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# Estimation of Vulnerability to Poverty Using a Multilevel Longitudinal Model: Evidence from the Philippines*

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

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**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

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# 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 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. Agriculture and industry sectors, on the other hand, suffered negative growth rates in 2009. The gross national income 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. Philippines, however, was subject to a variety of macroeconomic and other shocks and households were likely to be vulnerable to both covariate and idiosyncratic shocks in this period.

**(TABLE 1 to be inserted)**

An important question in this context is how macroeconomic conditions influenced household welfare. 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 (RC) 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 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 and is preferable to the fixed-effects (FE) model, both RC and FE models are estimated in this study. More specifically, we have applied the FE model to first differenced income to derive the predicted income in 2012 to examine how a household is below or above the poverty threshold. In all cases, the attrition bias was corrected by the method of Fitzgerald et al. (1998).

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 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.[2]

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 was 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 by introducing time as an additional level in the multilevel model.

**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. 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 Philippine Statistics Authority (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. 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.[3] 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.[4] Since per capita income is the welfare measure used in the generation of official poverty statistics in the country, (log of) per capita income is used as a dependent variable in the empirical model.

The set of covariates used in this study are selected based on previous poverty studies on the Philippines (Tabunda, 2001). Table 2 reports 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 included aggregate-level variables, namely the 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. Regional dummies were also included to account for regional characteristics. Except for squares of household size and age of head, all main effect variables included in the model are not strongly correlated.[5] 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 a direct impact on household income. 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.

## 4. Methodology

The methodology proposed in Günther and Harttgen (2009) is extended in this study by applying it to panel data with hierarchical structure where time (or 'occasion') is included as another level. Here we also take into account observable shocks in predicting income. 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 (FE) model to derive the vulnerability estimate without decomposing it into covariate and idiosyncratic components, and to see how different methods yield different vulnerability estimates. Furthermore, the FE model is used for the first differenced income to predict income in 2012 to define the vulnerability status.

We will use multilevel model or random-coefficient (RC) model to analyse hierarchically structured data with variables defined at all levels of the hierarchy (Hox, 2000; Gibbons et al., 2010; Dupont and Martensen, 2007; Singer and Willett, 2003). The 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).

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

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

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. It is noted that all the explanatory variables, such as those representing the shocks, are included in "the fixed part".

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 $\mathbf{v}_{j} \sim N(\mathbf{0},\mathbf{\Sigma}_{v})$. 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: $\mathbf{u}_{ij} \sim N(\mathbf{0},\mathbf{\Sigma}_{u})$. The matrix $\mathbf{Z}_{tij}^{T}$ contains the vectors of 1's for the random intercept and the time variable $\boldsymbol{z}$ 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: $e_{tij} \sim N(0,\sigma_{e}^{2})$. Residuals at different levels, $e_{tij}$, $\mathbf{v}_{j}$, and $\mathbf{u}_{ij}$ may contain the impacts of aggregate or idiosyncratic shocks as well as measurement errors and non-stochastic heterogeneity at different levels, which are 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. 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.

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 which Bell and Jones (2015) put forward as an extension of Mundlak (1978). This formulation 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.

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

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 or RC that covariates and unobservable terms are correlated and thus coefficient estimates of covariates are biased in the panel data settings (Bell and Jones, 2015).

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 fail 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).

We have also applied the FE model to the panel data in levels and in first differences by introducing $\mu_{ij}$, the unobservable fixed-effect at the household level, as in equations (3) and (3,).

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

$$\Delta \ln y_{tij} = \mathbf{x'}^T_{(1)tij}\,\boldsymbol{\beta'}_{(1)} + \mathbf{x'}^T_{(3)tj}\,\boldsymbol{\beta'}_{(3)} + \mu'_{ij} + e'_{tij} \qquad (3')$$

An advantage of the FE model is that we do not have to assume that $\mu_{ij}$ 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.

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 its square, educational attainment particularly elementary- and secondary-level education, employment), household size and its square, urban/rural, and labour market shocks and attrition rate within the province[6]. The results of the post-estimation Wald test and F-test for attrition[7], revealed that attrition in the household-level panel data was non-random, suggesting that attrition bias needs to be accounted for. 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). 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.

