shock	-0.0356 (0.0929)

Online Appendix Table 2. (continued)

Variable	Parameter
Interactions with attrition dummy	
Log of per capita income	1.0000 (0.0000)***
Household head's sex	0.0806 (0.0265)***
Household head's age	-0.0133 (0.0038)***
Household head's square of age	0.0001 (0.0000)*
Household head's educational attainment: at least elementary graduate	-0.1907 (0.0187)***
Household head's educational attainment: at least secondary graduate	-0.5209 (0.0225)***
Household head's educational attainment: at least college graduate	-1.1751 (0.0378)***
Household head's employment	-0.2094 (0.0175)***
Household size	0.1336 (0.0159)***
Square of household size	-0.0045 (0.0012)***
Dependency ratio	0.6821 (0.0451)***
Urban/rural	-0.1047 (0.0190)***
Regional Dummies	**Yes**
Transportation infrastructure index	0.0090 (0.0120)
Economic and social infrastructure index	-0.0210 (0.0084)**
Irrigation development index	-0.0014 (0.0005)***
Agriculture index	0.0398 (0.0131)***
Utilities index	-0.0264 (0.0135)*
Fuel price shock	0.0356 (0.0929)
Rainfall shock	0.1261 (0.0520)**
More jobless members	-0.0339 (0.0202)*
More members engaged in vulnerable employment	-0.0298 (0.0199)
More members with non-permanent jobs	0.0241 (0.0188)
Fewer overseas contract worker (OCW) members	-0.2976 (0.0480)***
Attrition rate within a province	-0.0034 (0.0013)***

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

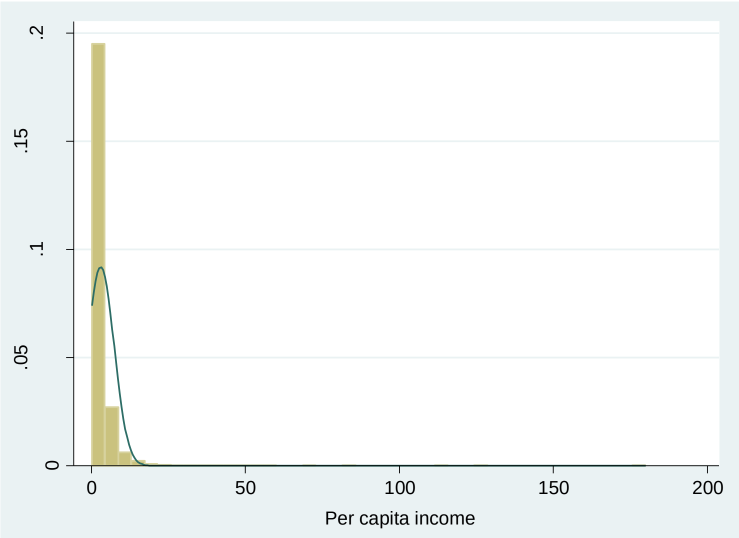
[a/] base category: At most elementary level

[b/] base category: Caraga; National Capital Region (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. The dummy for the MIMAROPA region (Occidental and Oriental Mindoro, Marinduque, Romblon, Palawan) was dropped because none of the sample households in that region were included in the estimation sample.

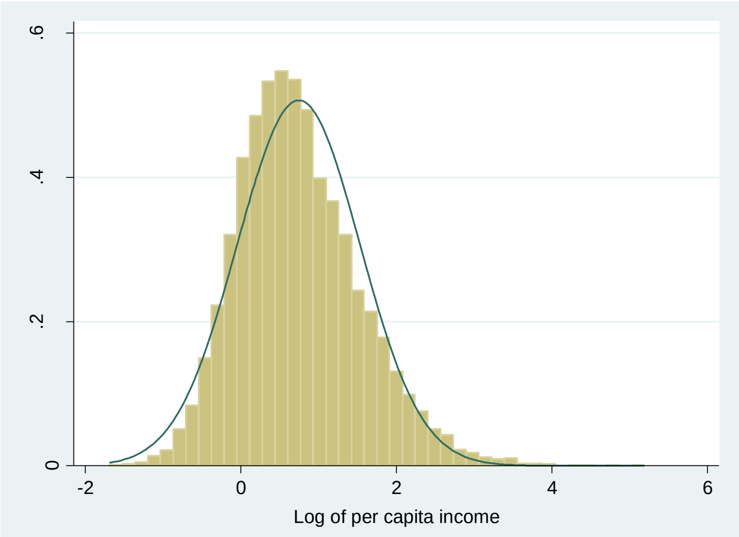
[c/] Rice price shock was dropped from the analysis.

Online Appendix Table 3. Results of Likelihood ratio tests for inclusion of random coefficients

