Measuring Income Mobility using Pseudo-Panel Data

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To reconcile the need of providing a more dynamic perspective of the evolution of income distribution with the lack of panel data, several techniques have been offered to construct pseudo-panel data from repeated cross-sectional surveys. Using actual panel data from the Philippines, this study evaluates the performance of four pseudo-panel techniques in measuring a wide array of income mobility indicators. Preliminary results suggest that methods with more flexible income model specifications perform better than those with highly parameterized models. More importantly, these flexible pseudo-panel procedures produced estimates of poverty dynamics and movement-based indices which are quite close to the estimates computed from the actual panel data. Nevertheless, further improvements are warranted to be able to develop a more satisfactory estimation procedure for indices measuring temporal dependence and the inequality-reducing effect of income mobility.

***Keywords**: panel survey, cross-sectional survey, temporal dependence, income distribution*

1. Introduction

Studying the evolution of a country's income distribution is useful when examining its economic progress. Two of the most commonly used analytical tools when studying income distribution are the cross-sectional indices of poverty and inequality. Although these measures provide valuable information about the country's socioeconomic progress, there are also pitfalls in drawing conclusive inferences solely based on these estimates. For instance, negligible changes in cross-sectional estimates of poverty and inequality over time may deceivingly portray a stagnant income distribution. However, it is easy to illustrate that this is not always true. In particular, consider an absolute income reversal example wherein a person with the highest income at the initial time period swaps income with the poorest individual, the second highest swaps with the second poorest, and so on. In this case, the cross-sectional indicators will produce the same estimates of poverty and inequality for the two time periods. However, such scenario mirrors a highly dynamic yet unstable income distribution. Fields and Ok (1999) provides more examples which portray the importance of probing beyond changes in the marginal distribution of income. In general, Ravallion (2001) noted that sole-reliance on marginal indicators of poverty and inequality may cloud the impact of economic growth on a country's welfare which in turn, could misinform policy-makers.

Examination of mobility is an alternative approach to the conventional poverty and inequality analyses. Compared to static indicators of poverty and inequality, measures of mobility provide more detailed information about the dynamic evolution of a country's well-being. Given this advantage, mobility analysis is rapidly gaining prominence among development researchers (Ferreira et al. 2013; Fields 2011). Nevertheless, there is still much to learn despite the significant advances in the literature. For instance, a quick review of previous studies reveals that much of the empirical investigation have centered on examining income mobility patterns in industrialized countries (Jenkins 2011). On the other hand, income mobility research in developing countries was almost an uncharted field until recently (Fields 2011). In addition, sparse studies about income mobility patterns in developing countries only cover short to medium-term observation periods. This prevents researchers from doing more in-depth examination of developing countries' long-term income trajectories[1].

One of the main factors that contribute to the dearth of income mobility studies in developing countries is the cost of collecting panel data (Fields 2011; Cuesta, Nopo and Pizzolitto 2011; Deaton 1997). Instead of panel data, most of the developing countries regularly conduct cross-sectional surveys to monitor the living standards and well-being of the country. While cross-sectional survey data facilitates straightforward estimation of conventional indices of poverty and inequality, estimation of income mobility is more complicated because the same set of sample units is not necessarily tracked over time. With only repeated cross-sectional data available at hand, the main issue is how to create synthetic or pseudo-panels. There are several ways of doing this. Three of the most recent developments in the literature are the methods proposed by Bourguignon, Goh and Kim [BGK] (2004), Antman and McKenzie [AM] (2007) andDang, Lanjouw, Luoto and McKenzie [DLLM] (2011).These methods employ different procedures of creating synthetic panels. For instance, the AM approach is akin to the procedure initially developed by Deaton (1985) which entails grouping all observations into different mutually exclusive and exhaustive cohort groups. The characteristics of interest are then averaged for each cohort group, and in turn, the cohort averages serve as the pseudo-panels. On the other hand, the BGK and DLLM approaches are anchored on estimating structural models to impute the unobserved incomes of respondents from a specific cross-sectional survey wave while maintaining the original respondents as the units of analysis. In general, although each method is originally designed to measure a specific income mobility measure, Cruces, Fields and Violaz (2013) recently examined the feasibility of these approaches in estimating a wider array of income mobility indices. However, their results show that these pseudo-panel techniques did not perform well in capturing the income mobility patterns in the Chilean panel data. Whether this provides conclusive proof undermining the usefulness of pseudo-panel methods in estimating income mobility merits further investigation. For one, the Chilean panel data is not representative of the population of data sets to which the pseudo-panel techniques can be applied. In other words, this panel data could have specific characteristics that make pseudo-panel techniques less attractive. Thus, the main objective of this study is to replicate the same exploratory exercise using another data set. In addition to the three methods examined by Cruces, Fields and Violaz (2013), this study also evaluates the performance of the modified DLLM approach recently proposed by Dang and Lanjouw [DL] (2013). In particular, we use panel data from the Philippines to answer the following research questions:

- Are the proposed pseudo-panel techniques useful for measuring income mobility? In general, which of the techniques are most desirable?
- Do the pseudo panel techniques' performance depend on the type of income mobility measure being estimated?
- How can the existing pseudo-panel techniques be improved?

The rest of the paper is structured as follows: Section 2 provides a brief review of how income mobility is measured using longitudinal data. Section 3 reviews the AM, BGK, DLLM and DL pseudo-panel methodologies. More importantly, the section also presents a detailed discussion of how these methods can be extended to estimate a wide array of income mobility measures. Section 4 discusses the main data source used for the succeeding analyses. Section 5 discusses the findings of this exploratory exercise. Section 6 draws a summary of the main results and provides directions for future research.

2. What is Income Mobility and How Do We Measure It?

Income mobility is broadly defined as the shifting of socioeconomic units (e.g., individuals, households, etc.) in the income hierarchy. When viewed in terms of how much incomes are increasing or decreasing, the concept of income mobility can be linked to economic growth. On the other hand, when viewed in terms of how much initial income status dictates future income trajectories, mobility can be linked to social justice. Furthermore, when viewed in terms of its impact on the equality of the income distribution, mobility can be linked to accessibility of socioeconomic opportunities. In general, the multidimensional feature of the income mobility concept can be contextualized in different ways.

Consider an income trajectory process $\{Y_{it}\}$ where Y_{it} refers to the income of (socioeconomic) unit i at time t. Most of the income mobility measures proposed in the literature estimate the amount of income dynamics transpiring in a society into a single scalar value. Mathematically, these measures can be expressed as a population average of some function $f(Y_t, Y_t+s)$ that captures the degree of income dynamics or mobility between income pairs $(Y_{it}, Y_{it}+s) \in \mathrm{R}^{2N}$ derived from the joint density function Φ of Y_{it} and $Y_{it}+s$. Different functional forms of $f(\ )$ leads to different mobility concepts. Although a number of studies have identified ideal properties for $f(\ )$, there is no consensus which of them should always be satisfied (Fields and Ok 1996). Drawing from the taxonomy developed by Fields (2008), the following discussions enumerate some of the mobility concepts that are commonly used in the literature. Their corresponding functional forms are provided in Appendix Table A1. For a more detailed discussion, readers may refer to Fields (2008 and 2010).

$$M\left(Y_{it}, Y_{it+s}\right) = \int f\left(Y_{it}, Y_{it+s}; \phi\left(Y_t; Y_{t+s}\right)\right); \ \mathrm{i} = 1,2,\ldots, \mathrm{N},\ \mathrm{t} = 1,2,..,\mathrm{T} \qquad (1)$$

One of the simplest and most intuitive concepts of mobility is based on movements of incomes.Income movements can be measured in two ways. In particular, it can be measured in terms of changes in income levels or changes in income ranks. Note that it is possible for a unit to change income rank without experiencing any change in the income level, and vice-versa. The class of indices proposed by Fields and Ok (1999) and indices based on transition matrices that use absolute income cut-off points are examples of movement-based measures expressed in terms of changes in income levels. On the other hand, the average rank jump index is an example of an income mobility measure based on changes in income ranks. This index is minimum when all income ranks remain the same and maximum when all income ranks are completely reversed. Other examples include indices derived from transition matrices which use income quantiles as cut-off points. Furthermore, the index proposed by King (1983) is an example of movement-based measure that takes into account both changes in income levels and changes in income ranks. King's index reaches is minimum when all units have the same income in the initial and final time periods and maximum when all units change income ranks at the same time that the changes in income levels are sufficiently large.

