Can the Limitations of Panel Datasets be Overcome by Using Pseudo-Panels to Estimate Income Mobility?

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Abstract

This paper analyzes whether pseudo panels are suitable substitutes for true panels for estimating income mobility. We obtain evidence using Chilean panel data for the period 1996-2006 and constructing pseudo panels treating each round of the panel as if it were an independent cross-section survey. We consider three different pseudo-panel methods: the mean-based approach that identifies cohorts and follows cohort means over time, the method developed by Bourguignon, Goh and Kim (2004) that was designed to estimate vulnerability-to-poverty measures, and the method of Dang, Lanjouw, Luoto and McKenzie (2011) that predicts a lower and upper bound for the joint probabilities of poverty status in $t=1$ and $t=2$. The empirical evidence leads us to conclude that pseudo-panel methodologies do not perform well in this task. Our results indicate that pseudo panels fail in two respects when trying to predict the income mobility pattern observed in Chile. First, they do not give good results for the mobility concept each pseudo-panel method seeks to measure. Second, they also perform poorly in predicting a broader set of income mobility measures. We complete the analysis making a final point about the calculation of poverty transition rates using pseudo panels.

1. Introduction

The analysis of income mobility and poverty dynamics entails the identification of the same economic unit through time. This feature imposes a data requirement –longitudinal data that tracks individuals or households over time- that is difficult to meet in many cases. This data limitation has been of particular relevance for developing countries, suggesting that there is no direct way to analyze these issues. However, new methodologies based on cross-sectional data have been proposed and used in the last years in order to overcome this difficulty. These methodological innovations are commonly known as 'pseudo-panel approaches' or, less commonly, 'synthetic panels'. Recent developments on pseudo-panel analysis include Bourguignon, Goh, and Kim (2004), Antman and McKenzie (2007), and Dang, Lanjouw, Luoto, and McKenzie (2011). These pseudo-panel methods differ in several respects such as in their data demands, in the assumptions about structural parameters and functional forms, and more importantly, in the income mobility question they attempt to answer.

In this context, the main goal of this paper is to obtain evidence and give an answer to the question: *are pseudo panels a suitable substitute for true panels for estimating income mobility?* To this end, we work with Chilean panel data for the period 1996-2006 and compare "true" estimates of mobility –arising from the panel dataset- against mobility estimates from the three pseudo-panel methods implemented by treating the three rounds of the Chilean panel as if they were repeated cross-sectional surveys rather than a panel.

We organize the analysis proceeding in three steps. First, we distinguish various macro-mobility, micro-mobility, and poverty dynamics concepts and then calculate measures of each in the true panel. Second, we evaluate how the pseudo-panel methods perform in answering the specific income mobility question each was intended to answer. And third, for the full set of income mobility concepts and measures, we compute a broader set of income mobility measures and determine how close or far these methods come in approximating the "true" measures.

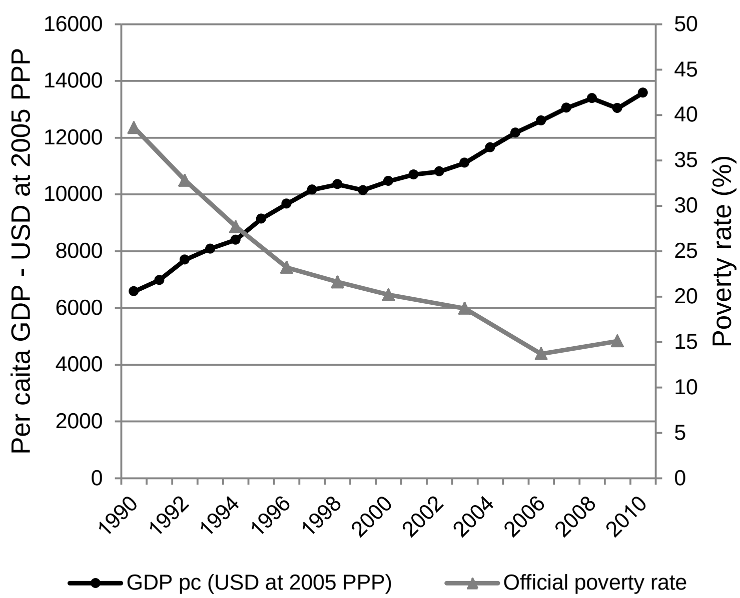
The structure of the paper is as follows. In the next section we present a broad set of income mobility concepts and measures of them calculated with Chilean panel data. In Section 3 we detail three pseudo-panel methodologies, while in Section 4 we put these methods into action. First, for the case of Chile, we compute income mobility measures to answer the specific question each method sought to answer when it was developed. Second, we calculate how much income mobility is found when the true panel is used to answer the same question. And third, using the constructed pseudo panels we compute other income mobility measures and analyze how close or far these pseudo-panel data sets come in approximating the true panel results. In Section 5 we focus on poverty dynamics, comparing true panel and pseudo-panel estimates of joint and conditional poverty probabilities. In Section 6 we conclude with final comments.

2. Chilean income mobility using true panel data

In this paper we analyze Chilean income mobility for the period 1996-2006. Over the last two decades, Chile has recorded high growth rates and a decreasing poverty trend. Despite the varied episodes of crises experienced by most Latin American countries, Chile has shown a stable macroeconomic situation. The per capita GDP annual growth rate averaged 3.6% from 1990 to 2010 while the official poverty rate fell from 38.6% in 1990 to 15.1% in 2009;[1] see Figure 1.

Figure 1: Economic performance of Chile

1990-2010



Source: World Development Indicators (World Bank).

[1] World Development Indicators, 2012 (The World Bank).

We use the 1996 and 2006 waves of the Chilean Panel Casen conducted by Fundación para la Superación de la Pobreza (FSP), Ministerio de Planificación (Mideplan) and Observatorio Social de la Universidad Alberto Hurtado (OSUAH). This survey is representative of only four of the thirteen regions in Chile (Metropolitan region and regions III, VII and VIII) and it is of great importance from the developing countries perspective due to its size and time span. A recent study using this dataset is Castro (2011), which also includes references to the Chilean income mobility literature.

Our income measure is the household per capita income (expressed in1996 prices) of household heads that reported valid data in 1996 and 2006. In order to control, at least partially, for the measurement error problem of income variables, we withdraw outliers from the data using the Mahalanobis distance measure as in Grimm (2007).[2] Applying this procedure, 1.8% of the households were excluded from the sample.