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 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 variance of residuals at each level is regressed on the aforementioned covariates (excluding the shock variables)[8], as in the following:

$$\sigma^2_{e\ tij} = \mathbf{x}^T_{(1)tij}\boldsymbol{\alpha}_{(1)} + \mathbf{x}^T_{(2)ij}\boldsymbol{\alpha}_{(2)} + \mathbf{x}^T_{(3)tj}\boldsymbol{\alpha}_{(3)} \qquad (4)$$

$$\sigma^2_{u\ 0ij} = \mathbf{x}^T_{(2)ij}\boldsymbol{\delta}_{(2)} + \mathbf{x}^T_{(3)tj}\boldsymbol{\delta}_{(3)} \qquad (5)$$

$$\sigma^2_{v\ 0j} = \mathbf{x}^T_{(3)tj}\boldsymbol{\gamma}_{(3)} \qquad (6)$$

$$\sigma^2_{s\ tij} = \mathbf{x}^T_{(1)tij}\boldsymbol{\theta}_{(1)} + \mathbf{x}^T_{(2)ij}\boldsymbol{\theta}_{(2)} + \mathbf{x}^T_{(3)tj}\boldsymbol{\theta}_{(3)} \qquad (7)$$

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. Based on these equations, the 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 $\hat{\sigma}^2_{s_{tij}}$ . The conditional probability of being poor, or vulnerability to poverty, of household *i* in province *j* at time *t*is estimated as follows:

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

where: $\Phi(\cdot)$ denotes the cumulative density of the standard normal distribution; $\ln z$ is the log of poverty threshold, z; $\ln \hat{y}_{tij}$ is log of per capita income of household predicted by equation (1); and, $\hat{\sigma}^2_{tij}$ is the expected total variance of residuals in 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.

It is noted here that the error terms at each level contain 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. If the error terms at each level contain non-stochastic heterogeneity and measurement errors, this will make the income distribution in the equation (8) more widespread (as the denominator, $\sqrt{\hat{\sigma}^2_{tij}}$ , increases) and will *reduce* the vulnerability measure ($\hat{V}_{tij}$), rather than increase it. While estimating variance terms by household and other characteristics in equations (4)-(7) will mitigate this problem, our inability to distinguish between stochastic error terms and non-stochastic error term or measurement error is admittedly a limitation of our study. However, the same limitation is also applied to a number of studies on vulnerability drawing upon Chaudhuri et al.'s (2002) method we have reviewed in Section 2. We will thus implement an alternative method based on the FE model for the first differenced household income.

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:

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

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; $P\left(\ln y_{tij} > \ln z\right)$ 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 with a time horizon 3 years. 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.

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 thosenot 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 in a similar way. 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’.

As a robustness check, we have derived the predicted household income per capita in 2012 as a sum of (i) the actual household income per capita in 2009 and (ii) the predicted income change from 2009-2012 based on the prediction of the FE model for the first differenced income for 2003-2006 and 2006-2009 (Equation (3’)). Then a household is defined as vulnerable or not depending on whether its predicted income per capita in 2012 is below or above the poverty line. This simple method has an advantage of modelling the unobservable household heterogeneity fixed over time. Hence, the prediction of income change reflects not only observable and time-variant household and community characteristics but also unobservable household heterogeneity. However, this method assumes that the income growth is *deterministic* in a sense that income growth derived as a prediction using the data in 2003-2009 will follow the same trend in 2009-2012.

Decomposition of the vulnerability into aggregate and idiosyncratic components is not feasible with this method. Given these limitations, we will use two different methods to characterise household vulnerability.

**5. Empirical results**

The results of RC and FE models are presented in Table 3. A dependent variable is log household income per capita (Models 1-4) or first difference of log household income per capita (Models 5-6). The first two columns of Table 3 show the results of RC model without and with interaction terms, based on 'within-between' formulation (Bell and Jones, 2015).[9] 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 last two columns show the result of Models 5 and 6, FE model applied to the first-differenced income. Attrition bias is corrected in all cases in Table 3 by using the method of Fitzgerald et al. (1998). The key results are discussed selectively below.

**(TABLE3 to be inserted)**

Highly significant variables include education of household head (positive for Models 1, 2 and 4; the interaction is positive for Model 3), household size (negative) and its square (positive), dependency ratio (negative for Models 1-3, 5 and 6; an interaction with household size is significant and negative for Models 4), and regional dummies. Households with more educated heads tend to have higher per capita income than those with less-educated. 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).[10] 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. Our results cannot be generalised in a broader context of developing countries as female-headed households are generally poorer and more vulnerable in other developing countries (e.g. Buvinić and Gupta, 1997, for Chile; Gangopadhyay and Wadhwa, 2004, for India).

Households residing in provinces that experienced rainfall and fuel price shocks tend to have relatively lower income (Models 1-4), while the rainfall shock tends to negatively influence the income growth (Model 5). 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.