Mobility can also be gauged in terms of the strength of relationship between past and present income (Lillard and Willis, 1978). In other words, income mobility can be measured in terms of temporal dependence or the extent to which each unit's previous income influences its current income. In this context,there is perfect mobility when the conditional distribution of a unit's current income given its previous income is the same as its unconditional distribution. On the other hand, there is perfect immobility when previous income perfectly predicts current income. Hart's (1976) proposed index which is based on the correlation of incomes between two time periods is an example of a mobility measure under the temporal dependence perspective. Like the Hart's index, income elasticity is another example of a temporal dependence type of mobility measure. It is computed as the slope of the model which regresses current income on previous income.[2] Higher absolute values for the income elasticity indicate more mobility.

Another perspective is linked to the extent up to which mobility contributes to a more equitable distribution of income in the long-run (i.e., permanent income). In other words, income mobility can be viewed in terms of its inequality-reducing effect. Since high income inequalities are less problematic if it is not permanent (Krugman, 1992), it is important to examine whether an increase in income mobility leads to a significant reduction in long-run inequality (Jarvis and Jenkins, 1998). Expectedly, mobility measures under this perspective can be expressed as functions of the existing inequality indices. Examples include the equalization indices proposed by Shorrocks (1978), Fields (2010) and Chakravarty, Dutta and Weywark (CDW) (1985). Higher values for these indices imply that mobility contributes to higher reduction of inequality.

3. Developments in Income Mobility Estimation using Repeated Cross-Sectional Data

Income mobility analysis provides more complete picture of economic progress than conventional static indicators of economic growth, poverty and inequality do (Fields et al., 2007). It helps us identify the winners and losers of a country's development process. In other words, income mobility measures are good analytical tools for examining a country's pace of economic development. However, measuring income mobility requires longitudinal data of incomes which are not commonly available in developing countries (Cuesta, Nopo and Pozzolitto, 2011; Fields et al., 2007; Antman and McKenzie, 2007; Bourguignon, Goh and Kim 2004, Deaton, 1997). To address this problem, several researchers have proposed a variety of statistical techniques which use information from repeated cross-sectional surveys to create synthetic panel data. This section reviews the methodological developments in measuring income mobility using pseudo-panel methods. The discussions begin with a review of the classical pseudo-panel estimation methodology pioneered by Deaton (1985) followed by presentation of four contemporary pseudo-panel approaches that are designed to answer specific income mobility-related questions.

3.1 What is pseudo-panel estimation?

In general, the pseudo-panel approach refers to a class of statistical and econometric methods that use repeated cross-sectional surveys to estimate indices or models that are typically suitable for longitudinal studies. For exposition, consider the following time-indexed static model

$$Y_{it}=\beta X_i + f_i + \varepsilon_i \quad i = 1, 2,\ldots,N, T= 1, 2, \ldots, T \tag{2}$$

where Y_{it} is the response outcome for unit i at time t, X_{it} is a vector of explanatory variables, f_i is an unobserved unit specific effect and ε_{it} is a random disturbance term. Conventionally, the parameters of this model can be estimated using fixed-effects (FE) or random effects (RE) methods when longitudinal data is available.[3]. However, estimation complexities arise when only repeated cross-sectional survey (RCS) data is available because in such case, $\mathbf{Y_{it}}$ and $\underline{X}_{it}$ are not fully observed. As an alternative to (2), we can consider the following model,

$$Y_{i(t)t}= \beta X_{i\,(t)} + f_{i\,(t)} + \varepsilon_{i\,(t)} \quad i(t) = 1, 2,\ldots,N_t, T= 1, 2, \ldots, T \tag{3}$$

Notice the change in subscripts used to denote the sampled units when comparing (2) and (3). Conventional RCS designs imply that $i(\tau)t \neq i(\Psi)t$ for every pair $(i(\tau)t, i(\Psi)t)$ in $\{1,2,\ldots,N_t\}$, t = $\{\tau, \Psi\}$. In other words, the i^{th} sampled unit at time period τ is not necessarily the same with the i^{th} unit at time period Ψ. If we simply use the pooled RCS data and proceed to ordinary least squares (OLS) estimation of the model, parameter estimates will be inconsistent if $f_{i(t)}$ is correlated with $X_{i(t)t}$. One way of addressing this issue is to find suitable instruments for $X_{i(t)t}$, i.e., variables that are correlated with $X_{i(t)t}$ but are asymptotically uncorrelated with the unobserved terms of (2). In a seminal work, Deaton (1985) proposed an approach which uses cohort-averaging as an indirect form of instrumentation. In particular, the author proposed the following model,

$$\overline{Y}_{ct} = \beta \overline{X}_{ct} + \overline{f}_{ct} + \overline{\varepsilon}_{ct} \quad c = 1, 2,\ldots, C , T = 1, 2,\ldots, T \tag{4}$$

where

$$\overline{Y}_{ct} = \frac{1}{n_{c_t}} \sum_{i=1}^{n_{c_t}} Y_{it}, \quad \overline{X}_{ct} = \frac{1}{n_{c_t}} \sum_{i=1}^{n_{c_t}} X_{it}, \quad \overline{f}_{ct} = \frac{1}{n_{c_t}} \sum_{i=1}^{n_{c_t}} f_i,$$

$$\overline{\varepsilon}_{ct} = \frac{1}{n_{c_t}} \sum_{i=1}^{n_{c_t}} \varepsilon_{it}$$

This approach groups the sampled units into C mutually exclusive classes such that each class is always represented from every cross-sectional survey round and that class membership is fixed over time. Since we do not observe the same set of units in RCS, the term f_{ct} is not fixed over time.[4] Thus, we cannot readily rely on conventional panel data estimation techniques such as the FE estimator to difference out this term. However, when n_c is sufficiently large (in proportion to N_c, the number of individuals in the population who are in the c^{th} class), Deaton (1985) argued that we can conveniently assume that the term f_{ct} will be constant. In such case, it will be straightforward to remove this term using data transformation. Moreover, Deaton (1985) introduced further adjustments to the conventional FE estimator to take into account that Y_{ct} and X_{ct} are error-ridden estimators of their population counterparts. Furthermore, Verbeek and Nijman (1993) proposed a general class of estimators that can be considered when estimating (2). This class of estimators employs a "within transformation" on the pseudo-panel and adjusts the moment matrices in the least squares to account for measurement error due to data aggregation. Verbeek and Nijman (1993) also improved Deaton's estimator after showing that the latter performed poorly in terms of the mean squared error when the cohort sample size is small.

The static model described in (2) can be extended to include a lagged term of the dependent variable (5). There are two estimation issues for (5). First, the term $Y_{i(t)t-1}$ is unobserved when using RCS data. Second, $f_{i(t)}$ is likely to be correlated with both $Y_{i(t)t-1}$ and $X_{i(t)t}$ prompting the need to find for suitable instruments.

$$Y_{i(t)t} = \alpha Y_{i(t)t-1} + \beta x_{i(t)t} + f_{i(t)} + \varepsilon_{i(t)t} \tag{5}$$

To be able to estimate (5), Moffitt (1993) ignored the term $f_{i(t)}$ and proposed using an instrument for $Y_{i(t)t-1}$ in the form of (6) where $W_{i(t)t-1}$ is vector of exogenous variables whose historical time-series are provided in the data and $Z_{i(t-1)}$ is a vector of time-invariant exogenous variables. In other words, Moffitt's (1993) idea is to first estimate a static model and use the predicted values as instrument for $Y_{i(t)t-1}$.

$$\hat{y}_{i(t)t-1} = \hat{\delta}_1 W_{i(t)t-1} + \hat{\delta}_2 Z_{i(t)} \tag{6}$$

Moffitt's approach is anchored on a strong data requirement that the historical time-series of $X_{i(t)t}$ is observed. This is hardly satisfied in most of the existing RCS designs. In turn, Collado (1997) improved Moffitt's (1993) approach by using less stringent data requirements and going back to the conventional cohort-based approach. In particular, Collado (1997) proposed a Generalized Method of Moments (GMM) estimator corrected for measurement error for the following model,

$$\bar{y}_{c(t)t} = \alpha \bar{y}_{c(t)t-1} + \beta \bar{x}_{c(t)t} + \bar{f}_{c(t)} + \bar{\varepsilon}_{c(t)t} \tag{7}$$

Unlike Moffitt (1993), Collado (1997) did not assume that the unit-specific effects cancel out at the cohort-level. The author also argued that in the cohort-based approach, there is a trade-off between the number of cohort groups and the sample size per group. In particular, when the number of sampled units per cohort becomes large, the issue on measurement error becomes less relevant. However, this may have potential costs on efficiency since in finite sample sizes, increasing the number of units per cohort calls for fewer cohort groups to be formed.