Our first interest is in macro-mobility. Thus, we ask how much mobility there was in Chile between 1996 and 2006 for six macro-mobility concepts: mobility as time-independence, positional movement, share movement, non-directional income movement, directional income movement, and mobility as an equalizer of longer-term incomes relative to initial.[3]

Estimates of one measure for each of the six concepts are shown in the first block of table 1. Mobility as time independence is gauged by the computation of one minus Pearson's correlation coefficient. The panel data result shows that per capita household income in 2006 was only vaguely determined by its value in 1996, the linear association between the two variables being only 0.2. Our measure of positional movement -mean absolute value of decile change- shows that household heads moved, on average, two deciles in this period. Share movement, computed as the mean absolute value of change in normalized income share, also reveals significant mobility, the change in normalized average income share having changed

[2] An observation is discarded if the Mahalanobis distance between the logarithms of per capita income exceeds a critical value equal to the mean plus two times the standard deviation of the distribution of the Mahalanobis distances in the sample.

[3] For a detailed description of the income mobility measures used in the case of Chile as well as other Latin American countries, see Fields et al. (2007).

by 0.63.[4] Non-directional income movement shows an average value of 58,548 pesos; compared to the mean income of 83,164 pesos in 1996, income mobility was significant according to this measure. Economy-side directional income movement was only one-third as large, indicating a large number of offsetting income gains and losses. While around 65% of the households moved upward between 1996 and 2006, the average income gains of upward movers were only somewhat larger than the average income losses of downward movers. Finally, Fields' index exhibits a positive value, which indicates that income mobility in Chile equalized longer-term income relative to initial income.

The second block of table 1 presents the results from several micro-mobility regressions. The question we seek to answer here is whether mobility was convergent or divergent in Chile. Income convergence is defined as a situation where the lower-income groups experience larger income gains than do higher-income groups. Likewise, income divergence occurs when the lower-income groups gain less than the higher-income groups. We test for two alternative hypotheses, weak and strong income convergence. Weak convergence is defined as a situation where the lower-income groups experience larger income gains than do higher-income groups *in percentages.* Weak convergence is analyzed using the change in the log of per capita income as the dependent variable and the log of initial income as the explanatory variable. By contrast, strong convergence occurs when the lower-income groups gain more than the higher-income groups *in pesos.* To test for strong convergence, the change in per capita income in pesos is regressed on the initial reported level of income in pesos. In times of economic growth, which characterized the analyzed decade in Chile, strong convergence implies weak convergence but not the other way around.

Our findings in the second block of table 1 show that lower-income groups had larger income gains than do higher-income groups both in percentages and in pesos. Thus, income mobility had a highly significant pattern of weak and strong convergence in Chile. The convergent pattern holds both unconditionally (that is, in a simple regression of income change on initial income) and conditionally (in which income change is regressed on initial income, age of household head and its square, years of education and its square, and region of residence).

[4] The share is normalized with respect to average income, so a value of 1.00 signifies going from having no income to have the mean income.

Finally, in the last block of table 1 we present some estimates of poverty dynamics. Here, we measure the probabilities of crossing the poverty line conditional on starting below or above the poverty line respectively. The results reveal that most of the Chilean households who were poor in 1996 escaped from poverty by 2006 (70.8%), and very few of those who were non-poor in 1996 fell into poverty by 2006 (5.9%).

To sum up, using true panel data for Chile for the period 1996-2006, we found 1) significant mobility for each of the macro-mobility concepts, 2) a clear pattern of income convergence conditionally and unconditionally, and 3) substantially more movement out of poverty than into poverty.

3. Pseudo-panel methodologies

Recent methodological developments provide us with different pseudo-panel approaches to analyze income mobility using repeated cross-sectional surveys. The use of repeated cross-sections allows some of the limitations associated with longitudinal data to be overcome. Non-random attrition is not an issue with pseudo panels since each individual or household is only observed once. A further advantage of pseudo panels is the wide availability of cross-sectional data that allows the construction of pseudo panels covering substantially longer periods than what can be covered by true panels.

In the next paragraphs we describe the principal pseudo-panel approaches available in the literature on income mobility. These techniques differ in data demands, in the assumptions about structural parameters and functional forms, and in the mobility question they attempt to answer. According to these characteristics we group pseudo-panel methodologies in those applying a *mean–based approach* and methodologies using a *dispersion-based approach*.

3.1. Mean-based approaches

Mean-based pseudo-panel approaches track cohorts of individuals or households over repeated cross-sectional surveys. A cohort is defined as “a group with fixed membership, individuals of which can be identified as they show up in the surveys" (Deaton, 1985). Some examples include birth cohorts, birth-education cohorts and birth-gender cohorts.

As well as the advantages associated with the use of repeated cross-sections, mean-based pseudo panels suffer less from problems related to measurement error at the individual level because they follow cohort means. However, this feature also imposes some limitations. First, mean-based pseudo panels do not provide information on intra-cohort mobility. Thus, changes in incomes, income shares, or positions among income recipients within a given cohort are simply averaged out. Second, estimates at the cohort level may be a potential source of bias if events like migration or death affect cohorts' sizes and composition (Antman and McKenzie, 2007). Last but not least, the construction of a pseudo panel involves a trade-off between the number of cohorts and the number of observations in each cohort. If the number of cohorts is large, estimations will suffer less from small sample problems. However, if the size of each cohort is not large enough, average characteristics per cohort will estimate true cohort population means with large sampling error (Deaton, 1985). Building on the earlier work of Moffitt (1993), Collado (1997), McKenzie (2001, 2004), and Verbeek and Vella (2005), Antman and McKenzie (2007) propose the following model of income at the individual level:[5]

$$Y_{i,t} = \alpha + \beta Y_{i,t-1} + u_{i,t}. \tag{1}$$

The authors interpret the coefficient β in (1) as a measure of (im)mobility. Taking cohort averages of equation (1) over the N_c individuals observed in cohort c at time t the model becomes:

$$\bar{Y}_{c(t),t} = \alpha + \beta \bar{Y}_{c(t),t-1} + \bar{u}_{c(t),t} \ , \tag{2}$$

Where $\bar{Y}_{c(t),t}$ denotes the sample mean of Y over the individuals in cohort c observed at time t. With repeated cross-sections, different individuals are observed each time period. As a result, the lagged mean $\bar{Y}_{c(t),t-1}$, representing the mean income in period $t-1$ of the individuals in cohort c at time t, is not observed. Therefore, the unobserved term is replaced with the sample means over the individuals who are observed at time $t-1$, leading to the following regression for cohorts $c = 1, 2, ..., C$ and time periods $t = 2, ..., T$:

[5]The next paragraphs rely heavily on Antman and McKenzie (2007). The interested reader is referred to the original paper for additional details.

$$\bar{Y}_{c(t),t} = \alpha + \beta \bar{Y}_{c(t-1),t-1} + \bar{u}_{c(t),t} + \lambda_{c(t),t}\,, \tag{3}$$

where

$$\lambda_{c(t),t} = \beta\left[\bar{Y}_{c(t),t-1} - \bar{Y}_{c(t-1),t-1}\right].$$

As the number of individuals in each cohort becomes large, $\lambda_{c(t),t}$ converges to zero and this term can be ignored (McKenzie, 2004).

