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 poor 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.

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1. Introduction

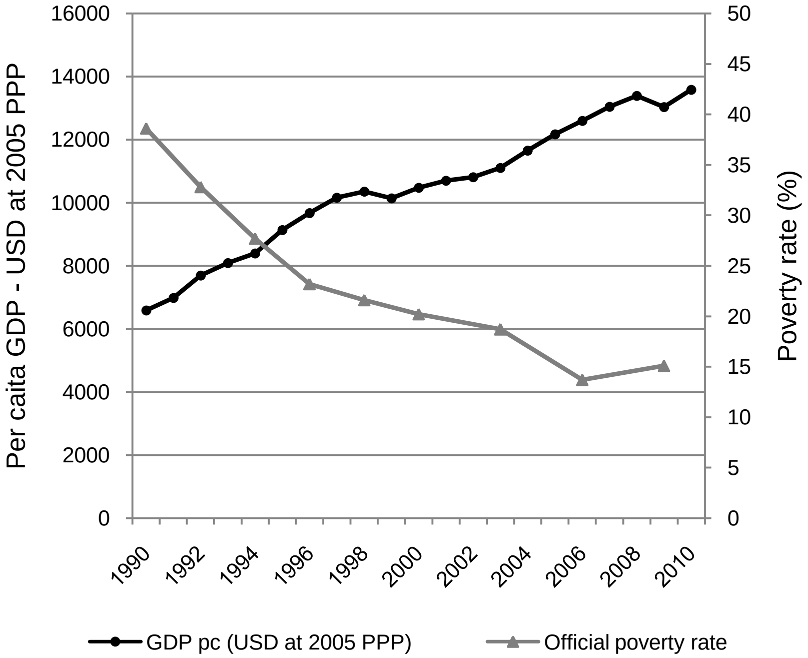
The analysis of income mobility and poverty dynamics entails the identification of the same economic unit through time. This feature imposes a data requirement –longitudinal data that tracks individuals or households over time- that is difficult to meet in many cases. This data limitation has been of 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’. 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 three pseudo-panel methods implemented by treating the rounds of the panel as if they were repeated cross-sectional surveys. We organize the analysis proceeding in two steps. First, we evaluate how the pseudo-panel methods perform in answering the specific income mobility question they are intended to answer. Second, using the constructed pseudo-panels we compute a broader set of income mobility measures and focus on how close or far these methods come in approximating the “true” measures.

Along the study we work with Chilean data. This country has shown high growth rates and a decreasing poverty trend during the last two decades. 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]

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

Figure 1: Economic performance of Chile
1990-2010



Source: World Development Indicators (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.

The structure of the paper is as follows. In the next section we present a broad set of income mobility measures calculated with Chilean panel data. In Section 3 we describe three pseudo-panel methodologies while in Section 4 we put these methods into action. First, we compute income mobility measures to answer the specific question each method seeks to answer, and then we analyze what do we get using the true panel data to answer the same question. Second, using the constructed pseudo-panels we compute other income mobility measures and analyze how close or far do these pseudo-panel data sets come in approximating the true panel results. In Section 5 we focus on poverty dynamics and analyze how pseudo-panels approximate true poverty transition rates. In Section 6 we conclude with final comments.

2. Chilean income mobility using panel data

In this section we compute several income mobility measures using Chilean panel data for the period 1996-2006. Our income measure is the household per capita income (expressed at 1996 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. We answer this question through different macro-mobility concepts.[3] Estimates are shown in the first panel 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 vaguely determined by its value in 1996. The linear association between both variables is only 0.2. The mean absolute value of decile change shows that household heads moved, on average, two deciles in this period. Mobility computed as the mean absolute value of share change also reveals significant mobility -the participation of individual income in average income changed by 0.63-. The non-directional income movement concept shows an average value of 58,548 pesos that gets reduced to one third of that figure when the direction of the changes is accounted for. While around 70% of the households moved upward during 1996 and 2006, the average income gains of upward movers almost equal the average income losses of downward movers. Finally, Field's index shows that mobility equalized longer-term income relative to initial income.

[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] A detailed description of the income mobility measures calculated in this paper can be found in Fields et al. (2007).

The second panel 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 *log* of per capita income as the explained variable and the *log* of initial income as the explanatory variable of interest. On the other hand, strong convergence occurs when the lower-income groups gain more than the higher-income groups *in pesos.* In this case, we regressed the change in per capita income *in pesos* 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 show that lower-income groups had larger income gains than do higher-income groups both in percentages and in pesos. Then, income mobility had a highly significant pattern of weak and strong convergence in Chile. We confirm this result both unconditionally and conditionally.[4]

Finally, in the last panel of table 1 we present some estimates related to movements into and out of poverty. The first two rows refer to poverty dynamics measures while the last ones present crossing-the-poverty-line measures. Results reveal that an important percentage of Chilean household heads who were poor in 1996 escaped from poverty in 2006 (70.8%), and very few of those who were non-poor in 1996 fell into poverty in 2006 (5.9%). Similarly, the percentage of those who crossed the poverty line, conditional on being upward movers, was higher (30.7%) than the percentage of those who did that conditional on being downward movers (12%).