Like Moffitt (1993), Girma (2000) departed from the conventional cohort-based approach and argued that a unit-based estimation method (i.e., maintaining the original observations as the units of analysis) will better optimize the use of available information from repeated cross-sectional data. Although Girma (2000) still grouped the units into cohorts, the author's approach did not involve transforming the data to cohort averages. Instead, Girma (2000) argued that different units within the same cohort (even across different time periods) exhibit nonzero correlations. In turn, such information can be used to find a suitable instrument when estimating (5). In particular, Girma (2000) proposed a pairwise quasi-differencing approach for the following model,

$$y_{i(t)t} = \alpha y_{j(t-1)t-1} + \beta x_{i(t)t} + f_{i(t)} + \eta_{i(t)t} \tag{8}$$

where i and j are units from the same cohort group. Implicitly, (8) suggests that any past and present value of y and x can be used as instruments. Without imposing other conditions, this would create an infinite number of candidate instruments. However, subsequent studies argued that relying on arbitrarily chosen units from the same cohort as instruments could be a noisy approximation of the unobserved value of $y_{i(t)t-1}$ which might lead to inaccurate estimation of (5) (Verbeek and Vella 2005).

McKenzie (2004) extended (5) to allow for different covariate effects across cohorts. This heterogeneous dynamic pseudo-panel model can be denoted by (9) and its corresponding cohort-level model is denoted by (10). The author also argued that a GMM estimator similar to the one adopted by Collado (1997) which is consistent as the number of cohort groups increases, may not work since the number of parameters to be estimated also increases with the former. Instead McKenzie (2004) used an approach analogous to the Arellano-Bond estimator typically used in genuine panel models wherein $\overline{y}_{c(t-2)t-2}$ is used as an instrument for $\lambda_{c(t)t} = \alpha\left[\overline{Y}_{c(t)t} - \overline{Y}_{c(t-1)t-1}\right]$ which in turn as unbiased estimator of $\overline{y}_{c(t)t-2}$. Although this instrumentation approach addresses the bias arising from the measurement error induced by not observing the same individuals for each time period, the author pointed out that this estimator may be less efficient relative to the OLS estimator. In other words, an OLS estimator may still be superior (with lower variability) unless the number of time periods and the cohort sample sizes are both large.

$$y_{i(t)t} = \alpha_c y_{i(t)t-1} + \beta_c x_{i(t)t} + f_{i(t)} + \varepsilon_{i(t)t} \tag{9}$$

$$\bar{y}_{c(t)t} = \alpha_c \bar{y}_{c(t)t-1} + \beta_c \bar{x}_{c(t)t} + \bar{f}_{c(t)} + \bar{\varepsilon}_{c(t)t} \tag{10}$$

Inoue (2008) further extended the discussion of pseudo-panel estimation of dynamic models by considering a model that contains time-invariant unit-specific and (cohort) group-specific fixed effects denoted by (11) where $Z_{c(t)}$ are cohort-level explanatory variables and δ_c. Inoue (2008) proposed a GMM-based estimator for (11) which is consistent under some stringent orthogonality and rank conditions.

$$\bar{y}_{c(t)t} = \alpha_c \bar{y}_{c(t)t-1} + \beta \bar{x}_{c(t)t} + \gamma Z_{c(t)} + \bar{f}_{c(t)} + \delta_c + \bar{\varepsilon}_{c(t)t} \tag{11}$$

In summary, there are two broad types of pseudo-techniques that have been proposed in the literature. The first type or what we refer to as Type I method in the succeeding discussions, uses cohort-averages as a form of instrumentation. In particular, all sampled units are grouped into mutually exclusive and exhaustive cohort classes. The cohort averages of the characteristics of interest are then used as the analytical units. In this context, the cohort averages act as the pseudo-panels. The approaches proposed by Deaton (1985), Verbeek and Nijman (1993), Collado (1997), McKenzie (2004) and Inoue (2008) can be considered as Type I methods. On the other hand, what we refer to as Type II methods maintain the original sampling units as the analytical units. Following this definition, the approaches developed by Moffitt (1993) and Girma (2000) can be considered as Type II methods. Overall, each type has its own advantages and limitations. For instance, the main advantage of Type I method is that its underlying statistical theory, particularly how the model parameters can be estimated consistently,has been discussed extensively in the literature (Verbeek 2008). However, aggregating the units into cohorts can lead to significant loss of information. In particular, it becomes less straightforward to examine variations of the characteristics of interest within cohorts. On the other hand, Type II method addresses this limitation as it maintains the original observations as the units of analysis. However, unlike the Type I methods, the underlying statistical theory of Type II methods has not been extensively discussed in the literature. Over the years, both methods have been used in different empirical applications. In the next section, we discuss four recently proposed pseudo-panel techniques that are specifically designed to measure income mobility.

3.2 Estimation of income mobility using pseudo-panel data

TYPE I METHOD

Antman and McKenzie's (AM) Approach

As pointed out in Section 2, mobility can be conceptualized as the temporal dependence between previous and current income. There are two ways of measuring temporal dependence. First, we can estimate the correlation between previous and current income. Subtracting this correlation from unity yields the Hart's index described in Section 2. On the other hand, Antman and McKenzie (2005 and 2007) used income elasticity in measuring mobility in Mexico. The approach entails expressing each unit's current income $Y_{i(t)}$ as a function of its lagged income $Y_{i(t)t-1}$, a vector of sociodemographic characteristics $X_{i(t)t}$ and a unit-specific effect $f_{i(t)}$. In this context, α is the mobility parameter of interest. In general, a large absolute value for α portrays strong temporal dependence, i.e., low mobility, while small values mirror weak relationship between previous and current incomes, i.e., high mobility. As pointed out in the previous section, the income mobility parameter α cannot be readily estimated using RCS data. In turn, the authors used the following model,

$$\overline{y}_{c(t)t} = \alpha \overline{y}_{c(t)t-1} + \beta \overline{x}_{c(t)t} + \overline{f}_{c(t)} + \lambda_{c(t)t} \tag{12}$$

where

$$\lambda_{c(t)t} = \alpha \left[\overline{Y}_{c(t)t} - \overline{Y}_{c(t-1)t-1} \right].$$

McKenzie (2004) argues that the term $\lambda_{c(t)t}$ can be ignored when the number of sampled units for every cohort is sufficiently large. Noticeably, (12) is exactly the same as (7). Thus, as can be inferred from the discussions in the previous section, consistent estimation of the parameters of (12) depends on the assumptions about the unobserved unit-specific effect as well as the sample size for each cohort[5]. Following Antman and McKenzie (2005 and 2007), a number of studies have applied this approach in estimating temporal dependence-based concept of income mobility (Navarro, 2006; Calonico, 2006; Cuesta, Nopo and Pizzolito, 2011).

TYPE II METHODS

Bourguignon, Goh and Kim's (BGK) Approach

Bourguignon, Goh and Kim (2004) proposed a method of estimating the probability of falling into poverty using the following model,

$$Y_{it}^{c} = \beta_{t}^{c} X_{it}^{c} + \varepsilon_{it}^{c}$$
$$\varepsilon_{it}^{c} = \rho^{c} \varepsilon_{it-1}^{c} + e_{it}^{c} \tag{13}$$

where Y_{it}^{c} is the income of unit *i* from (cohort) group *c* at time *t*, X_{it}^{c} is a vector of explanatory variables, β_{t}^{c} is the corresponding vector of covariate effects and ε_{it}^{c} is an AR(1) error term such that $V(e_{it}^{c}) = \sigma_{ect}^{2}$. With RCS data, ε_{it}^{c} and ε_{it-1}^{c} are not observed simultaneously. Nevertheless, the authors argued that the parameters of (13) can be estimated using RCS data using the variance of the residuals as shown in (14).

$$\sigma_{\varepsilon ct}^{2} = (\rho^{c})^{2} V(\varepsilon_{it-1}^{c}) + \sigma_{ect}^{2} \tag{14}$$

In particular, for each group *c* and time *t*, (13) can be estimated using OLS. The variance of the resulting residuals from (13) can then be used to estimate (14) while the residuals of (14) can be used as estimates of σ_{ect}^{2}. Given these parameter estimates and under the assumption that $e_{it}^{c} \sim N(0, \sigma_{ect}^{2})$, then the probability of falling into poverty at time *t*+1 is given by

$$P\left(Y_{it+1}^{c} < z \mid x_{it}^{c}, \hat{x}_{it+1}^{c}, \hat{\beta}_{t+1}^{c}, \hat{\sigma}_{ect+1}^{2}\right) = \Phi\left(\frac{z - \hat{\beta}_{t+1}^{c} \hat{x}_{it+1}^{c} - \hat{\rho}^{c} \hat{\varepsilon}_{it}^{c}}{\hat{\sigma}_{ect+1}^{2}}\right) \tag{15}$$

While the estimation methodology is quite straightforward to implement, there are several issues with this approach. First, estimating heterogenous models with varying parameters across cohort groups reduces the effective sample size. If some cohort groups comprise only few observations, then the corresponding parameter estimates might not be reliable. Second, to be able to estimate the probability of falling into poverty in the future, the formula calls for the availability of estimates for $\beta_{t+1^{c}}, X_{it+1^{c}}$ and σ_{ect+1}^{2}. In the absence of this information, a simple approach is to assume that these parameters and variables are time-invariant throughout the observation period.