The precise method for estimating equation (3) depends on the assumptions concerning the individual-level shocks to earnings, $u_{i,t}$, and on the dimensions of the pseudo panel. For instance, if the $u_{i,t}$ contain individual fixed effects but no time-varying cohort level component, β can be consistently estimated by OLS on the cohort average equation (3) with the inclusion of cohort dummies. This will be consistent as the number of individuals per cohort gets large (N_c). If the individual-level shocks to earnings contain a common cohort component, then in addition to a large number of individuals per cohort, a large number of cohorts or a large number of time periods is also needed for consistency. Moffitt (1993) and Collado (1997) propose instrumental variables methods to deal with a situation with many cohorts and fewer individuals per cohort, using lagged cohort means as instruments

The most basic specification assumes that there are no individual fixed effects, in which case the pseudo panel is used to estimate β in the following equation:

$$\bar{Y}_{c(t),t} = \alpha + \beta \bar{Y}_{c(t-1),t-1} + \bar{u}_{c(t),t}\,. \tag{4}$$

A value of β in the range $0 < \beta < 1$ represents a situation of income convergence –that is, households with relatively low income in period $t-1$ are likely to experience more rapid income growth than initially richer households. A value of β equal to 1 represents a situation of no income convergence, meaning that final incomes equal initial incomes on average, while β equal to zero signifies that all cohorts' final incomes equal one another.

If the data generating process contains individual fixed effects, the previous model can be estimated including cohort fixed effects:

$$\bar{Y}_{c(t),t} = \alpha_c + \beta \bar{Y}_{c(t-1),t-1} + \bar{u}_{c(t),t}\,. \tag{5}$$

In this case, an estimate of β which is less than unity in equation (5) can be interpreted as saying that a household which is below its *own* mean income grows faster. Thus, the models given by (4) and (5) answer different questions: in (4), cohorts are compared to the grand mean, while in (5) they are compared to the cohort's own mean.

Equations (4) and (5) estimate the degree of income convergence as a function of initial income alone. When models are expanded to include other covariates that may affect initial income, these models provide estimates of *conditional* income convergence. Mean-based pseudo-panel models of the type of (4) or (5) in which β is the object of interest have been estimated for Latin American countries by Calónico (2006), Navarro (2006), Antman and McKenzie (2007) and Cuesta et al. (2011), among others.

3.2. Dispersion-based approaches

Other pseudo-panel approaches rely on second order moments of error distributions to construct mobility estimates using repeated cross-sections. In next paragraphs we provide some details on the methodology developed by Bourguignon, Goh and Kim (2004) (hereafter BGK) and Dang, Lanjouw, Luoto and McKenzie (2011) (hereafter DLLM).[6]

Bourguignon, Goh and Kim methodology

These authors propose to use the parameters of individual earnings dynamics to obtain estimates of the vulnerability to poverty. They assume that the earnings of individual *i* belonging to cohort group *j* at time *t* can be represented by the following equation:

$$\ln w_{it}^{j} = X_{it}^{j}\beta_{t}^{j} + \xi_{it}^{j}, \qquad (6)$$

where X_{it} is a set of individual characteristics and ξ_{it} stands for unobserved permanent and transitory earnings determinants. This residual term follows an autoregressive process AR(1):

$$\xi_{it}^{j} = \rho^{j}\xi_{it-1}^{j} + \varepsilon_{it}^{j}, \qquad (7)$$

where ε_{it} is the innovation in earnings with variance $\sigma^2_{\varepsilon jt}$.

The model given by (6) and (7) cannot be estimated with repeated cross-sections. But some information can be extracted on the basic dynamic parameters ρ^j and $\sigma^2_{\varepsilon jt}$. Under the

[6] The interested reader is referred to the original publications for additional details on these methodologies.

assumption that individuals enter and exit the labor force randomly between two successive periods, the variance of ξ (that is, $\sigma^2_{\xi jt}$) behaves according to the following process:

$$\sigma^2_{\xi jt} = \rho^{j2}\sigma^2_{\xi jt-1} + \sigma^2_{\varepsilon jt} \, . \tag{8}$$

Equation (8) is used to recover the dynamic parameters $\rho^{\,j}$ and $\sigma^2_{\varepsilon jt}$. To this end, equation (6) is estimated by OLS separately for each period t to get estimates of the residual variance $\sigma^2_{\xi jt}$. Then ρ^j is obtained from equation (8) and the residuals of this model provide estimates of the variance of the innovation term $\sigma^2_{\varepsilon jt}$.

The question asked by BGK is how vulnerable are the individuals observed in cross-section t to poverty in $t+1$. Some additional assumptions are needed to estimate the answer. First, the authors assume that the innovation term has a normal distribution with mean 0 and variance $\hat{\sigma}^2_{\varepsilon jt}$. Thus, earnings are distributed as a log-normal variable, conditional on individual characteristics X. The second assumption states predictions are available for future individual characteristics $\hat{X}^j_{it+1}$. The same applies to future earning coefficients $\hat{\beta}^j_{it+1}$, and the variance of the innovation $\hat{\sigma}^2_{\varepsilon jt+1}$.

Under these assumptions and denoting $\hat{\xi}^j_{it}$ the estimated residual of the earning equation (6) in period t, the probability of earning less than a poverty threshold $\overline{w}$ at time $t+1$ is:

$$v^j_{it} = pr\left(lnw^j_{it+1} < ln\overline{w} \middle| X^j_{it}, \hat{X}^j_{it+1}, \hat{\beta}^j_{t+1}, \hat{\sigma}^2_{\varepsilon jt+1}\right) = \Phi\left(\frac{\mathrm{ln}\overline{\mathrm{w}} - \hat{X}^j_{it+1}\hat{\beta}^j_{t+1} - \hat{\rho}^j\hat{\xi}^j_{it}}{\hat{\sigma}^{\mathrm{j}}_{\varepsilon \mathrm{jt+1}}}\right), \tag{9}$$

where $\Phi(.)$ denotes the cumulative density of the standard normal. Thus, $\hat{v}^j_{it}$ is the probability of individual i belonging to cohort j and observed at time t, being in poverty at time $t+1$.

The authors evaluated this methodology using Korean panel data and obtain satisfactory results in the sense that the parameters of earnings dynamics obtained using repeated cross-sections do not significantly differ from the true parameters obtained from panel data. Moreover, vulnerability-to-poverty measures are very close to each other.

Dang, Lanjouw, Luoto and McKenzie methodology

These authors explore an alternative statistical methodology for analyzing movements in and out of poverty based on two or more rounds of cross-sectional data. Briefly, a model of income is estimated in the first round of cross-section data, using a specification which includes only time-invariant covariates. Parameter estimates from this model are then applied to the same time-invariant regressors in the second survey round to provide an estimate of the (unobserved) first period's income for the individuals surveyed in that second round. Analysis of mobility can then be based on the actual income observed in the second round along with this estimated income from the first round. These observations make up the pseudo panel or, according to the authors' words, the "synthetic panel".