On the results of idiosyncratic shocks, having fewer overseas contact workers (OCW) members in the household would lead to lower household income per capita for Models 1 and 2. This is understandable as the income from OCW would be a valuable source to supplement household income or mitigate the household income shocks. But they are not significant in FE models (Models 3-6). Having more members with non-permanent or vulnerable job are associated with higher income for Models 3-4. This implies that the increase in adult members in employment – even if they work as temporary workers in vulnerable employment – will have a positive effect on the household income, while an overall increase in household size or dependency ratio tends to reduce it.

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). Most of other interaction terms are statistically significant.[11]

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.

**(TABLE4 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.

Our result that households are more vulnerable to idiosyncratic shocks rather than covariate shocks - the pattern of which is broadly same at different income percentiles - implies that there is imperfect risk-sharing because under perfect risk-sharing households should be able to insure against idiosyncratic shocks, but not covariate shocks. Our result is not specific to the Philippines and broadly consistent with the evidence from other parts of the developing world. For instance, it is consistent with Gaiha and Imai's (2009) study on rural India which shows that the idiosyncratic component is much larger than the aggregate component in household vulnerability, as well as with a number of empirical studies that rejected the perfect risk-sharing hypotheses (e.g. Townsend, 1994; Ravallion and Chaudhuri, 1997). Our result rather suggests that without policy interventions targeting households it is difficult for a household to insure the idiosyncratic shocks. Possible policy options are Conditional Cash Transfers (CCTs) (Skoufias, 2007) or microfinance (Feigenberg et al. 2013). Table 5 implies that the policies which develop infrastructure and irrigation facilities at the village or province levels are likely to reduce household vulnerability, but these may be more effective in reducing aggregate vulnerability, rather than idiosyncratic vulnerability.

If we use the FE model (Model 4, applied to log household income per capita in levels) 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.

Furthermore, we have used an alternative method to define vulnerability according to whether household's per capita income is below the poverty line on the basis of the predicted household income in 2012 as a sum of (i) the actual household income per capita in 2009 and (ii) the predicted household income per capita using the FE model for the first differenced income. In this case 19.4% of the households are classified as vulnerable, while 80.6% were as non-vulnerable in 2009 (Table 4). Most of the vulnerable households are either chronically poor or transitory poor, implying that the vulnerability status based on the alternative method is positively correlated with the long-term poverty status.

In the last panel of Table 4, we have cross-tabulated vulnerability statuses based on different measures to examine how they are correlated. 17.2% of the total households were classified as vulnerable in both measures and 60.1% of the households were non-vulnerable in either of these two measures. On the other hand, 20.5% (= 3.3% + 17.2%) of the households were either highly or relatively vulnerable based on the RC model but non-vulnerable based on the FE model for the first differenced income, while 8.9% (= 6.6% + 2.3%) of the households are non-vulnerable based on the RC model but vulnerable based on the FE model. We can conclude that these two measures are broadly correlated with each other.

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 have shown the results of both FE and RC models, we will take the RC model as our preferred model to derive the vulnerability estimates.

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) a higher dependency ratio; (iii) being located in rural areas; and (iv) lack of access to irrigation. A larger household with more members is to less likely to be vulnerable (as suggested by a negative and significant coefficient estimate for vulnerability) and is more likely to move up to "non-poverty" (a positive and significant estimate for "moving up"), but more likely to be chronically poor (positive and significant for "chronic poverty"). This result appears to be consistent with negative and significant estimates for (i) (having) 'more members engaged in vulnerable employment' in the first column to show the determinants of "vulnerability", as well as for (ii) (having) "more members with non-permanent jobs" in the first column, whilst having more members in vulnerable employment prevented them from "moving up" from poverty to non-poverty. So these factors may serve as insurance for the household coping with risks, but may not help them escape from the poverty situations. To be able to escape from poverty, households may have to have more members with secure employment.

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, lack of economic and social infrastructure is - contrary to our expectations - associated with the higher probability of 'moving up'. 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, consistent with our expectations, 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 (RC) 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. As a robustness check we have applied the fixed-effects (FE) model for the level of household income per capita and its first-differences. In case the FE model is applied for the first differenced income, the predicted income is derived as a sum of the actual income in 2009 and the predicted growth in income. We define the vulnerability status according to whether the predicted income is below the poverty line or not in 2012.

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 (e.g. Balisacan, 1997; Tabunda, 2000), 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 RC 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. We have noted that the vulnerability statuses based on the FE model applied to the first differenced income are broadly consistent with those based on the RC model.