Dang, Lanjouw, Luoto and McKenzie's (DLLM) Approach

Like Bourguignon, Goh and Kim, Dang, Lanjouw, Luoto and McKenzie (2011) focused on measuring dynamics in the low income range. In particular, consider the following models,

$$Y_{i(1)1} = \beta_{1} X_{i(1)1} + v_{i(1)1} \tag{16}$$

$$Y_{i(2)2} = \beta_{2} X_{i(2)2} + v_{i(2)2} \tag{17}$$

where Y is individual (or household) income and $\underline{X}$ is a vector of individual (or household) characteristics whose values are fixed over time. These models can be estimated using two waves of RCS. However, to be able to estimate indicators of poverty dynamics, we need either $Y_{i(1)2}$ or $Y_{i(2)1}$, both of which are unobserved in RCS data. Thus,the main idea behind the DLLM approach is to impute the values of $Y_{i(2)1}$ or $Y_{i(1)2}$ using the information provided in (16) and (17). Without loss of generality, we will focus on the imputation of $Y_{i(2)1}$. Following the approach initially developed by Elbers, Lanjouw and Lanjouw (2003) for small area estimation of poverty, Dang et al. (2011) proposed the "out-of-sample" imputation formula depicted in (18) which assumes that the explanatory variables are constant over time.

$$\begin{aligned}\widehat{Y}_{i(2)1} &= \hat{\beta}_1 X_{i(2)1} + \tilde{v}_{i(2)1} \\ &= \hat{\beta}_1 X_{i(2)2} + \tilde{v}_{i(2)1}\end{aligned} \tag{18}$$

In addition to β_1 and $X_{i(2)2}$, (18) calls for an estimate of the error term $v_{i(2)1}$. To do this, Dang et al. (2011) first assumed that ($v_{i(2)1}$ and $v_{i(2)2}$) ~ BVN(0, Σ_{ϑ}) such that[6]

$$\sum \vartheta = \begin{bmatrix} \sigma_{\vartheta 1}^2 & \rho\sigma_{\vartheta 1}\sigma_{\vartheta 2} \\ \rho\sigma_{\vartheta 1}\sigma_{\vartheta 2} & \sigma_{\vartheta 2}^2 \end{bmatrix} \tag{19}$$

The parameters $\hat{\sigma}_{\vartheta 1}^2$ and $\hat{\sigma}_{\vartheta 2}^2$ can be estimated from (16) and (17). On the other hand, the authors adopted a naïve approximation for ρ by assuming that it is either equal to zero or one. This produces lower and upper bounds for different indicators of poverty dynamics (Dang et al. 2011) as shown below.

$$\phi\left(\frac{z-\beta_1 X_{i(2)2}}{\sigma_{\vartheta 1}}, \frac{z-\beta_2 X_{i(2)2}}{\sigma_{\vartheta 2}} \mid \rho = 0\right) \le P\left(\hat{Y}_{i(2)1} < z, Y_{i(2)2} < z\right) \le \phi\left(\frac{z-\beta_1 X_{i(2)2}}{\sigma_{\vartheta 1}}, \frac{z-\beta_2 X_{i(2)2}}{\sigma_{\vartheta 2}} \mid \rho = 1\right) \tag{20}$$

$$\phi\left(-\frac{z-\beta_1 X_{i(2)2}}{\sigma_{\vartheta 1}}, -\frac{z-\beta_2 X_{i(2)2}}{\sigma_{\vartheta 2}} \mid \rho = 1\right) \le P\left(\hat{Y}_{i(2)1} > z, Y_{i(2)2} < z\right) \le \phi\left(-\frac{z-\beta_1 X_{i(2)2}}{\sigma_{\vartheta 1}}, -\frac{z-\beta_2 X_{i(2)2}}{\sigma_{\vartheta 2}} \mid \rho = 0\right) \tag{21}$$

$$\phi\left(-\frac{z-\beta_1 X_{i(2)2}}{\sigma_{\vartheta 1}}, \frac{z-\beta_2 X_{i(2)2}}{\sigma_{\vartheta 2}} \mid \rho = 1\right) \le P\left(\hat{Y}_{i(2)1} > z, Y_{i(2)2} < z\right) \le \phi\left(-\frac{z-\beta_1 X_{i(2)2}}{\sigma_{\vartheta 1}}, -\frac{z-\beta_2 X_{i(2)2}}{\sigma_{\vartheta 2}} \mid \rho = 0\right) \tag{22}$$

$$\phi\left(-\frac{z-\beta_1 X_{i(2)2}}{\sigma_{\vartheta 1}}, -\frac{z-\beta_2 X_{i(2)2}}{\sigma_{\vartheta 2}} \mid \rho = 0\right) \le P\left(\hat{Y}_{i(2)1} > z, Y_{i(2)2} > z\right) \le \phi\left(-\frac{z-\beta_1 X_{i(2)2}}{\sigma_{\vartheta 1}}, -\frac{z-\beta_2 X_{i(2)2}}{\sigma_{\vartheta 2}} \mid \rho = 1\right) \tag{23}$$

Dang and Lanjouw's(DL) Approach

The DLLM approach which entails constructing lower and upper bounds using $\rho = 0$ and $\rho = 1$ for poverty dynamics is intuitive. A value of zero for ρ implies that after accounting for correlates of income, the temporal fluctuations in each unit's income are independent. This (temporal) independence is expected to induce more mobility, i.e., more movements into or out of poverty. On the other hand, if ρ is equal to one, then there is perfect inertia in the temporal fluctuations in one's income which is expected to minimize mobility, i.e., less movements into or out of poverty.

The good thing about DLLM approach is that it maintains the original observation as the unit of analysis, making it straightforward to estimate the bounds depicted in (20) to (23) for different subpopulation groups which in turn, enriches the analysis[7]. In addition, since this approach allows for heterogeneous covariate effects wherein the parameters β_1 and β_2 are estimated separately, it may be able to capture structural changes in the income distribution[8]. However, one of the obvious limitations of DLLM method is that it does not provide point estimates for the different poverty indicators. In addition, the width of the bounds depend on how much income variation can be attributed to differences in time-invariant individual or household characteristics. As the model fit improves (higher R^2), the bounds become narrower (Dang et al. 2011). However, R^2 is high when the underlying income distribution regime is rigid wherein differences in time-invariant characteristics are the primary determinants of income variation. In other words, when much of the income variations arise from factors other than these fixed characteristics, the DLLM approach may not provide optimal estimates of poverty dynamics. To address this issue, Dang and Lanjouw (2013) proposed a point estimator for ρ which they derived as follows

$$\rho\left(Y_{i(2)1}, Y_{i(2)2}\right) = \frac{Cov\left(Y_{i(2)1}, Y_{i(2)2}\right)}{\sqrt{V\left(Y_{i(2)1}\right)V\left(Y_{i(2)2}\right)}}$$

$$\rho\left(Y_{i(2)1}, Y_{i(2)2}\right) = \frac{Cov\left(\beta_1' X_{i(2)1} + \vartheta_{i(2)1}, \beta_2' X_{i(2)2} + \vartheta_{i(2)2}\right)}{\sqrt{V\left(Y_{i(2)1}\right)V\left(Y_{i(2)2}\right)}} = \frac{\beta' V\left(X_{i(2)}\right)\beta_2 + \rho\sqrt{\sigma^2_{\vartheta_1}\sigma^2_{\vartheta_2}}}{\sqrt{V\left(Y_{i(2)1}\right)V\left(Y_{i(2)2}\right)}}$$

$$\rho = \frac{\rho\left(Y_{i(2)1}, Y_{i(2)2}\right)\sqrt{V\left(Y_{i1}\right)V\left(Y_{i2}\right)} - \beta_1' V\left(X_i\right)\beta_2}{\sigma_{\vartheta_1}\sigma_{\vartheta_2}}$$

$$\hat{\rho} = \frac{\hat{\rho}\bar{y}_{c1}\bar{y}_{c2}\sqrt{V\left(Y_{i1}\right)V\left(Y_{i2}\right)} - \hat{\beta}_1' V\left(X_i\right)\hat{\beta}_2}{\hat{\sigma}_{\vartheta_1}\hat{\sigma}_{\vartheta_2}} \qquad (23)$$