The authors consider the case of two rounds of cross-sectional surveys, denoted round 1 with a sample of N_1 households and round 2 with a sample of N_2 households. The vector x_{i1} contains characteristics of household *i* in survey round 1 which are observed (for different households) in both the round 1 and round 2 surveys. This will include time-invariant characteristics (language, religion, ethnicity), time-invariant characteristics of the household head if his identity remains constant across rounds (sex, education, place of birth, parental education as well as deterministic characteristics such as age), time-varying characteristics of the household that can be easily recalled for round 1 in round 2 (whether or not the household head was employed in round 1, the place of residence in round 1).

For the population as a whole, the linear projection of round 1 income (y_{i1}) onto $x_{i1}$is given by:

$$y_{i1} = \beta_1' x_{i1} + \varepsilon_{i1} \,. \tag{10}$$

Similarly, letting x_{i2} denote the set of household characteristics in round 2 that are observed in both the round 1 and round 2 surveys, the linear projection of round 2 income (y_{i2}) onto x_{i2} is given by:

$$y_{i2} = \beta_2' x_{i2} + \varepsilon_{i2} \,. \tag{11}$$

Let z_1 and z_2 denote the poverty line in period 1 and period 2 respectively. The objective is to estimate the joint distribution of poverty-non poverty in t_1 and t_2. For instance:

$$P(y_{i1} < z_1 and y_{i2} > z_2)\ , \tag{12}$$

which represents the probability of being poor in t_1 and not being poor in t_2.

The identification of the point-estimate in (12) is not possible without imposing a lot of structure on the data generating processes. Considering that the probability in (12) depends on the joint distribution of the two error terms, the estimation of bounds is easier:

$$P(\varepsilon_{i1} < z_1 - \beta_1' x_{i1} and \varepsilon_2 > z_2 - \beta_2' x_{i2})\ . \tag{13}$$

The correlation between the two error terms captures the correlation of those parts of household income in the two periods which are unexplained by the household characteristics x_{i1} and x_{i2}. Intuitively, more people will cross the poverty line the smaller is the correlation between ε_{i1} and ε_{i2}. One extreme case thus occurs when the two error terms are completely independent of each other. Another extreme case occurs when these two error terms are perfectly correlated.

Some assumptions are needed by this methodology. One of them requires the underlying population sampled to be the same in survey round 1 and survey round 2. This assumption will not be satisfied if the underlying population changes through births, deaths, or migration out of sample. The second assumption restricts the correlation of ε_{i1} and ε_{i2} to be non-negative. This assumption is to be expected in most applications using household survey data for at least three reasons: (i) if the error term contains a household fixed effect, then households which have income higher than predicted based on *x* variables in round 1 will also have income higher than predicted based on *x* variables in round 2; (ii) if shocks to income have some persistence, and income reacts to these shocks, then income errors will also exhibit positive autocorrelation; (iii) the kind of factors that can lead to a negative correlation in incomes over time are unlikely to apply to an entire population at the same time.

Given these assumptions, the upper bound estimates of poverty mobility are given by the probability in expression (13) when the two error terms are completely independent of each other, while the lower bound estimates of poverty mobility are given by the probability in expression (13) when the two error terms are identical. Two approaches to estimate the bounds on mobility are possible: a non-parametric approach where no assumptions about the joint distribution for the error terms are needed and a parametric approach where this joint distribution is assumed to be bivariate normal.

This methodology was applied by Dang et al. (2011) to data from Indonesia and Vietnam. They found that the estimates of poverty status in t_1 and t_2 obtained from true panel data (measured as a four-way variable poor-poor, poor-nonpoor, nonpoor-poor, and nonpoor-nonpoor) are generally sandwiched between the lower-bound and upper-bound pseudo-panel estimates. Their analysis also reveals that the width between the upper- and lower-bound estimates is narrowed as the prediction models are more richly specified. In a follow-up paper, Cruces et al. (2011) applied the DLLK non-parametric approach in three different settings where good panel data also exists (Chile, Nicaragua and Peru). There too, the lower-bound and upper-bound estimates sandwich "true" panel measures, particularly when richer model specifications were estimated. The technique also passed a set of robustness and sensitivity tests including changes in the poverty line, changes in the length of the panel, changes in the welfare measure, and changes in the forecasting direction.

Using the DLLK lower-bound approach, Ferreira et al. (2013) estimated that Latin America has experienced dramatic mobility in the last two decades. Out of every 100 Latin Americans, 43 changed their economic status from the beginning to the end of the period. The study reports considerably more upward than downward mobility: out of the 43 people changing economic status, 23 exited poverty, 18 entered the middle class, while only 2 experienced a worsening of their status. And despite the large levels of mobility, more than one in five Latin Americans were poor at both the beginning and the end of the whole period. The study also concluded that while the poor are moving up, on average they do not enter the middle class but instead remain vulnerable to poverty. It did not, however, perform a validation test of the type carried out by Dang et al. or Cruces et al.

4. Chilean income mobility: comparing pseudo panels with true panels

Each of the pseudo-panel methods previously introduced was applied to a specific mobility question: the mean-based approach to estimate a convergence/divergence parameter β, the BGK method to obtain a vulnerability-to-poverty rate, and the DLLM approach to compute the joint probabilities of poverty/non-poverty in t_1 and t_2.

In this section we calculate income mobility measures applying these pseudo-panel methodologies to Chilean data, treating each round of the panel dataset as a cross-section survey. In order to perform this exercise, we start working with the same sample of household heads from the panel and then apply the pseudo-panel calculations. The main goal is to compare the performance of the pseudo-panel methods with the "true" mobility measures –those obtained using the actual panel data. In order to organize the analysis, we proceed in two steps. First, we evaluate how the pseudo-panel methods perform in answering the specific income mobility question posed by the authors who devised each of the methods. Second, we compute a broader set of income mobility measures and focus on how close or far pseudo-panel methods come in approximating the macro-mobility measures, micro-mobility regression coefficients, and poverty dynamics estimates presented in table 1.

4.1. Pseudo panels' performance answering specific questions

We begin by analyzing the question of those studies applying the mean-based pseudo-panel approach. Papers like Antman and McKenzie (2007) and Cuesta et al. (2011) evaluate the following question: *What are the values of beta unconditionally and conditionally in a model where the logarithm of income in t=1 is regressed on the logarithm of income in t=0?*

Using a mean-based approach these authors estimate a model like equation (4). In order to estimate the same model we construct cohorts based on year of birth and gender of the household head.[7] We include household heads born in two-year span in order to get a balance between the number of cohorts and the number of observations in each cohort. We consider household heads born between 1931 and 1976 or, equivalently, aged 20 to 65 at the start of the panel in 1996. Table 2 displays the number of observations in each of the birth-gender cohorts and years. The pseudo panel comprises a total of 5,112 individual observations that collapse in 92 "synthetic" observations. We then averaged observations in each birth-gender cohort and year using the expansion factors in each survey. In this way, we can follow cohort means between 1996 and 2006 for each birth-gender cohort.