To sum up, we found significant mobility using Chilean panel data for the period 1996-2006 for each of the macro-mobility concepts. We also found a clear pattern of income

[4] We include as control variables the age of the household head and its square, gender, years of education and its square, and region of residence.

convergence conditionally and unconditionally, and substantial movement into and out of 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 overcoming some of the limitations associated to longitudinal data. Non-random attrition is not an issue since each individual or household is only observed once. A further advantage 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 real panels.

In the next paragraphs we describe the 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 more importantly, 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-panels 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 to 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. Second, estimates at 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 be error-ridden measurement of the true cohort population values (McKenzie, 2004).

Moffitt (1993), Collado (1997), McKenzie (2001, 2004), and Verbeek and Vella (2005) discuss conditions to obtain consistent (mobility) estimates from linear dynamic models using pseudo-panels that follow cohorts of individuals or households over time.

Antman and McKenzie (2007) propose the following model of income at the individual level to estimate the degree of income mobility:[5]

$$Y_{i,t} = \alpha + \beta Y_{i,t-1} + u_{i,t} \qquad (1)$$

Taking cohort averages of equation (1) over the N_c individuals observed in cohort c at time t the model becomes:

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

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 $t = 2, ..., T$:

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

where

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

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).

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

The precise method for estimating equation (3) depends on the assumptions on 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. Collado (1997) states that with many cohorts and fewer individuals per cohort, instrumental variables methods can be used. Arellano and Bond (1991) and Moffit (1993) made some applications of this method.

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:

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

$\beta < 1$ represents a situation of income convergence where a household with income below the mean in period $t-1$ will experience more rapid income growth than richer households. A value of β equal to 1 represents a situation of no income convergence, while β equal to zero is an extreme case of total mobility.

If the data generating process contains individual fixed effects, 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.

Both equation (4) and (5) estimate the degree of income mobility *unconditionally*. When models are expanded to include other covariates that may affect present income, these models provides estimates of the degree of income mobility *conditionally*.

The mean-based approach was applied by Calónico (2006), Navarro (2006), Antman and McKenzie (2007) and Cuesta et al. (2011). Calónico (2006) analyzed several Latin American countries for the period 1992-2002 and found very low mobility around the general mean for almost all the countries –β close to 1 in equation (4)- and different patterns of mobility around the individual mean –for instance, β close to 1 for Argentina in equation (5) and β close to 0.3 for the case of Chile-. Navarro (2006) computed income mobility for the period 1985-2004 in Argentina and found a convergent pattern to the general mean, but her estimates show a higher degree of income mobility compared to Calónico's results. Antman and McKenzie (2007) estimated the degree of earnings mobility for the Mexican case from 1987 to 2001. Their results indicate that overall mobility in earnings, income, and expenditure is low, whereas households are quite mobile around their individual effects. Cuesta et al. (2011) performed the analysis for the Latin American region combining information from 14 countries during 1992 and 2003. They found a very low degree of income mobility in the region with estimates of β ranging between 0.60 for the conditional version of equation (4) and 0.97 in the unconditional case.

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) -BGK-, and Dang, Lanjouw, Luoto and McKenzie (2011) -DLLM-.[6]

Bourguignon, Goh and Kim methodology

These authors propose to use the parameters of individual earnings dynamics to obtain estimates on 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:

$$\ln w_{it}^{j} = X_{it}^{j}\beta_{t}^{j} + \xi_{it}^{j} \tag{6}$$

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):

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

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

where ε_{it} is the innovation in earnings and is supposed to have a variance $\sigma^{2}_{\varepsilon jt}$.

Model (6)-(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 assumption that individuals enter and exit randomly the labor force between two successive periods, the variance of ξ ($\sigma^{2}_{\xi jt}$) behaves according to the following process:

$$\sigma_{\xi jt}^{2} = \rho^{j\,2}\sigma_{\xi jt-1}^{2} + \sigma_{\varepsilon jt}^{2} \qquad (8)$$

Equation (8) is used to recover the dynamic parameters ρ^{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 $\sigma^{2}_{\varepsilon jt}$.