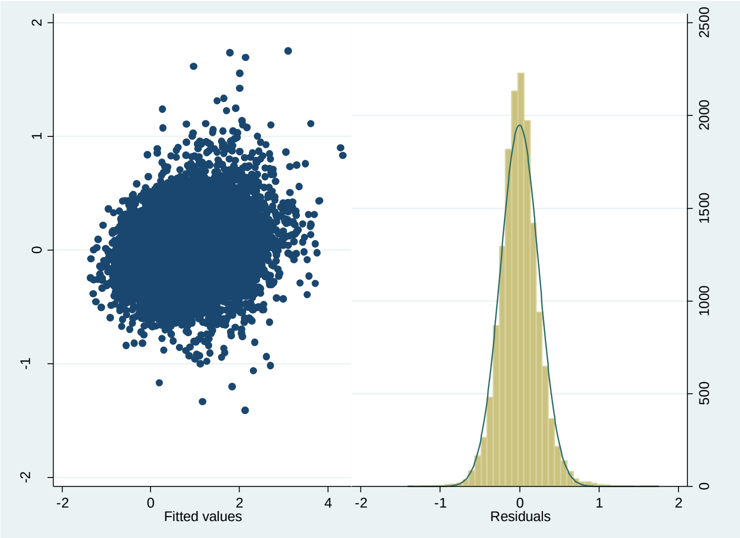
Likelihood ratio test 1: Model (without random coefficient) vs. Model (with random coefficient at level 2): LR χ^2_2 = 89.37, Pr > χ^2 = 0.0000
Likelihood ratio test 2: Model (with random coefficient at level 2) vs. Model (with random coefficients at levels 2 & 3): LR χ^2_4 = 40.54, Pr > χ^2 = 0.0000
Note: All models have identical fixed-effects specifications.



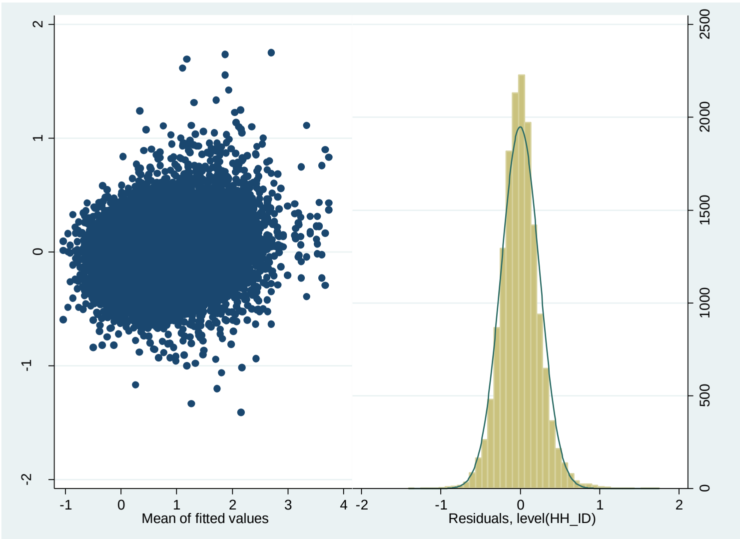
Online Appendix Figure 1a. Histogram (with normal-density plot) of per capita income



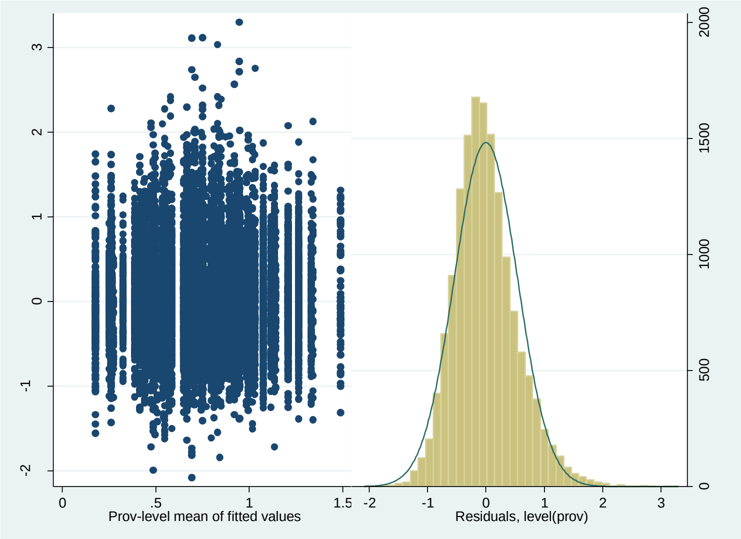
Online Appendix Figure 1b. Histogram (with normal-density plot) of log of per capita income



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



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



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

Endnotes

[1] The figures are based on Family Income and Expenditure Surveys, Philippine Statistics Authority (PSA) in 2003, 2006 and 2009.

[2] 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.

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

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

[5] The official poverty thresholds, both at the regional and provincial level, are estimated by the PSA 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.

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

[7] The model can also contain both time-varying and time-invariant variables.

[8] Province is the largest unit in the political structure of the Philippines, consisting of municipalities and, in some cases, of component cities (PSA, 2014).

[9] Under fixed occasion design; wherein all households are measured at the same, regularly spaced time points (Snijders and Bosker, 2012)

[10] See Bell and Jones (2015) for details.

[11] Employment is included only in the attrition probit models as it was believed to be a key factor that affects attrition. It has been excluded from the income equations given its possible endogeneity.

[12] Attrition rate within the province, which can serve as a measure of the quality of the interview (Maluccio, 2004), is also included because it is related to attrition albeit not directly related to household income (Baulch and Quisumbing, 2011).

[13] Wald test's $Chi^2(14) = 754.55$ and Prob > chi2 = 0.0000; F-test's F(33, 7968) = 180.07 and Prob > F = 0.0000.

[14] Auxiliary variables used were characteristics of household head, household's demographic composition, lagged value of income, economic and labour market shocks, location dummies, and community-level variables; leaving only household size and its square as regressors in the restricted attrition probit model.

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

[16] 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.

[17] Interaction terms are reported selectively in Table 3. A full set of the results will be provided on request.