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 policies could include conditional cash transfers or microfinance to help communities or villages to strengthen risk-insurance mechanisms. Other policies are employment and skills training programs, which can be implemented on a regular basis and can be intensified in times of crisis. Furthermore, policies to improve transportation infrastructure and/or irrigation facilities are also deemed important for reducing vulnerability.

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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.

TABLE3. Results of the Random Coefficient Model (RC) and Fixed-effects (FE) Model
(with correction of attrition based on Fitzgerald et al. (1998))

| | RC Model: 'within-between' formulation | | FE Model Level Data | | FE Model First Differenced Data | |
|---|---|---|---|---|---|---|
| **Dependent Variable** | log household income pc | | log household income pc | | D.log household income pc | |
| **Explanatory Variables** | **Model 1** | **Model 2** | **Model 3** | **Model 4** | **Model 5** | **Model 6** |
| **Fixed part** | | | | | | |
| Time | **0.0595 (0.0032)*** ** | **0.0605 (0.0026)*** ** | **0.0652 (0.0016)*** ** | **0.0672 (0.0018)*** ** | **-0.0277 (0.0151)* ** | -0.0376 (0.0398) |
| *Household composition* | | | | | | |
| ›ld size [a] | **-0.1970 (0.0093)*** ** | **-0.2646 (0.0188)*** ** | **-0.1998 (0.0106)*** ** | **-0.3161 (0.0245)*** ** | **-0.2433 (0.0239)*** ** | **-0.2427 (0.0239)*** ** |
| 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)*** ** | **0.0103 (0.0018)*** ** | **0.0092 (0.0020)*** ** |
| 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) | **-0.2062 (0.0720)*** ** | **-0.1977 (0.0719)*** ** |
| 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) | -0.0201 (0.0151) | -0.0206 (0.0398) |
| Age [a] | **0.00822 (0.0031)*** ** | - [d] | **0.0084 (0.0032)*** ** | 0.0054 (0.0036) | **0.0235 (0.0001)** ** | **0.0232 (0.0095)** ** |
| 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)** ** | **-0.0002 (0.0001)** ** | **-0.0002 (0.0001)*** ** |
| 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)** ** | 0.0408 (0.0365) | 0.0422 (0.0365) |
| At least secondary graduate | **0.400 (0.0146)*** ** | **0.5130 (0.0339)*** ** | 0.0158 (0.0216) | **0.0804 (0.0393)** ** | 0.01823 (0.051) | 0.0172 (0.0514) |
| At least college graduate | **0.889 (0.0226)*** ** | **0.7830 (0.110)*** ** | 0.0003 (0.0383) | 0.0664 (0.1577) | -0.0815 (0.0505) | 0.1756 (0.1533) |
| *Location* | | | | | | |
| Urban/rural | **0.253 (0.0159)*** ** | 0.0623 (0.0396) | - | - | - | - |
| *Regional Dummies* | **Yes** | **Yes** | **No** | **No** | **No** | **No** |
| *Aggregate-level variables* | | | | | | |
| Transportation infrastructure index [a] | -0.0259 (0.0251) | - [d] | **-0.0323 (0.0155)** ** | **-0.0290 (0.0167)* ** | -0.4642 (0.0472) | -0.0508 (0.0473) |
| 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)* ** | **-0.0291 (0.0113)*** ** | **-0.0290 (0.0113)*** ** |
| 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) | 0.0028 (0.0023) | 0.00160 (0.00230 |
| 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) | -0.0077 (0.0252) | 0.0055 (0.0254) |
| 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) | - | - |
| Utilities index (between) [b] | 0.0199 (0.0169) | - [d] | **-** | - | | |