Some additional assumptions are needed to obtain the vulnerability of individuals observed in cross-section *t* to poverty in *t+1*. First, authors assume that the innovation term is distributed as a normal with mean 0 and variance $\hat{\sigma}_{\varepsilon jt}^{2}$. Thus, earnings are distributed as a log-normal variable, conditional on individual characteristics *X*. The second assumption states that some prediction of future individual characteristics $\hat{X}_{it+1}^{j}$ is available. The same applies to future earning coefficient $\hat{\beta}_{it+1}^{j}$ and the variance of the innovation $\hat{\sigma}_{\varepsilon jt+1}^{2}$.

Under these assumptions and denoting $\hat{\xi}_{it}^{j}$ 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:

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

where Φ(.) denotes the cumulative density of the standard normal. Thus, $\hat{v}_{it}^{j}$ is the vulnerability of individual *i* belonging to cohort *j* and observed at time *t,* to falling into poverty at time *t+1*. The authors evaluated this methodology using Korean panel data and obtain satisfactory results. The parameters of earnings dynamics obtained using repeated cross-sections do not significantly differ from true parameters –those 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 estimate from the first round. These observations make up the pseudo-panel or, according to 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:

$$y_{i1} = \beta_1' x_{i1} + \varepsilon_{i1} \qquad (10)$$

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:

$$y_{i2} = \beta_2' x_{i2} + \varepsilon_{i2} \qquad (11)$$

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:

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

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:

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

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, mobility will be greater the less correlated are 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 "true" estimate of the extent of mobility obtained from panel data as a joint probability of poverty status in t_1 and t_2 is generally sandwiched between the lower-bound and upper-bound assessments of mobility. The analysis also reveals that the width between the upper- and lower-bound estimates is narrowed as the prediction models are more richly specified. Cruces et al. (2011) applied the non-parametric approach in three different settings where good panel data also exists (Chile, Nicaragua and Peru). The methodology performed well in all three settings –lower and upper bounds sandwich "true" panel measures-, particularly when richer model specifications were estimated. The technique also overcame 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 among others tests.

Using the same methodology, Ferreira et al. (2013) showed that Latin America has experienced dramatic mobility in the last two decades. Out of every 100 Latin Americans, 43 have changed their economic status during the period. There is 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 1 in five Latin Americans remained chronically poor throughout the whole period. The study also showed that while the poor are moving up, on average they do not enter the middle class but instead remain vulnerable to poverty.

4. Chilean income mobility using pseudo-panels

Each of the pseudo-panel methods previously introduced is usually applied to analyze some specific concept of income mobility, i.e. the mean-based approach is applied to obtain information about the pattern of income convergence or divergence, BGK method seeks to obtain vulnerability-to-poverty measures, while DLLM approach computes joints probabilities of poverty status 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. The main goal is to compare the performance of the 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 they are intended to answer. 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 transition rates 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. 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 are shown in the first panel of table 3. The value of β in the unconditional version of equation (4) is predicted correctly by the pseudo-panel. The slope coefficient is 0.4 –significant in statistical terms- indicating a pattern of income convergence in Chile between 1996 and 2006. On the contrary, the pseudo-panel fails to predict the value of β in the conditional version of equation (4). To estimate this model 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).

Looking at the pseudo-panel R^2, they are twice as high as the R^2 using the true panel. In other words, pseudo-panel reveals only about half as much mobility-as-time-independence compared to true.

The Dang et al. (2011) methodology estimates the joint distribution of poverty-non poverty status in t_1 and t_2. More specifically, the question they seek to answer is: *what is the joint distribution of poor-non poor in initial and final year?*

In order to calculate the upper and lower bounds for the four mobility measures resulting from this method –the joint probabilities of poverty status in t_1 and t_2-, we followed the steps described in the original paper. 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 $\hat{\varepsilon}_{i1}$.[8] 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 –equation (12)- are obtained using this income prediction and the observed income level of household heads in round 2. This procedure is repeated *R* 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

[8] 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 superior level of 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.

joint probabilities are obtained using this income prediction and the observed income level of household heads in round 2.

The second panel 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 that was 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 that was poor in both periods and for those that enter into poverty. For the group that was no poor in both years, the true panel rate lies outside the range of the pseudo-panel estimates. 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.

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).

The last pseudo-panel methodology is that proposed by Bourguignon et al. (2011) to compute vulnerability-to-poverty mobility measures. The question these authors seek to answer is: *which is the probability of income below a poverty threshold conditional on initial income and characteristics?* We implemented this methodology using Chilean data and following the procedure described in previous section. At least three time periods are required to be able to estimate income dynamic coefficients in equation (8). Given that restriction, we expand our dataset including the 2001 round of the panel. However, authors point out that with three cross sections 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. 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 stationary of observables characteristics $\hat{X}_{it+1}^{j}$, earnings coefficients $\hat{\beta}_{t+1}^{j}$ and variance of the innovation term $\hat{\sigma}_{\varepsilon jt+1}^{2}$.