As shown in (23), the point estimator is a function of the parameter estimates of (16) and (17), variance of the observed incomes as well as the variance of the cohort means of the observed incomes. To arrive at this formula, the authors used the correlation between the two sets of cohort averages as a rough approximation of $\rho(Y_{i(1)1}, Y_{i(1)2})$. Furthermore, it is straightforward to show that when $\hat{\beta}_1' = \hat{\beta}_2$, $\hat{\rho}$ can be re-expressed as a function of the correlation between the cohort means and the coefficient of determination of each cross-sectional model. In addition to (24), Dang and Lanjouw (2013) also provided more informative lower and upper bounds for ρ as shown in (25) and (26). In turn, formula analogous to (20) to (23) can be derived using the estimated values of ρ.

$$\hat{\rho} = \frac{\hat{\rho}_{\bar{y}_{c1}\bar{y}_{c2}} - \sqrt{R_1^2 R_2^2}}{\sqrt{(1-R_1^2)(1-R_2^2)}} \tag{24}$$

$$\hat{\rho}_{LB} = \rho_{\bar{y}_{c1}\bar{y}_{c2}} \tag{25}$$

$$\hat{\rho}_{UB} = \frac{\hat{\beta}_1' V\left(X_i\right)\hat{\beta}_2}{\sqrt{V\left(Y_{i1}\right)V\left(Y_{i2}\right)}} \tag{26}$$

3.3 *Extending pseudo-panel methods to measure broad class of income mobility measures*

Thus far, the four pseudo-panel techniques discussed earlier are designed to answer different income mobility-related questions. In particular, the AM approach answers the question, "*Up to what extent can previous income predict current income*?" On the other hand, the BGK approach is designed to answer the question, "*what is the risk of falling into poverty in the future*," while both DLLM and DL approaches answer "*what is the probability of staying, moving into or moving out of poverty?*" (Cruces, Fields and Viollaz 2013). Similar to Cruces, Fields and Viollaz (2013), our objective is to examine the feasibility of using these approaches in estimating a wider array of income mobility measures. To do this, we need to construct a micro-based pseudo-panel data of incomes. For simplicity, suppose we have two cross-sections denoted by $\{Y_{i(1)1}\}$ and $\{Y_{i(2)2}\}$. Our main task is to provide imputed values for either $\{Y_{i(1)2}\}$ or $\{Y_{i(2)1}\}$ that can be used to estimate any mobility measure $M(Y_{i1}, Y_{i2})$. This section provides the step-by-step procedures of extending the algorithms of AM, BGK, DLLM and DL to be able to estimate other mobility indices which these techniques were not originally designed for.

AM Approach

Step 1: For each time period $t = 1, 2$, group all sampled units into different cohort groups.

Step 2: Compute the average income of each cohort. Do the same for other characteristics of interest.

Step 3: Estimate the model $\overline{y}_{c(t)t} = \alpha \overline{y}_{c(t-1)t-1} + \varepsilon_{ct}$

(Note: This model can be expanded to include other control factors).

Step 4: Compute the variance of the residuals $V\left(\hat{\varepsilon}_{ct}\right)$.

Step 5: Estimate $\hat{Y}_{i(1)2} = \hat{\alpha} Y_{i(1)1} + \tilde{\varepsilon}_{i(1)2}$ where $\tilde{\varepsilon}_{i(1)2}$ is a randomly drawn data point from N(0, Var($(\hat{\varepsilon}_{ct})$)).

Step 6: Estimate the mobility measure $M(Y_{i(1)1}, \hat{Y}_{i(1)2})$.

Step 7: Repeats Steps 5 and 6 for R times.

Step 8: Take the average of $M(Y_{i(1)1}, \hat{Y}_{i(1)2})$ across all iterations.

BGK Approach

Step 1: For each time period t = 1, 2, 3, group all sampled units into different cohort groups.

Step 2: For each cohort group c, estimate $Y^c_{i(1)1} = \beta^c_t X^c_{i(1)1} + \varepsilon^c_{i(1)1}$, $Y^c_{i(2)2} = \beta^c_t X^c_{i(2)2} + \varepsilon^c_{i(2)2}$ and $Y^c_{i(3)3} = \beta^c_t X^c_{i(2)2} + \varepsilon^c_{i(2)2}$.

Step 3: Retrieve the residuals $\hat{\varepsilon}^c_{i(1)1}, \hat{\varepsilon}^c_{i(2)2}, \hat{\varepsilon}^c_{i(3)3}$ from the models estimated in Step 2. Compute their respective variances $\hat{\sigma}^2_{\varepsilon 1}, \hat{\sigma}^2_{\varepsilon_{c2}}, \hat{\sigma}^2_{\varepsilon_{c3}}$.

Step 4: For each cohort c, estimate $\sigma^2_{\varepsilon ct} = (\rho^c)^2 V(\varepsilon^c_{it-1}) + \sigma^2_{ect}$.

Step 5: From the model in Step 4, retrieve the residuals $\hat{\sigma}^2_{ect}$.

Step 6: Estimate $Y^c_{i(1)2} = \hat{\beta}^c_2 X^c_{i(1)1} + \hat{\rho}^c \hat{\varepsilon}^c_{i(1)1} + \tilde{e}^c_{it}$ where $\tilde{e}^c_{it}$ is a randomly drawn data point from $Y_{i(t)t} = \beta_t X_{i(t)t} + \vartheta_{i(t)t}$.

Step 7: Estimate the mobility measure $M(Y_{i(1)1}, \hat{Y}_{i(1)2})$.

Step 8: Repeats Steps 6 and 7 for R times.

Step 9: Take the average of $M(Y_{i(1)1}, \hat{Y}_{i(1)2})$ across all iterations.

DLLM Approach

Step 1: For each time period *t*, estimate $Y_{i(t)t} = \beta_t X_{i(t)t} + \vartheta_{i(t)t}$. Retrieve the parameter estimates $\hat{\beta}_t$, and the residuals $\hat{\varepsilon}_{i(t)t}$.

Step 2: Compute the mean and the variance of the residuals, $\hat{\mu}_{\vartheta_t}$ and $\hat{\sigma}^2_{\vartheta_t}$.

Step 3: Set the residual correlation $\hat{\rho}_j$, j ∈ { LB, UB}, such that $\hat{\rho}_{LB} = 0$ and $\hat{\rho}_{UB} = 1$.

Step 4: Sort the residuals $\hat{\varepsilon}_{i(2)2}$ from lowest to highest.

Step 5: For each $j \in \{\text{LB, UB}\}$, draw n_2 pairs of residuals $(\tilde{\varepsilon}_{i(2)1}, \tilde{\varepsilon}_{i(2)2})$ from BVN $(0, \hat{\Sigma}_{\vartheta})$ where

$$\hat{\Sigma}_{\vartheta} = \begin{bmatrix} \hat{\sigma}^2_{\vartheta 1} & \hat{\rho}_j \hat{\sigma}_{\vartheta 1} \hat{\sigma}_{\vartheta 2} \\ \hat{\rho}_j \hat{\sigma}_{\vartheta 1} \hat{\sigma}_{\vartheta 2} & \hat{\sigma}^2_{\vartheta 2} \end{bmatrix}$$

Rank the residual pairs $(\tilde{\varepsilon}_{i(2)1}, \tilde{\varepsilon}_{i(2)2})$ in ascending order according to the values of $\tilde{\varepsilon}_{i(2)2}$.

Step 6: Pair the first element $\tilde{\varepsilon}_{i(2)2}$ of each sorted residual pair $(\tilde{\varepsilon}_{i(2)1}, \tilde{\varepsilon}_{i(2)2})$ with the sorted $\hat{\varepsilon}^j_{i(2)1}$.

Step 7: For each $j \in \{\text{Est, LB, UB}\}$, estimate $Y^j_{i(2)1} = \hat{\beta}_1 X_{i(2)2} + \tilde{\varepsilon}^j_{i(2)1}$. .

Step 8: Estimate the mobility measure $M_j\left(\hat{Y}^j_{i(2)1}, Y_{i(2)2}\right)$.

Step 9: Repeats Steps 5 to 8 for R times.

Step 10: For each $j \in \{\text{LB, UB}\}$, take the average of $M_j\left(\hat{Y}^j_{i(2)1}, Y_{i(2)2}\right)$ across all iterations.

DL Approach

Step 1: For each time period $t = 1, 2$, group all sampled units into different cohort groups. Compute the correlation of $\overline{Y}_{c(1)1}$ and $\overline{Y}_{c(2)2}$ and denote it by $\hat{\rho}_{\overline{y}_{c1}\overline{y}_{c2}}$.

Step 2: Compute the variances $V(Y_{i(1)1})$ and $V(Y_{i(2)2})$.

Step 3: For each time period t, estimate $Y_{i(t)t} = \beta_t X_{i(t)t} + \vartheta_{i(t)t}$. Retrieve the parameter estimates $\hat{\beta}_t$, residuals $\hat{\varepsilon}_{i(t)t}$, and the coefficients of determination R^2_t.