| | | | | | | |
|---|---|---|---|---|---|---|
| *Idiosyncratic shocks* | | | | | | |
| More jobless members | 0.00807<br>(0.0086) | 0.01191<br>(0.0087) | 0.0057<br>(0.0091) | 0.0099<br>(0.0092) | -0.0072<br>(0.0203) | 0.1283<br>(0.1119) |
| More members engaged in vulnerable employment | 0.00102<br>(0.0086) | 0.0168<br>(0.0105) | 0.0031<br>(0.0085) | 0.0187<br>(0.0107)* | -0.0372<br>(0.0195)* | -0.1083<br>(0.0712) |
| More members with non-permanent jobs | -0.00029<br>(0.00903) | 0.0021<br>(0.0091) | 0.0147<br>(0.0089)* | 0.0181<br>(0.0089)** | 0.0322<br>(0.0215) | -0.0476<br>(0.0504) |
| Fewer overseas contract worker (OCW) members | 0.109<br>(0.0198)*** | 0.101<br>(0.0197)*** | -0.0147<br>(0.0221) | -0.0148<br>(0.0219) | 0.0011<br>(0.0512) | -0.0656<br>(0.0564) |
| *Covariate shocks* | | | | | | |
| Rainfall shock | -0.0679<br>(0.0132)*** | -0.0425<br>(0.0169)** | -0.0708<br>(0.0119)*** | -0.054<br>(0.0155)*** | -0.1197<br>(0.0289)*** | 0.2419<br>(0.2374) |
| Rice price shock | 0.00762<br>(0.0819) | -0.0323<br>(0.07469) | 0.0007<br>(0.0548) | 0.0020<br>(0.0536) | 0.0407<br>(0.0289) | 0.0766<br>(0.1003) |
| Fuel price shock | -0.0374<br>(0.00661)*** | -0.0363<br>(0.0075)*** | -0.0459<br>(0.0063)*** | -0.0404<br>(0.0075)*** | -0.1271<br>(0.0455) | -0.1244<br>(0.1120) |

TABLE 3. (continued).

| Variable | RC Model: 'within-between' formulation | | FE Model | | FE Model First Differenced Data | |
|---|---|---|---|---|---|---|
| | Model 1 | Model 2 | Model 3 | Model 4 | Model 5 | Model 6 |
| *Interactions* | | | | | | |
| [Time × Region Dummies or Province Variables] | No | Yes | No | Yes | No | Yes |
| [Household Characteristics –cross-Interactions] | No | Yes | No | No | No | No |
| [Household Characteristics X Region Dummies] | No | Yes | No | Yes | No | No |
| [Household Characteristics X Province Variables] | No | Yes | No | Yes | No | No |
| [Region Dummies X Province Variables] | No | Yes | No | Yes | No | No |
| Sex X Age [a)] | - | 0.0019<br>(0.0017) | - | 0.0023<br>(0.0012)* | - | - |
| Sex X Age (between) [b)] | - | 0.0310<br>(0.0010)*** | - | - | - | - |
| Sex X Education, College | - | 0.163<br>(0.0417)*** | - | -0.0246<br>(0.0608) | - | - |
| Education, College X Age [a)] | - | 0.011<br>(0.0025)*** | - | 0.0018<br>(0.0028) | - | - |
| Education, College X Age (between) [b)] | - | 0.00418<br>(0.00172)** | - | - | - | - |
| Education, Elementary X Rain | - | -0.04839<br>(0.0235)** | - | -0.0501<br>(0.0226)** | - | - |
| Education, Secondary X Household size [a)] | - | -0.02229<br>(0.0073)*** | - | -0.0120<br>(0.0060)** | - | - |
| Education, Secondary X Household size (between) [b)] | - | -0.02416<br>(0.00738)*** | - | - | - | - |
| Education, College X Household size [a)] | - | -0.02839<br>(0.01084)*** | - | -0.0287<br>(0.0109)*** | - | - |
| Education, College X Household size (between) [b)] | - | -0.03337<br>(0.01173)*** | - | -0.0177<br>(0.0272) | - | - |
| Education, College X Transport Infrastructure [a)] | - | -0.18925<br>(0.05737)*** | - | -0.0177<br>(0.0272) | - | - |
| Education, College X Transport Infrastructure (between) [b)] | - | -0.06311<br>(0.01876)*** | - | - | - | - |
| Household size [a)] X Dep. Ratio [a)] | - | -0.08814***<br>(0.02992) | - | -0.0684<br>(0.0132)*** | - | - |
| Household size (between) [b)]X Dep. Ratio (between) [b)] | - | -0.18906<br>(0.02084)*** | - | - | - | - |
| Irrigation [a)] X Utility Index [a)] | - | -0.01126<br>(0.00347)*** | - | 0.0013<br>(0.0005)*** | - | - |
| Irrigation (between) [b)]X Utility Index (between) [b)] | - | 0.00110<br>(0.00045)*** | - | - | - | - |
| Fuel price shock XMore members engaged in vulnerable employment | - | -0.04435<br>(0.01684)*** | - | -0.0437<br>(0.0170)** | - | - |
| Time X Education (college) | - | - | - | - | - | -0.0656<br>(0.0160)** |
| Time X Rainfall | - | - | - | - | - | -0.0655<br>(0.0368)* |
| Time X More jobless members | - | - | - | - | - | 0.0147 |