[7] The use of the gender of the household head as a variable to construct the pseudo-panels is explained by the sustained trend of increasing female participation in labor markets (Cuesta et al., 2011).

Our results for the mean-based pseudo-panel approach are shown in the first block of table 3. The value of β in the log-log version of equation (4), estimated unconditionally, is predicted correctly by the pseudo panel. The slope coefficient is 0.4 and statistically significant, indicating a pattern of income convergence in Chile between 1996 and 2006. On the contrary, when the model is estimated conditionally with other covariates included, the pseudo panel fails to approximate the value of β in the conditional version of equation (4).[8]

It bears mention that β is often interpreted as answering the question: *how much immobility in the sense of time-dependence is there in a country?* See, for example, Cuesta et al. (2011). As noted by Solon (1999, 2002), β also will approximately equal the correlation between initial and final earnings (if measured in pesos) or log-earnings (if measured in log-pesos) if and only if the variance (if measured in pesos) or log-variance (if measured in log-pesos) is about the same in the initial and final distributions. This variance condition tends to be ignored in the literature.

A more direct measure of correlation is, of course, the correlation coefficient or, equivalently, R-squared. Cuesta et al. report R-squareds in pseudo-panel data for each of fourteen Latin American countries on the order of 0.998-0.999. How do R-squareds in pseudo panels compare with R-squareds in true panels? Answering this question for the case of Chile, we find R-squareds in our pseudo panel of 0.54-0.69 and R-squareds in the true panel of 0.26-0.36 (see Table 3). That is, compared to the true panel, the pseudo panel produces an R-squared that is much too large - that is, much too much time-dependence and hence too little mobility-as-time-independence. Analysts interested in using pseudo panels to measure time-dependence/independence are duly forewarned.

Turning now to the Dang et al. (2011) model, the issue of interest to them is poverty dynamics. More specifically, the question they seek to answer is: *what is the joint distribution of poor-nonpoor in initial and final year?*

In order to calculate the upper and lower bounds for the four joint distribution categories resulting from this method, we followed the steps described in the original paper.

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[8] We include as control variables some characteristics of the household head like age and its square, gender, years of education and its square and mean number of children at home (12 years old or less).

First, using the data in survey round 1 we estimate equation (10) for household heads aged 25 to 55 using time-stable control variables and obtain the predicted coefficients $\hat{\beta}_1$and predicted residuals $\hat{\varepsilon}_{i1}$.[9] Second, taking a random draw with replacement from the empirical distribution of the predicted residuals obtained in step 1 –denoted as $\tilde{\varepsilon}_{i1}$- we estimate for each household head in round 2 its income level in round 1 as $\hat{\beta}_1 x_{2i} + \tilde{\varepsilon}_{1i}$. Estimates of the joint probabilities, for example equation (12), are obtained using this income prediction and the observed income level of household heads in round 2. This procedure is repeated a number of times; we iterated 50 times. The averages of these 50 replications are the upper bound estimations for the joint probabilities. In order to obtain the lower bound estimates, the prediction of the income level in round 1 for each household head in round 2 is obtained using the predicted residuals $\hat{\varepsilon}_{i2}$ from an income regression in round 2: $\hat{\beta}_1 x_{2i} + \hat{\varepsilon}_{i2}$. Estimates of the joint probabilities are obtained using this income prediction and the observed income level of household heads in round 2.

The second block of table 3 shows our results using Chilean data. For the three rates involving poor, the ranges are quite wide. While the "true" percentage of people who were poor in 1996 and not poor in 2006 is 20%, the pseudo-panel estimates range between 17% and 26%. A similar pattern is observed for the fraction of people who were poor in both periods and for those who enter into poverty. For the group that was not poor in both years, the true panel rate lies outside the range of the pseudo-panel estimates – that is, both pseudo-panel approaches show too few people starting out of poverty and remaining out of poverty compared to truth. The comparison of each of the bounds with the panel data estimates shows that the lower bound tends to be closer to the true value for the first three categories, but the upper bound is virtually spot on for the poor-poor category.[10]

[9] We include as control variables gender of the household head, age and its square, years of education, region of residence and characteristics at the regional level like the proportion of female household heads, the proportion of household heads with primary, secondary and higher education, proportion of the population that participates actively in the labor market and the regional average of housing characteristics like quality of houses. The model also includes the interaction between variables at the regional level and variables that capture characteristics of the household head.

[10] An important clarification has to do with the differences between our estimations and those presented in Cruces et al. (2011) for Chile. There are at least two points that can explain the discrepancies. First, we are restricting the sample to household heads aged 25-55, as Dang et al. (2011) recommended, while Cruces et al. (2011) include household heads aged 25-65. Second, our dataset excludes outliers using the methodology described in Grimm (2007). For these reasons, our results are different, but only somewhat, from those in Cruces et al. (2011).

The last pseudo-panel methodology is that proposed by Bourguignon et al. (2004) to compute vulnerability-to-poverty mobility measures. The question these authors seek to answer is: *what is the probability of having an income below a poverty threshold conditional on initial income and characteristics?* We implemented this methodology using Chilean data and following the procedure described in equations (6)-(9). At least three time periods are required to be able to estimate the income dynamics coefficients in equation (8). Given that restriction, we expand our Chilean dataset to include the 2001 round of the panel. However, BGK point out that with three cross sections it is very likely that the parameter ρ^j will be very imprecisely estimated. In fact, for some of the cohorts –defined by birth and gender as in the mean-based approach- we obtained values not acceptable for a correlation due to the reduced sample size.[11] In those cases, we impose the coefficient ρ^j to be the same across a number of cohorts using the nearest acceptable value. In order to compute the vulnerability-to-poverty measure (equation (9)) we assumed stationarity of observable characteristics $\hat{X}^j_{i,t+1}$, earnings coefficients $\hat{\beta}^j_{t+1}$,and variance of the innovation term $\hat{\sigma}^2_{\varepsilon j,t+1}$.

The comparison of the true panel and pseudo-panel estimates is shown in the last block of table 3. While the actual frequency of people falling into or remaining in poverty in 2006 is 14.47%, the pseudo-panel method predicts a value almost twice as high as the panel figure (24.64%). Even though the difference is very large, it is important to consider the restriction imposed by the small number of cross-section surveys.

To conclude, for the most part, we do not obtain good estimations using pseudo panels to answer the specific questions each author proposed (where good is close to the true panel result). The only question for which the pseudo-panel method approximates the true panel result is the estimate of the unconditional β coefficient.