Step 4: Compute the mean and the variance of the residuals, $\hat{\mu}_{\vartheta_t}$ and $\hat{\sigma}^2_{\vartheta_t}$.

Step 5: Compute the residual correlation $\hat{\rho}_j$, $j \in \{\text{Est, LB, UB}\}$.

$$\hat{\rho}_{est} = \frac{\hat{\rho}_{\overline{y}_{c1}\overline{y}_{c2}} \sqrt{V(Y_{i1})V(Y_{i2})} - \hat{\beta}_1' V(X_i) \hat{\beta}_2}{\hat{\sigma}_{\vartheta 1} \sigma_{\vartheta 2}}$$

$$\hat{\rho}_{LB} = \hat{\rho}_{\overline{y}_{c1}\overline{y}_{c2}}$$

$$\hat{\rho}_{UB} = \frac{\hat{\beta}_1' V(X_i) \hat{\beta}_2}{\sqrt{V(Y_{i1})V(Y_{i2})}}$$

Step 6: Rank the residuals $\hat{\varepsilon}_{i(2)2}$ from lowest to highest.

Step 7: For each $j \in \{\text{Est, LB, UB}\}$, draw n_2 pairs of residuals $(\tilde{\varepsilon}_{i(2)1}, \tilde{\varepsilon}_{i(2)2})$ from BVN $(0, \hat{\Sigma}_{\vartheta})$ where

$$\hat{\Sigma}_{\vartheta} = \begin{bmatrix} \sigma_{\vartheta 1}^2 & \hat{\rho}_j \hat{\sigma}_{\vartheta 1} \hat{\sigma}_{\vartheta 2} \\ \hat{\rho}_j \hat{\sigma}_{\vartheta 1} \hat{\sigma}_{\vartheta 2} & \sigma_{\vartheta 2}^2 \end{bmatrix}$$

Rank the residual pairs $(\tilde{\varepsilon}_{i(2)1}, \tilde{\varepsilon}_{i(2)2})$ in ascending order according to the values of $\tilde{\varepsilon}_{i(2)2}$.

Step 8: Pair the first element $\tilde{\varepsilon}_{i(2)1}$ of each sorted residual pair $(\tilde{\varepsilon}_{i(2)1}, \tilde{\varepsilon}_{i(2)2})$ with the sorted $\hat{\varepsilon}^j_{i(2)1}$.

Step 9: For each j$\in$\{Est, LB, UB\}, estimate $\hat{Y}^j_{i(2)1} = \hat{\beta}_1 X_{i(2)2} + \tilde{\varepsilon}^j_{i(2)1}$.

Step 10: Estimate the mobility measure $M_j\left(\hat{Y}^j_{i(2)1}, Y^j_{i(2)2}\right)$.

Step 11: Repeats Steps 7 to 10 for R times.

Step 12: For each j$\in$\{Est, LB, UB\}, take the average of $M_j\left(\hat{Y}^j_{i(2)1}, Y^j_{i(2)2}\right)$ across all iterations.

4. Data

The income measure used in this study is per capita household consumption derived from the Philippine Family Income and Expenditure Survey (FIES). The FIES is a triennial income and consumption household survey conducted by Philippines' National Statistics Office (NSO) starting in 1957.[9] Technically, FIES is a cross-sectional survey but starting in 2003, it follows a scheme where random subsample households used in previous waves of FIES are rotated back for the succeeding waves (Ericta and Fabian, 2009).

Our working sample consists of households appearing in 2003, 2006 and 2009 FIES rounds. Preliminary investigation reveals that the income distribution of the full cross-sectional sample is significantly different from the distribution of the longitudinal subsample. To address this issue, we introduced survey weight adjustments by estimating logistic models of the probability of appearing in 2003, 2006 and 2009 waves using income, age of household head, sex of household head and urbanity as controls. Table 1 compares the unadjusted and adjusted estimates of average consumption, US$2 headcount poverty rate and income inequality. Here, we can see that the difference in the distribution between the full cross-sectional sample and longitudinal subsample is less pronounced after using the weight-adjustments. The final sample is restricted to households whose heads were born between 1948 to 1983, or equivalently, those who were aged 20 to 65 in 2003.

For the AM approach, the cohorts are constructed by grouping households according to the head's year of birth and gender. In particular, we follow the approach of Cruces, Fields and Viollaz (2013) which uses two-year span to be able to strike a balance between the number of cohorts and sample size per cohort. In estimating the conditional models, we include the cohort's average

Table1. Representativeness of the Longitudinal Subsample

Time period	2003			2006			2009		
	Mean	US$2 FGT0	Gini	Mean	US$2 FGT0	Gini	Mean	US$2 FGT0	Gini
Full sample									
2003	101.5 0.765	0.435 0.004	0.44 0.003						
2006				98.99 0.886	0.455 0.004	0.441 0.003			
2009							103.7 1.036	0.416 0.005	0.43 0.003
Longitudinal subsample (Unadjusted)									
2003, 2006 and 2009	94.87 1.543	0.451 0.009	0.428 0.005	94.4 1.557	0.476 0.01	0.438 0.005	96.64 1.448	0.438 0.009	0.414 0.004
Longitudinal subsample (Adjusted)									
2003, 2006 and 2009	99.36 1.743	0.428 0.009	0.431 0.005	99.17 1.751	0.455 0.01	0.445 0.005	101.8 1.684	0.418 0.009	0.423 0.005

Source: Authors' computations using FIES 2003, 2006 and 2009.

family size, average proportion of household members less than 15 years old, average proportion of household members who are employed and proportion of households relying on agricultural income. For the BGK, DLLM and DL approaches, the income correlates included in the model are provincial dummies, household head's age and its square, gender of the household head and educational attainment of the household head.

5. Discussion of Empirical Results

Following the procedures outlined in Section 3.3, we estimated four measures of poverty dynamics which include the proportion of population moving into poverty, moving out of poverty, staying in poverty and staying nonpoor. In addition, we also estimated seven of the most commonly used income mobility indices in the literature covering three different mobility concepts – movement (average rank jump, Fields-Ok's, King's indices), temporal dependence (Hart's index) and equalizer of income (Chakravarty, Dutta and Weywark's, Fields' and Shorrocks' indices). Before proceeding to the discussion of the results, some remarks are in order. First, when computing income mobility from time t to $t+1$, we always choose a reference period. For the chosen reference period, the actual income data from FIES is used. On the other hand, the income values for the other time period are imputed following the approach outlined in Section 3.3. In general, the choice of reference period is different for each method. For the AM and BGK approaches, the initial time period is always chosen as the reference period while the income values for the final time period are imputed. In contrast, the DLLM and DM approaches use the final time period as the reference while the income values for the initial time period are imputed. Given that the final sample for each cross-sectional wave is representative of the same population, we suspect that the differences in the estimates will not depend on the choice of reference period. Second, unlike the original AM, BGK, DLLM and DL methods which strictly use either parametric or nonparametric procedures, we adopt a semi-parametric approach. As outlined in Section 3.3, the semiparametric algorithm for estimating income mobility entails iteratively drawing random disturbance terms from the Gaussian distribution with pre-specified parameters. For each mobility index, every iteration corresponds to an estimated value. The results provided in the succeeding discussions are the based from 100 replicates. Third, we provide a point estimate for the DLLM approach by taking the midpoint of the lower and upper bounds. Fourth, to be able to fine-tune the estimates for the DLLM and DL approaches, we introduce a structure preserving technique that takes into account the rank of the residuals from the reference period. Lastly, there are three components that contribute to the estimated standard error of the mobility estimates – sampling error, model error and the iterative sampling procedure for the stochastic disturbance term.

Dynamics in the low income range

Despite the moderate to high economic growth that the Philippines has experienced in the second half of the 2000s, poverty rates remained high during this period. From 2003 to 2009, the proportion of the population living below US$2 a day barely changed at 43%. This can be partially attributed to the increase in poverty from 2003 to 2006 offsetting the poverty reduction observed from 2006 to 2009. Using the actual panel data, we estimate that the gross outflow from poverty from 2003 to 2009 is approximately 10% of the population while the gross inflow accounts for 9% (Table 4). The proportion of the population who remained poor and nonpoor during these two periods are 38% and 47%, respectively.