| | | | | | | |
|---|---|---|---|---|---|---|
| | | | | | | (0.0145) |
| Time X More members engaged in vulnerable employment | - | - | - | - | - | 0.0000<br>(0.0000) |
| Time X More members with non-permanent jobs | - | - | - | - | - | **0.00003**<br>**(0.00002)*** |
| Fewer overseas contract worker (OCW) members | | | | | | |
| Rainfall X Farm size | - | - | - | - | - | 0.0012<br>(0.0008) |
| Agriculture index [a)] X More jobless members | - | - | - | - | - | -0.0088<br>(0.0179) |
| Rainfall X More members engaged in vulnerable employment | - | - | - | - | - | 0.0860<br>(0.0622) |
| More members with non-permanent jobs X Fewer overseas contract worker (OCW) members | - | - | - | - | - | **0.3396**<br>**(0.1386)**** |
| Education (Secondary) X More members engaged in vulnerable employment | - | - | - | - | - | 0.0249<br>(0.0438) |
| Intercept | 0.194<br>(0.135) | 0.5219<br>(0.1068)*** | 1.0066<br>(0.1097)*** | 1.864<br>(0.2040)*** | 1.0066<br>(0.1097)*** | 0.5888<br>(0.3649) |
| **Random part** | | | | | | |
| Province-level | | | | | | |
| Variance (Random slope) | **0.0004**<br>**(0.0001)***** | **0.0002**<br>**(0.00007)***** | - | - | - | - |
| Variance (Random intercept) | **0.0265**<br>**(0.0081)***** | **0.00716**<br>**(0.0034)**** | - | - | - | - |
| Covariance (Random slope, Random intercept) | **-0.0025**<br>**(0.0009)***** | **-0.0008**<br>**(0.0004)*** | - | - | - | - |
| Household-level: | | | | | | |
| Variance (Random slope) | **0.0027**<br>**(0.0003)***** | **0.0027**<br>**(0.0003)***** | - | - | - | - |
| Variance (Random intercept) | **0.2973**<br>**(0.0155)***** | **0.2859**<br>**(0.0152)***** | - | - | - | - |
| Covariance (Random slope, Random intercept) | **-0.0164**<br>**(0.0020)***** | **-0.0167**<br>**(0.0019)***** | - | - | - | - |
| Occasion-level: | | | | | | |
| Time 0: Variance (Residual) | **0.0811**<br>**(0.0057)***** | **0.0805**<br>**(0.0056)***** | - | - | - | - |
| Time 3: Variance (Residual) | **0.1152**<br>**(0.0034)***** | **0.1130**<br>**(0.0033)***** | - | - | - | - |
| Time 6: Variance (Residual) | **0.0862**<br>**(0.0056)***** | **0.0869**<br>**(0.0055)***** | - | - | - | - |

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 RandomCoefficient 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 |
| **Based on Fixed-Effects Model for the first differenced log household income per capita (based on Model 6 of Table 3)** | | | | |
| Vulnerable | 9.9 | 8.7 | 0.8 | 19.4 |
| Not vulnerable | 2.4 | 19.3 | 58.9 | 80.6 |

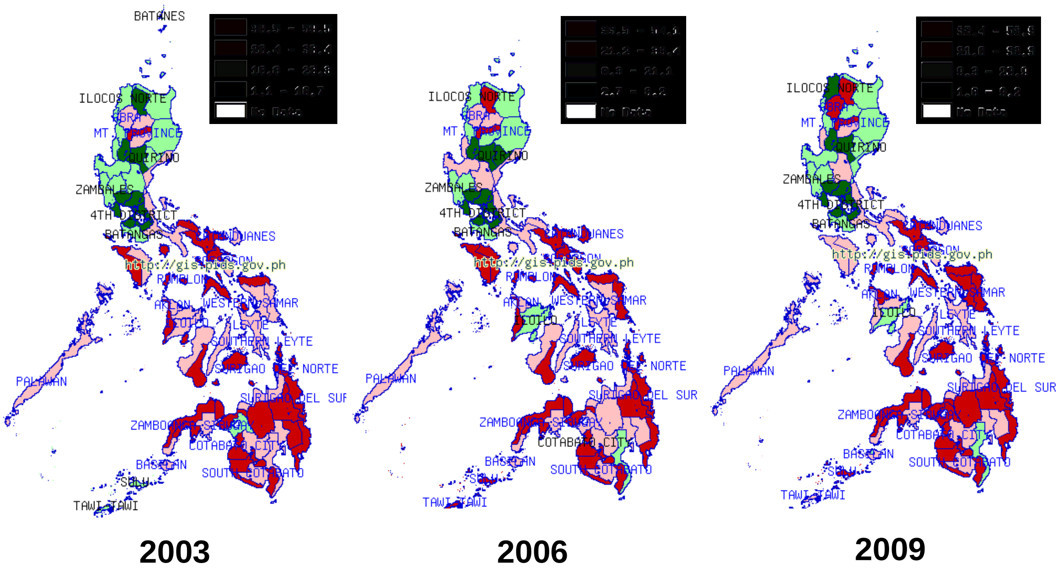
| | **Based on Fixed-Effects Model for the first differenced log household income per capita (based on Model 6 of Table 3)** | | |
|---|---|---|---|
| **Vulnerability status** | Vulnerable | Not vulnerable | **All** |
| **Based on Random Coefficient Model** | | | |
| **Total vulnerability** | | | |
| Highly vulnerable | 10.6 | 3.3 | 13.9 |
| Relatively vulnerable | 6.6 | 17.2 | 23.8 |
| Not vulnerable | 2.3 | 60.1 | 62.4 |