4.2 Pseudo panels' performance answering general questions

[11] OLS estimation of equation (8) does not automatically satisfy the condition that the estimated coefficient must be between zero and one. BGK establish that this might be remedied by imposing some restriction on the parameter ρ^j across cohorts *j*.

We now compute a broader set of income mobility measures and focus on how close or far pseudo-panel methods come in approximating the full set of macro-mobility measures, micro-mobility regression coefficients, and poverty transition rates presented in table 1.

Our results are shown in table 4. As shown in the first block of the table, for the macro-mobility measures the pseudo-panel estimates are quite far off and tend to underestimate substantially the true degree of income mobility. They show too much time dependence, and therefore too little mobility-as-time-independence, with the exception of the upper bound estimation using the DLLM methodology that is closer to the true value; about the right amount of positional movement, with the exception of the BGK estimate that shows too little mobility; too little share movement, although the upper bound is closer to the true value; too little non-directional income movement– that is, incomes change much more in the true panel than is seen in the pseudo panels- and again the upper bound is closer to the true value; about the right amount of directional income movement, especially for the mean-based approach and the BGK methodology, but this is true only *on average*, the pseudo panels show too little of upward and downward movements; the mean-based approach and the upper bound show too much equalization of longer-term income relative to initial, while the lower bound and the BGK pseudo panel show too little.

To sum up, none of the pseudo-panel approaches gives good approximations for *all* of the macro-mobility concepts. Furthermore, the lower and upper bounds do not contain the true value for some of the measures, and we cannot conclude that one of the bounds provides better estimates than the other.

Our findings on the micro-mobility regression coefficients are shown in the second block of table 4. For the true panel, we find substantial convergence, both in logs ("weak") and in pesos ("strong"), both unconditionally and conditionally. The mean-based approach also predicts a pattern of income convergence both in logs and in pesos, but this approach underestimates the degree of strong income convergence and overestimates the degree of weak income convergence. The DLLM lower and upper bounds contain the regression coefficients estimated using true panel data. However, the width of these bounds is so wide as to be useless. For instance, the lower bound predicts a pattern of income divergence under the strong convergence hypothesis, while the upper bound predicts negative coefficients that are larger (in absolute value) than panel data estimations. Finally, the BGK pseudo panel predicts coefficients with the right sign but they are very far from the true values in a systematic direction: the BGK method estimates considerably less convergence than the true panel does. As was mentioned before, we start working with the same sample of household heads from the panel and then apply the pseudo-panel calculations. The lower number of observations in DLLM micro-regression coefficients compared with the panel is explained by the age restriction of the method (it predicts future incomes for household heads between 25 and 55 years old) and the missing values in the explanatory variables used in the income regressions, while the lower number of observations in BGK micro-regression coefficients compared with the panel is explained by the birth-cohort construction (people belonging to some cohort are between 20 and 65 years of age).

In the last block of table 4 we show our poverty dynamics results. The conclusion is that pseudo-panel methods fail to predict accurately the percentage that crossed the poverty line. Two of the pseudo-panel methods (the DLLM method and BGK method) substantially understate the probability of those who were poor in period 1 escaping from poverty by period 2, and all of the pseudo-panel methods understate the probability of falling into poverty in period 2 conditional on not being in poverty in period 1. In short, the pseudo-panel methods reveal way too few poverty transitions compared to the true panel.

In sum, using Chilean data for the period 1996-2006 we conclude that not only do pseudo panels fail to predict the mobility measures they were intended to estimate (with the only exception of the mean-based approach estimating beta unconditionally), but also they perform poorly in predicting a broader set of income mobility measures.

5. Joint probability of poverty status versus poverty dynamics

The pseudo-panel method proposed by DLLM calculates the joint probability of poverty status in t_1 and t_2. Even though those estimates provide valuable information about movements into and out of poverty, they do not represent poverty dynamics, which by definition is a conditional concept. For instance, the probability of being non-poor in $t=2$ for those who were poor in $t=1$ is a poverty dynamic measure, and likewise for the other conditional transition rates. In the bottom block of table 4 we reported our poverty dynamics estimates using the DLLM pseudo-panel method applied to our data for Chile. As we mentioned before, the results are not encouraging. The panel data estimate does not lie between the lower and upper bound estimates, and none of the bounds gives a good prediction of the true poverty transition rates.

In this section we reproduce the results obtained by Cruces et al. (2011) for the case of Chile (top block of table 5) and reformulate them as conditional probabilities (bottom block of table 5).[12] The main objective is to compare how close true panel poverty transition rates are to the pseudo-panel figures. The findings indicate that "true" poverty transition rates lie between the lower and upper bounds predicted by the DLLM method. However, the width of the bounds in the conditional formulation is much greater than in the original calculations as joint probabilities. For instance, in the top block of the table, we see that the probability of being poor in 1996 *and* not being poor in 2006 is predicted to range between 11% and 21%, i.e., the width of the bounds is 10 percentage points. On the other hand, in the bottom block of the table, we see that the probability of not being poor in 2006, *conditional* on being poor in 1996, ranges between 67.5% and 89.9%, i.e., the width of the bounds is 22 percentage points. Thus, the width of the bounds when the probability is computed as a poverty dynamic measure is twice as large as in the joint probability formulation. In this sense, the DLLM pseudo panel provides only limited information about poverty transition rates.

6. Conclusions

The general question this paper intended to answer was: *are pseudo panels a suitable substitute for true panels for estimating income mobility?* In order to obtain evidence and give an answer to this question we constructed pseudo panels using Chilean panel data and treating each round of the panel as if it were an independent cross-section survey. We considered three different pseudo-panel methods available in the literature. First, the mean-based approach that identifies cohorts, and follows cohort means over time. Second, the method developed by Bourguignon, Goh and Kim that was designed to estimate vulnerability-to-poverty measures in the absence of panel data. Third, the pseudo-panel

[12] As we mentioned in section 4, results in Cruces et al. (2011) differ from our estimates. These differences are explained by (i) the restriction of the sample to household heads aged 25-55, while Cruces et al. (2011) use a wider age group (25-65); (ii) our dataset excludes outliers as in Grimm (2007).

method of Dang, Lanjouw, Luoto and McKenzie that predicts a lower and upper bound for the joint probabilities of poverty status in $t=1$ and $t=2$. These techniques differ from one another in terms of data demands, assumptions about structural parameters and functional forms, and in the mobility question they attempt to answer.

In order to organize the analysis, we proceeded in two steps. First, we evaluated how the pseudo-panel methods perform in answering the specific income mobility question they were devised to answer. Second, we computed a broader set of income mobility measures and focused on how close or far pseudo-panel methods come in approximating macro-mobility measures, micro-mobility regression coefficients, and poverty transition rates.