Tables 2 to 4 compare the estimated proportion of each category of poverty status across the different pseudo-panel methods. For the AM approach, we find that both the unconditional and conditional pseudo-panel estimates are quite different from the proportions estimated from the actual panel data. Interestingly for all time periods considered, the unconditional estimates for the poverty outflow and inflow are consistently lower than the actual panel data-based estimates while the proportion of persistent poverty and nonpoverty are consistently higher. A slightly different pattern emerges when we look at the conditional estimates of the AM approach. In particular, pseudo-panel estimates of poverty outflow and persistence of nonpoverty are consistently higher while poverty inflow and poverty persistence are consistently lower than the panel estimates. On the other hand, the

Table 2. Estimates of Poverty Dynamics in the Philippines, 2003-2006

Indicator	PANEL	PSEUDO-PANEL								
		AM (A)	AM (B)	BGK	DLLM (A)	midpt	DLLM (B)	DL (A)	DL (B)	DL (C)
Poverty outflow	6.40	2.53	11.58	18.59	2.31	8.32	14.33	4.91	6.26	10.25
Poverty inflow	9.06	3.71	4.68	8.35	1.36	9.86	18.35	4.63	6.65	12.52
Stay in Poverty	37.57	41.95	32.90	25.52	28.27	36.77	45.26	34.10	39.98	42.00
Stay NonPoor	46.97	51.81	50.84	47.54	39.04	45.05	51.07	43.12	47.11	48.47

Table 3. Estimates of Poverty Dynamics in the Philippines, 2006-2009

Indicator	PANEL	PSEUDO-PANEL								
		AM (A)	AM (B)	BGK	DLLM (A)	midpt	DLLM (B)	DL (A)	DL (B)	DL (C)
Poverty outflow	10.23	6.74	14.43	21.75	7.51	12.38	17.26	8.45	9.32	13.63
Poverty inflow	6.43	0.99	2.11	6.32	0.38	8.25	16.11	1.92	3.18	10.17
Stay in Poverty	36.24	39.89	32.20	24.87	26.56	34.42	42.29	32.51	39.50	40.75
Stay NonPoor	47.10	52.38	51.26	47.05	40.07	44.94	49.82	43.70	48.00	48.87

Table 4. Estimates of Poverty Dynamics in the Philippines, 2003-2009

Indicator	PANEL	PSEUDO-PANEL								
		AM (A)	AM (B)	BGK	DLLM (A)	midpt	DLLM (B)	DL (A)	DL (B)	DL (C)
Poverty outflow	10.37	7.16	17.65	21.29	7.33	11.86	16.39	9.54	10.89	13.14
Poverty inflow	9.14	2.23	4.35	8.92	2.06	9.54	17.01	5.12	7.26	11.01
Stay in Poverty	33.53	37.32	26.83	22.83	25.66	33.14	40.62	31.67	35.41	37.56
Stay NonPoor	46.95	53.29	51.17	46.97	40.93	45.47	50.00	44.19	46.44	47.79

performance of the BGK approach yields mixed signals. For instance, while the pseudo-panel estimates for poverty inflow and persistence of nonpoverty are quite close to the estimates derived from actual panel data, the pseudo-panel estimates for poverty outflow and persistence of poverty are quite off. Compared to the AM and BGK approaches, the DLLM and DL methods performed better. For instance, the estimates using the actual panel data fall in between the estimated lower and upper bounds produced by DLLM. While these bounds could be restrictively wide as pointed out by Cruces, Fields and Violaz (2013), taking its midpoint yields estimates that are quite close to the actual panel-based estimates. Furthermore, the bounds estimated using the DL method are much narrower compared to that of the DLLM. This is expected given that the DL approach uses more informative estimates of the residual correlation. The point estimates using the DL approach are also reasonably close to the actual panel-based figures. Nevertheless, it is worth pointing out that the point estimates of the DL approach are always lower for movements into and out of poverty and always higher for poverty immobility.

Other dimensions of income mobility

From 2003 to 2009, average per capita consumption barely moved, changing by approximately 2%. This is also accompanied by a small reduction in income inequality where the Gini coefficient changed from 0.44 in 2003 to 0.43 in 2009. However, turning to a broader set of income mobility measures, we find a much more dynamic income distribution over the six-year period, especially when viewed in terms of income movements. In particular, the mean absolute percentage change in per capita consumption is about 36%. This is equivalent to a 14-step change in income ranks, on the average. On the other hand, mobility is less pronounced when viewed in terms of temporal dependence and equalizer of income. For instance, the correlation of the logarithm of incomes in 2003 and 2009 is about 0.8. Furthermore, the observed income mobility reduces long-run inequality by only 6%.

Tables 5 to 7 compare the estimated values of different mobility indices using the actual panel and pseudo-panel data. For the AM approach, we find that the estimates derived from the conditional models are closer to the actual panel-based figures for indices designed to gauge movement and temporal dependence of incomes. In contrast, the unconditional models performed better than the unconditional models in estimating income mobility indices under the equalizer of income perspective. On the other hand, the pseudo-panel estimates computed using the BGK approach are at least two times higher than the values estimated using actual panel data. Turning to the DLLM and DL approaches, we find that the values of all mobility indices using actual panel data fall in between the lower and upper bounds estimated using the pseudo-panel approach. Unlike the indices of poverty dynamics for which Dang et al. (2011) provided a theoretical proof that the approach produces valid lower and upper bounds, we have not

Table 5. Estimates of Income Mobility in the Philippines, 2003-2006

Indicator	PANEL	PSEUDO-PANEL								
		AM (A)	AM (B)	BGK	DLLM (A)	midpt	DLLM (B)	DL (A)	DL (B)	DL (C)
Movement										
Ave. Rank Jump	11.72	4.34	9.43	19.86	3.19	13.14	23.09	7.27	9.66	16.38
Fields-Ok	0.32	0.11	0.27	0.84	0.09	0.35	0.61	0.20	0.26	0.43
King	0.34	0.23	0.22	0.51	0.10	0.30	0.50	0.19	0.25	0.39
Temporal Dependence										
Hart	0.15	0.02	0.10	0.42	0.01	0.26	0.52	0.05	0.09	0.27
Equalizer of Income										
CDW	0.02	0.02	0.11	-0.20	-0.02	0.03	0.07	-0.01	0.00	0.03
Fields	0.01	0.02	0.13	-0.17	-0.17	0.03	0.07	-0.02	-0.01	0.02
Shorrocks	0.06	0.01	0.06	0.20	0.20	0.11	0.22	0.02	0.04	0.12

Table 6. Estimates of Income Mobility in the Philippines, 2006-2009

Indicator	PANEL	PSEUDO-PANEL								
		AM (A)	AM (B)	BGK	DLLM (A)	midpt	DLLM (B)	DL (A)	DL (B)	DL (C)
Movement										
Ave. Rank Jump	11.70	4.53	7.92	19.89	3.14	13.30	23.45	6.46	8.35	16.96
Fields-Ok	0.32	0.14	0.25	0.88	0.16	0.38	0.60	0.21	0.25	0.45
King	0.33	0.23	0.21	0.52	0.10	0.29	0.49	0.17	0.22	0.38
Temporal dependence										
Hart	0.15	0.02	0.07	0.44	0.01	0.27	0.53	0.04	0.07	0.28
Equalizer of Income										
CDW	0.06	0.04	0.10	-0.22	0.01	0.06	0.10	0.02	0.02	0.06
Fields	0.05	0.074	0.11	-0.17	0.01	0.06	0.11	0.01	0.02	0.06
Shorrocks	0.07	0.01	0.04	0.18	0.01	0.12	0.23	0.02	0.03	0.13

Table 7. Estimates of Income Mobility in the Philippines, 2003-2009

Indicator	PANEL	PSEUDO-PANEL								
		AM (A)	AM (B)	BGK	DLLM (A)	midpt	DLLM (B)	DL (A)	DL (B)	DL (C)
Movement										
Ave. Rank Jump	13.88	13.09	15.11	21.78	6.16	14.92	23.67	10.41	12.99	17.24
Fields-Ok	0.36	0.35	0.41	0.93	0.20	0.41	0.61	0.29	0.35	0.46
King	0.36	0.31	0.27	0.57	0.18	0.34	0.49	0.26	0.31	0.39
Temporal Dependence										
Hart	0.20	0.18	0.25	0.51	0.06	0.30	0.54	0.12	0.17	0.29
Equalizer of Income										
CDW	0.05	0.09	0.16	-0.19	0.04	0.07	0.10	0.05	0.05	0.07
Fields	0.05	0.10	0.18	-0.15	0.03	0.07	0.11	0.04	0.05	0.07
Shorrocks	0.09	0.08	0.13	0.21	0.03	0.13	0.23	0.05	0.08	0.13

done so for the mobility indices considered in this section. Thus, this result is encouraging. In other words, it provides us reason to believe that the DLLM and DL approaches can also be useful for estimating mobility indices other than what they were originally designed to measure. Furthermore, comparing the midpoint of the bounds derived using DLLM with the DL's point estimator, we find that for 2003-2006 and 2006-2009 periods, the estimated values from DLLM are quite closer to the movement-based indices computed using the actual panel data. For the rest, the DL estimates performed better. In addition, we find that the midpoints from the DLLM approach consistently overestimate mobility while the DL's point estimates are always lower than the values of indices computed from actual panel data.