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

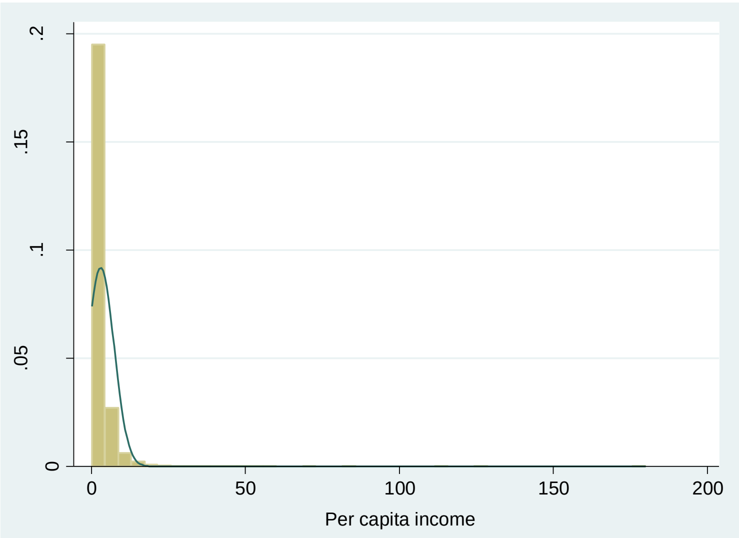
<u>Likelihood ratio test 1</u>:
Model (without random coefficient) vs. Model (with random coefficient at level 2):

LR $\chi^2_2$ = 89.37, Pr> $\chi^2$ = 0.0000

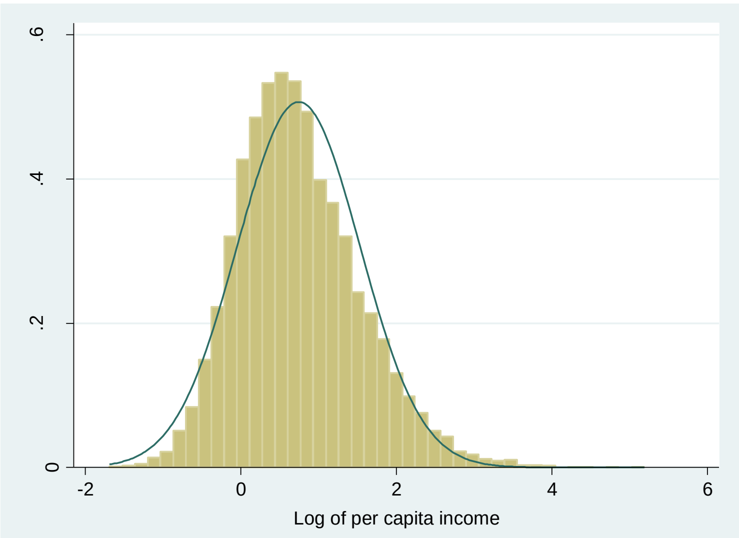
<u>Likelihood ratio test 2</u>:
Model (with random coefficient at level 2) vs. Model (with random coefficients at levels 2 & 3):