According to the empirical evidence we have obtained using Chilean panel data for the period 1996-2006, our conclusion is that pseudo-panel methodologies do *not* perform well in this task. Our results indicate that pseudo panels fail in two respects when trying to predict the income mobility pattern observed in Chile. First, they do not give good results for the mobility concept each pseudo-panel method sought to measure. The only exception was the unconditional estimation of the mean-based approach. Second, they also perform poorly in predicting a broader set of income mobility measures.

Finally, we extended the analysis including a reformulation of the calculations proposed by Dang, Lanjouw, Luoto and McKenzie. These authors calculated the joint probabilities of poverty status in t_1 and t_2. Using the results presented by Cruces et al. (2011) for the case of Chile, we re-expressed them as poverty dynamics measures, i.e., conditional probabilities. The results were not encouraging. Even though the "true" poverty transition rates lie between the lower and upper bounds predicted by the method, the width of the bounds in the conditional formulation is much greater than in the original calculations as joint probabilities. In this sense, the DLLM pseudo panel provides only limited information about poverty transition rates.

7. References

Antman, F. and McKenzie, D. (2007): “Earnings Mobility and Measurement Error: A Pseudo-Panel Approach”. *Economic Development and Cultural Change*, vol. 56(1), pp. 125-161.

Bourguignon, F. Goh, Ch. and Kim, D. (2004): “Estimating Individual Vulnerability to Poverty with Pseudo-Panel Data”. World Bank Policy Research Working Paper No. 3375.

Calónico, S. (2006): “Pseudo-Panel Analysis of Earnings Dynamics and Mobility in Latin America”. Mimeo, Inter-American Development Bank.

Castro, R. (2011): “Getting Ahead, Falling Behind and Standing Still. Income Mobility in Chile”. Estudios de Economía, Vol. 38, N 1, pp. 243-258.

Collado, D. (1997): “Estimating Dynamic Models from Time Series of Independent Cross Sections”. *Journal of Econometrics*, 82, pp. 37–62.

Cruces, G., Lanjouw, P., Lucchetti, L., Perova, E., Vakis, R. and Viollaz, M. (2011): “Intra-generational Mobility and Repeated Cross-Sections. A Three-country Validation Exercise”. World Bank Policy Research Working Paper No. 5916.

Cuesta, J., Ñopo, H. and Pizzolitto, G. (2011): “Using Pseudo-Panels to Measure Income Mobility in Latin America”. *The Review of Income and Wealth*, serie 57(2).

Dang, H., Lanjouw, P., Luoto, J. and McKenzie, D. (2011): “Using Repeated Cross-Sections to Explore Movements into and out of Poverty”. World Bank Policy Research Working Paper No. 5550.

Deaton, A.(1985): “Panel Data from Time Series of Cross-Sections”. *Journal of Econometrics* 30, pp. 109-216.

Ferreira, F., Messina, J., Rigolini, J., López-Calva, L.F., Lugo, M.A. and Vakis, R. (2013): “Economic Mobility and the Rise of the Latin American Middle Class”. Washington, DC: World Bank.

Fields, G., Duval Hernandez, R., Freije Rodriguez, S. and Sanchez Puerta, M.L. (2007): “Intergenerational Income Mobility in Latin America”. *Journal of LACEA.*Latin American and Caribbean Economic Association.

Grimm, M. (2007): “Removing the Anonymity Axiom in Assessing Pro-Poor Growth”, *Journal of Economic Inequality*, 5(2), pp 179–197.

McKenzie, D. (2001): “Estimation of AR(1) models with unequally spaced pseudo-panels”. *Econometric Journal*, Royal Economic Society, vol. 4(1).

McKenzie, D. (2004): “Asymptotic Theory for Heterogeneous Dynamic Pseudo-Panels”. Journal of Econometrics, Elsevier, vol. 120(2), pp. 235-262.

Moffitt, R. (1993): “Identification and Estimation of Dynamic Models with a Time Series of Repeated Cross-Sections”. *Journal of Econometrics*, vol. 59, pp. 99–124.

Navarro, A. (2006): “Estimating Income Mobility in Argentina with Pseudo-Panel Data”. Mimeo, Universidad de San Andrés.

SEDLAC (2012). *Socio-Economic database for Latin America and the Caribbean*, CEDLAS and The World Bank. http://sedlac.econo.unlp.edu.ar/eng/index.php.

Verbeek, M. and Vella, F. (2005): “Estimating Dynamic Models from Repeated Cross-Sections”. Mimeo, K.U. Leuven Center for Economic Studies.

WDI (2012). *World Development Indicators*, The World Bank. http://data.worldbank.org/data-catalog/world-development-indicators

Tables

Table 1: Income mobility measures using panel data

Chile 1996-2006

Macromobility concept	
Time independence	
[1 - Pearson's correlation coefficient]	0.810
Positional movement	
Mean absolute value of decile change	2.172
Share movements	
Mean absolute value of share change	0.628
Non-directional income movement	
Mean absolute value of income change	58,548
Directional income movement	
Mean income change	17,586
std. desv.	171,935
Percentage of upward movers	64.35
Percentage of downward movers	35.65
Average income gains of the upward movers	59,158
Average income losses of the downward movers	-57,447
Mobility as an equalizer of longer-term incomes	
$\varepsilon \equiv 1-(I(a)/I(y_1))$	0.168
Micromobility regression	
Change in pesos – unconditional regression coefficient	-0.628
Standard error	[0.057]***
R^2	0.10
N	2552
Change in pesos – conditional regression coefficient	-0.761
Standard error	[0.048]***
R^2	0.12
N	2465
Change in log pesos – unconditional regression coefficient	-0.579
Standard error	[0.030]***
R^2	0.40
N	2527
Change in log pesos – conditional regression coefficient	-0.709
Standard error	[0.034]***
R^2	0.48
N	2441
Poverty dynamics and crossing the poverty line measures	
Probability of not being poor in t=2, conditional on being poor in t=1	70.83
Probability of being poor in t=2, conditional on not being poor in t=1	5.94

Source: Own elaboration based on CASEN 1996-2006 and SEDLAC (CEDLAS and World Bank).
Notes: Shares are computed as the participation of per capita household income in average national income in each of the years.
Conditional regressions include age of the household head and its square, gender, years of education and its square, and region of residence.
In the mobility as an equalizer of longer-term incomes a is the vector of average incomes, y_1 is the vector of first-year incomes, and $I(.)$ is a Lorenz-consistent inequality measure. We use the Gini coefficient.