Our result is shown in the last panel 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 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, 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 exception is the beta coefficient unconditionally.

4.2 Pseudo panels performance answering general questions

We now 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 transition rates presented in table 1.

Our results are shown in table 4. For the macro mobility measures the pseudo-panel estimates are quite far off and tend to underestimate the degree of income mobility. They show too much time dependence, with the exception of the upper bound estimation of 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 -i.e. 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 one of the bounds provides better estimates than the other.

Our findings on the micro-mobility regression coefficients are shown in the second panel of table 4. The mean-based approach predicts a pattern of income convergence both in percentages and in pesos. This approach underestimates the degree of strong income convergence. While an additional peso in 1996 is associated to an income change that is 0.4 pesos lower on average according to the pseudo-panel estimate, this prediction is of 0.6 using panel data and the unconditional version of the model. On the contrary, the mean-based pseudo-panel predicts larger income gains in percentages for the lower-income groups –in comparison with the higher-income groups- than that predicted by actual panel data. In other words, the mean-based approach overestimates the degree of weak income convergence. The DLLM lower and upper bounds contain the regression coefficients estimated using panel data. However, the width of these bounds is unreasonable wide. 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) to panel data estimations. Finally, the BGK pseudo-panel predicts coefficients with the right sign but they are very far from the true value, i.e. the pattern of income convergence is less pronounced according to this pseudo-panel method.

In the last panel of table 4 we show our poverty dynamics results. The conclusion is that pseudo-panel methods fail to predict the percentage that crossed the poverty line and the poverty dynamics measures. There are some exception, like the upper bound prediction of the probability of going out of poverty, and the lower bound prediction for the percentage that moved from above to below the poverty line, conditional on being a downward mover. However, neither method is good predicting all of the poverty dynamics measures. We can conclude that: i) all of the pseudo-panel methods seriously underestimate the probability of a household not in poverty in 1996 falling into poverty in 2006; ii) the DLLM upper bound and lower bound estimates do not contain the true panel poverty dynamics figures; and iii) BGK method reveals way too few poverty transitions compared to the true panel.

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

5. Pseudo-panels and poverty transition rates

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 dynamic or poverty transition measures. By definition, the dynamics of poverty or the poverty transition rates are conditional concepts. For instance, the probability of being non-poor in $t=2$ for those who were poor in $t=1$ is a poverty dynamic measure. In the last panel of table 4 we reported our poverty dynamics estimates using the DLLM pseudo-panel data. 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 is good predicting the true poverty transition rates.

In this section we reproduce the results obtain by Cruces et al. (2011) for the case of Chile and we reformulate them as conditional probabilities. The main objective is to compare how close panel data poverty transition rates are to the pseudo-panel figures. The results are shown in table 5.[9] The findings indicate that "true" poverty transition rates lie between the lower and upper bounds predicted by the method. However, the width of the bounds in the conditional formulation is much greater than in the original calculations as joint probabilities. For instance, 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. The probability of not being poor in 2006, *conditional* on being poor in 1996, ranges between 67.5% and 89.9%. 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 is not informative 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

[9] 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).

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 consider 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 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 are different in aspects such as data demands, assumptions about structural parameters and functional forms, and more importantly, 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 are intended to answer. Second, we computed a broader set of income mobility measures and focus 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 indicated 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. The only exception was the unconditional estimation of the mean-based approach. Second, they also perform poor in predicting a broader set of income mobility measures.

Finally, we extended the analysis including a reformulation to the calculations proposed by Dang, Lanjouw, Luoto and McKenzie. These authors calculate 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 dynamic 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 is not informative about poverty transition rates.

7. Refrences

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.

Arellano, M. and Bond, S. (1991): "Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations". *Review of Economic Studies*, vol. 58, pp. 277-97.

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.

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	
Fields, 2005	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
Percentage who moved from below to above the poverty line, conditional on being an upward mover	30.73
Percentage who moved from above to below the poverty line, conditional on being a downward mover	12.03

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.

Table 2: Definition and size of birth-gender cohorts
Chile 1996-2006

Year-birth	**Time period**		Total synthetic	**Time period**		Total household
cohort	1996	2006	individuals	1996	2006	observations
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**
	Lower bound	*Upper bound*	**data**
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

		Pseudo-panel			
	Panel data	*Mean based approach*	*Dispersion 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					
Fields, 2005	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
Percentage who moved from below to above the poverty line, conditional on being an upward mover	30.73	7.32	20.24	38.24	19.61
Percentage who moved from above to below the poverty line, conditional on being a downward mover	12.03	0.00	14.67	6.25	0.55

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

Notes: 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).