LR $\chi^2_4$ = 40.54, Pr> $\chi^2$ = 0.0000

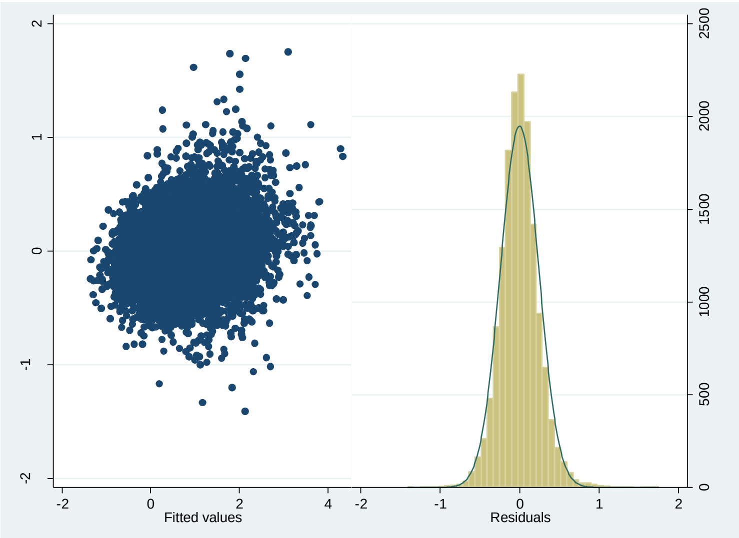
**Note:**All models have identical fixed-effects specifications.



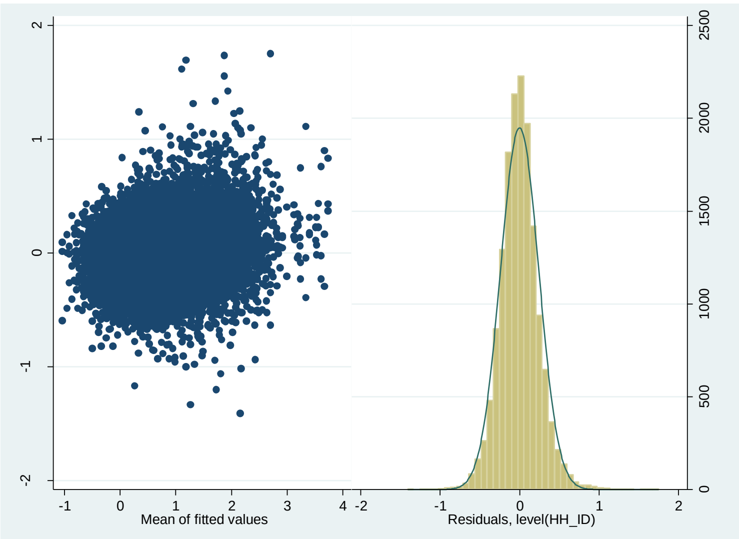

Online Appendix Figure 1a. Histogram (with normal-density plot) of per capita income



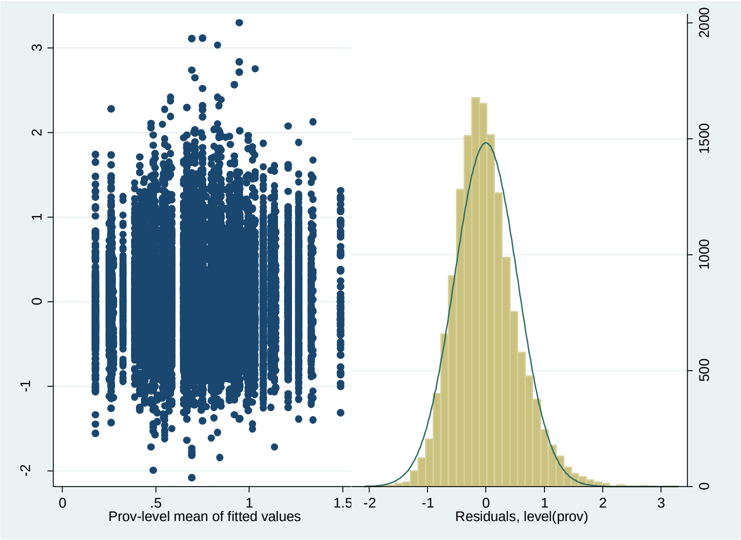

Online Appendix Figure 1b. Histogram (with normal-density plot) of log of per capita income



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]Based on Family Income and Expenditure Surveys, Philippine Statistics Authority.

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

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

[4] 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.

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

[6] Attrition rate within the province is also included because it is related to attrition albeit not directly related to household income (Baulch and Quisumbing, 2011).

[7] 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.

[8]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.

[9] For RC models (Models 1-2 in Table 3) the estimated model with random effects is preferred to OLS 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). Meanwhile, the normality assumption of income and residuals are satisfied at all levels (Online Appendix Figures 1-2). Scatter plots also indicate that outliers would not create a problem in the analysis.

[10] 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.

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