Table 2: Definition and size of birth-gender cohorts

Chile 1996-2006

Year-birth cohort	**Time period**		Total synthetic individuals	**Time period**		Total household observations
	1996	2006		1996	2006	
1931-1932	2	2	4	101	116	217
1933-1934	2	2	4	81	91	172
1935-1936	2	2	4	79	94	173
1937-1938	2	2	4	109	114	223
1939-1940	2	2	4	120	129	249
1941-1942	2	2	4	121	134	255
1943-1944	2	2	4	111	125	236
1945-1946	2	2	4	120	137	257
1947-1948	2	2	4	127	134	261
1949-1950	2	2	4	112	125	237
1951-1952	2	2	4	106	135	241
1953-1954	2	2	4	117	142	259
1955-1956	2	2	4	143	165	308
1957-1958	2	2	4	142	168	310
1959-1960	2	2	4	152	169	321
1961-1962	2	2	4	122	153	275
1963-1964	2	2	4	124	160	284
1965-1966	2	2	4	97	125	222
1967-1968	2	2	4	70	96	166
1969-1970	2	2	4	62	98	160
1971-1972	2	2	4	41	80	121
1973-1974	2	2	4	27	83	110
1975-1976	2	2	4	6	49	55
Total	46	46	92	2,290	2,822	5,112

Source: Own elaboration based on CASEN 1996-2006 and SEDLAC (CEDLAS and World Bank).

Table 3: Pseudo-panel performance answering specific income mobility questions
Chile 1996-2006

Mean-based approach

	Pseudo panel	Panel data
β - unconditional	0.438	0.421
Standard error	[0.067]***	[0.030]***
R^2	0.54	0.26
β - conditional	0.150	0.291
Standard error	[0.129]	[0.034]***
R^2	0.69	0.36

Dispersion-based approach
DLLM methodology

	Pseudo - panel		Panel data
	Lower bound	*Upper bound*	
Poor - Non Poor	17.41	25.60	20.22
Non Poor - Poor	2.70	9.18	4.97
Non Poor - Non Poor	62.92	56.31	64.93
Poor - Poor	16.96	8.91	9.88

BGK methodology

	Pseudo panel	Panel data
Predicted rate of poverty in 2006	24.64	
Rate of poverty in 2006		14.47

Source: Own elaboration based on CASEN 1996-2006 and SEDLAC (CEDLAS and World Bank).

Table 4: Pseudo-panel performance answering other income mobility questions
Chile 1996-2006

	Panel data	Pseudo-panel			
			Dispersion based approach		
		Mean based approach	DLLM method		BGK method
			Lower bound	Upper bound	
Macromobility concept					
Time independence					
[1 - Pearson's correlation coefficient]	0.810	0.365	0.151	0.766	0.094
Positional movement					
Mean absolute value of decile change	2.172	1.609	1.061	2.432	0.743
Share movements					
Mean absolute value of share change	0.628	0.219	0.278	0.575	0.269
Non-directional income movement					
Mean absolute value of income change	58,548	23,508	34,846	60,994	30,808
Directional income movement					
Mean income change	17,586	18,905	30,414	37,075	22,709
std. desv.	171,935	25,815	42,490	69,845	36,360
Percentage of upward movers	64.35	89.13	85.97	79.69	88.39
Percentage of downward movers	35.65	10.87	14.03	20.31	11.61
Average income gains of the upward movers	59,158	23,792	37,957	61,534	30,273
Average income losses of the downward movers	-57,447	-21,176	-15,791	-58,876	-34,876
Mobility as an equalizer of longer-term incomes					
$\varepsilon \equiv 1-(I(a)/I(y1))$	0.168	0.202	0.091	0.345	0.123

Table 4: Pseudo-panel performance answering other income mobility questions – cont.
Chile 1996-2006

	Panel data	Pseudo-panel			
		Mean based approach	***Dispersion based approach***		
			DLLM method		**BGK method**
			Lower bound	*Upper bound*	
Micromobility regression					
Change in pesos – unconditional regression coefficient	-0.628	-0.409	0.271	-0.751	-0.155
Standard error	[0.057]***	[0.158]**	[0.052]***	[0.077]***	[0.035]***
R^2	0.10	0.23	0.11	0.35	0.13
N	2552	46	1525	1525	2124
Change in pesos – conditional regression coefficient	-0.761	-0.627	0.269	-1.043	-0.290
Standard error	[0.048]***	[0.202]***	[0.056]***	[0.050]***	[0.024]***
R^2	0.12	0.41	0.18	0.57	0.66
N	2465	46	1520	1520	2124
Change in log pesos – unconditional regression coefficient	-0.579	-0.613	-0.111	-0.744	-0.224
Standard error	[0.030]***	[0.052]***	[0.015]***	[0.037]***	[0.012]***
R^2	0.40	0.73	0.05	0.58	0.37
N	2527	46	1525	1525	2124
Change in log pesos – conditional regression coefficient	-0.709	-0.891	-0.063	-0.995	-0.385
Standard error	[0.034]***	[0.116]***	[0.018]***	[0.027]***	[0.010]***
R^2	0.48	0.84	0.18	0.74	0.82
N	2441	46	1520	1520	2124
Poverty dynamics and crossing the poverty line measures					
Probability of not being poor in t=2, conditional on being poor in t=1	70.83	75.00	37.51	66.80	56.03
Probability of being poor in t=2, conditional on not being poor in t=1	5.94	0.00	1.76	1.08	0.09

Source: Own elaboration based on CASEN 1996-2006 and SEDLAC (CEDLAS and World Bank).
Notes: In the mobility as an equalizer of longer-term incomes a is the vector of average incomes, y_1 is the vector of first-year incomes, and $I(.)$ is a Lorenz-consistent inequality measure. We use the Gini coefficient.
The lower number of observations in DLLM micro-regression coefficients compared with the panel is explained by the age restriction of the method (it predicts future incomes for household heads between 25 and 55 years old).The lower number of observations in BGK micro-regression coefficients compared with the panel is explained by the birth-cohort construction (people belonging to some cohort are between 20 and 65 years of age).

Table 5: DLLM method – Joint and conditional probabilities
Chile 1996-2006

Joint probabilities

	Panel data	DLLM method		Width of the bounds
		Lower bound	Upper bound	
Probability of being poor in t=1 and t=2	4.64	5.35	2.61	-2.74
Probability of being poor in t=1 and not being poor in t=2	19.59	11.09	21.50	10.41
Probability of not being poor in t=1 and t=2	72.82	81.31	70.90	-10.41
Probability of not being poor in t=1 and being poor in t=2	2.96	2.25	4.98	2.73

Conditional probabilities

	Panel data	DLLM method		Width of the bounds
		Lower bound	Upper bound	
Probability of being poor in t=2, conditional on being poor in t=1	19.15	32.54	10.15	-22.39
Probability of not being poor in t=2, conditional on being poor in t=1	80.85	67.46	89.85	22.39
Probability of being poor in t=2, conditional on not being poor in t=1	3.91	2.69	6.77	4.08
Probability of not being poor in t=2, conditional on not being poor in t=1	96.09	97.31	93.23	-4.08

Source: Own elaboration based on Cruces et al. (2011).