In summary, the results of these analyses allow us to address the three research questions:

1. Are the proposed pseudo-panel techniques useful for measuring income mobility? In general, which of the pseudo-panel techniques are most desirable?

   Overall, the results using Philippine data suggest that the DLLM and DL approaches performed reasonably well in estimating poverty dynamics and other measures of mobility. On the other hand, the AM and BGK approaches provided satisfactory results for selected indicators only: the proportion of population moving into poverty and proportion of population remaining nonpoor for BGK and indices under the equalizer of income perspective for AM. There are several possible explanations for this. For instance, the pseudo-panel approaches considered in this study are not originally designed for estimating varied income mobility measures. Rather, these methods are proposed for specific mobility indicators only. If the structural parameters of the underlying models are not flexible enough, it would not be surprising to note that the pseudo-panel estimators will not always perform well for all types of income mobility measures. Of the four pseudo-panel methods considered here, we argue that the DLLM and DL approaches use more flexible model specifications than the AM and BGK methods.

2. Do the pseudo panel techniques' performance depend on the type of income mobility measure being estimated?

   Our empirical findings suggest that in most cases, the pseudo-panel methods performed better when estimating indices under the mobility as income movement perspective. On the other hand, indices measuring temporal dependence of income and its inequality-reducing effect are harder to impute using the pseudo-panel methods considered here. A possible reason why this is the case is that unlike the temporal dependence and equalizer of income-based measures, most of the movement-based indices are less sensitive to the detailed features of the joint temporal distribution of incomes.

3. How can the existing pseudo-panel techniques be improved?

   Compared to the findings by Cruces, Fields and Violaz (2013), the use of pseudo-panel methods especially the DLLM and DL approaches in estimating income mobility in the Philippines produced more encouraging results. We suspect that the differences in the characteristic features of the income distributions of the two countries contribute to the diverging findings about the usefulness of the pseudo-panel methods. For instance, the Chilean panel data spans a ten-year period while the Philippine data covers a shorter six-year period. Given this, it is reasonable to expect that there is more mobility in the Chilean panel data than in the Philippine data. However, as we have initially pointed out, the use of time-invariant variables in DLLM and DL are probably more suitable when the true income mobility regime is low because it imputes the value of permanent income. This could potentially justify why we have noted more satisfactory results than Cruces, Fields and Violaz (2013) found. Nevertheless, it is difficult to provide a conclusive explanation without doing further studies. To be able to move forward, we recommend doing simulation studies that will outline a more objective characterization of the performance of each pseudo-panel method considered in this paper.

There are several areas for improvement that could be explored further. First, it would be worthwhile to extend the BGK, DLLM and DL algorithms to allow the use of time-varying correlates of income in the model specification. Adding time-varying correlates may significantly improve the prediction power of the models and in turn, improve the pseudo-panel estimates of income mobility. Second, incorporating structural preserving techniques in the existing pseudo-panel algorithms may prove useful in estimating a wider array of income mobility indices. At present, it appears that income mobility measures which are sensitive to the overall structure of the income distribution are harder to impute than indices which focus on capturing movements of individual incomes. Third, statistical inference will enrich the income mobility analysis because it will allow comparison of income mobility across space and over time. However, much of the existing discussions are centred on estimation of mobility indices. Thus, further research is needed to be able to provide a theoretical framework that will serve as a practical guide for conducting statistical inference in the context of income mobility estimation using pseudo-panel data.

6. Summary and Future Directions

Measures of income mobility are commonly used in socio-economics literature as analytical tools for examining the evolution of the income distribution. In general, proponents of these measures believe that incorporating a longitudinal perspective enriches the analysis of income distribution. In particular, they argue that income mobility measures provide a more dynamic perspective of the evolution of a country's living standards than simply examining changes in cross-sectional indices of poverty and inequality over time. Panel data that tracks the incomes of the same set of households or individuals is the appropriate data source for measuring income mobility. However, factors like cost and risks of attrition often lead to the use of cross-sectional data.

Unlike panel surveys, cross-sectional surveys do not necessarily follow the same set of households or individuals. Recently, several pseudo-panel estimation methods have been proposed in estimating different concepts of mobility. The development of pseudo-panel methods reconciles the need for incorporating a longitudinal perspective when examining income distribution with the absence or lack of panel data. In particular, it offers researchers with the opportunity to depart from conventional methods of examining static indicators of well-being and delve deeper into the multi-dimensional issue of equality of socioeconomic opportunities using cross-sectional survey data.

There are several ways of creating synthetic or pseudo-panels out of repeated cross-sectional data. This study reviews four recent developments in the pseudo-panel estimation of income mobility literature. The first method proposed by Antman and McKenzie (2007) entails transforming the unit-level data into cohort averages. These cohort averages serve as the synthetic panels. On the other hand, the approaches proposed by Bourguignon, Goh and Kim (year), Dang, Lanjouw, Luoto and McKenzie (2011) and Dang and Lanjouw (2013) estimates income models while maintaining individuals or households as the units of analysis. Originally, these methods are designed to answer varying concepts of mobility. In this study, we outlined algorithms which extend these approaches to be able to measure a wider array of income mobility indices. Our results suggest that the proposed methods by Dang, Lanjouw, Luoto and McKenzie (2011) and Dang and Lanjouw (2013) which employ the weakest assumption about the structural parameters and functional form of the income models performed satisfactorily in terms of estimating different mobility concepts. Nevertheless, several areas for improvement remain. These include exploring techniques that would accommodate time-varying correlates for the BGK, DLLM and DL income models, employing structural preserving strategies to provide better estimates of mobility indices which are sensitive to the overall structure of the income distribution and outlining the framework for carrying out statistical inferences.

NOTES

1 For interested readers, a brief review of the main findings about income mobility patterns in developing countries is provided in Fields (2011).

2 The advantage of using income elasticity index over Hart's index is that we can control for other correlates of income in the former.

3 Even in the presence of genuine panel data, ordinary least squares (OLS) estimation of (1) will produce inconsistent estimates for β if f_i is correlated with X_{it}. On the other hand, even if f_i can be reasonably assumed to be orthogonal with X_{it}, OLS estimators will still be nonoptimal due to the serial correlation induced by the term f_i. In lieu of this, a fixed effects (FE) (or a random effects in the case that f_i is uncorrelated with X_{it}) estimator can be considered. The FE estimator implements a data transformation that removes the correlation between the explanatory variables X_{it} with the unobserved terms of (1).

4 Note that at the population-level, this term is fixed under the assumption that the population is closed.

5 In the next section, we adopt the simplifying assumption that conditional on previous income, there is no persistent unit-specific effect. Hence, the model parameters can be estimated using OLS.

6 Dang et al. (2011) also proposed an analogous nonparametric approach.

7 Intuitively, this is subject to the sample size available for the subpopulation group under consideration.

8 For instance, if the level of importance that a (social) opportunity structure attributes to fixed individual characteristics like race, ethnicity, religion and parental education changes significantly over time, then such changes are implicitly incorporated in the estimation of the model parameters.

9 Before 1985 (i.e.,1957 – 1979), FIES was conducted every five years. The FIES waves from 1957 to 1975 used the annual recall method while starting 1985, the semestral recall method was utilized.

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Appendix Table A1. Income Mobility Indices based on Different Conceptualizations

Concept	Index	Formula
Nondirectional income flux	Fields-Ok	$\frac{1}{N}\sum_{i=1}^{N}\left\lvert \ln\left(\frac{income_{it}}{income_{it-1}}\right)\right\rvert$
Positional movement	King	$1-\exp\left[-\frac{\gamma}{N}\sum_{i=1}^{N}\frac{\lvert z_i - income_{it}\rvert}{\overline{income_t}}\right]$
	Average Rank Jump	$\sum_i \lvert rank(Income_{it}) - rank(Income_{it-1})\rvert$
	Poverty Persistence	$P(Income_{it} \leq povline, Income_{it-1} \leq povline)$
	Poverty Inflow	$P(Income_{it} \leq povline, Income_{it-1} > povline)$
Time dependence	Hart	$1 - Correl\left(\ln(Income_{it-1}), \ln(Income_{it})\right)$
Mobility as Equalizer of Income	Shorrocks	$1 - I(\sum_{t=1}^{T} Income_{it}) / \sum_{t=1}^{T} w^t I(Income_{it})$
	Fields	$1 - I(\sum_{t=1}^{T} Income_{it}) / I(Income_{it-1})$
Ethical Mobility	Chakravarty, Dutta and Weywark (CDW)	$\frac{I(Income_{agg})}{(Income_{it-1})} - 1$

Source: Fields (2008); Fileds et al. (2007)