Inter-American Development Bank
Banco Interamericano de Desarrollo (BID)
Research Department
Departamento de Investigación
Working Paper #625

Using Pseudo-Panels to Measure Income Mobility in Latin America

by

José Cuesta*
Hugo Ñopo*
Georgina Pizzolitto**

*Inter American Development Bank
**World Bank

December 2007

Cataloging-in-Publication data provided by the
Inter-American Development Bank
Felipe Herrera Library

Cuesta, José A.

Using pseudo-panels to measure income mobility in Latin America / by José Cuesta, Hugo Ñopo, Georgina Pizzolitto.

p. cm.
(Research Department Working paper series ; 625)
Includes bibliographical references.

1. Income distribution—Latin America. I. Ñopo, Hugo. II. Pizzolitto, Georgina. III. Inter-American Development Bank. Research Dept. IV. Title. V. Series.

HC130.I5 C26 2007

Inter-American Development Bank
1300 New York Avenue, N.W.
Washington, DC 20577

The Research Department (RES) produces a quarterly newsletter, *IDEA (Ideas for Development in the Americas)*, as well as working papers and books on diverse economic issues. To obtain a complete list of RES publications, and read or download them please visit our web site at: http://www.iadb.org/res.

Abstract

This paper presents a comparative overview of mobility patterns in 14 Latin American countries between 1992 and 2003. Using three alternative econometric techniques on constructed pseudo-panels, the paper provides a set of estimators for the traditional notion of income mobility as well as for mobility around extreme and moderate poverty lines. The estimates suggest very high levels of time-dependent unconditional immobility for the Region. However, the introduction of socioeconomic and personal factors reduces the estimate of income immobility by around 30 percent. There are also large variations in country-specific income mobility (estimated to explain some additional 10 percent of inter-temporal income variation). Analyzing the determinants of changes in poverty incidence within cohorts revealed statistically significant roles for age, gender and, to a lesser degree, education of the household head and dwelling characteristics.

JEL Codes: D3; I3 ; O1
Keywords: Income Mobility, Poverty, Pseudo-Panels, Latin America

1. Introduction

Latin American nations persistently rank among the most unequal in the world in terms of distribution of earnings and wealth. Discussion of this problem has produced agreement on some of its causes: the Region's disappointing distributive performance has been due to pervasive levels of macroeconomic vulnerability, inequality in political voice and problems of social exclusion that are rooted in history.[1] However, the notion of mobility has not yet taken a central place in this discussion. That mobility has not played a role in the discussion of inequality for the Region reflects a lack of both appropriate data and methodological tools. In the literature in the developed world, the traditional framework for analyzing mobility demands data requirements that Latin America has not been able to fully supply yet, namely panel data. Only recently have pseudo-panel methods begun to be developed to overcome this data limitation. This paper is an attempt to apply these new methodological developments to a broad set of data from Latin America and in this way collaborate in putting this discussion on the empirical research agenda of inequality in the Region.

The role of mobility in the analysis of inequality has already been emphasized in the economic literature (see Fields, 2005, and Galiani, 2006, for recent reviews). Static measures of inequality, however, are insufficient to portray the well-being of individuals in a society and must be complemented by the dynamics of mobility. The welfare of individuals in two societies with similar levels of income inequality but different patterns of income mobility would be expected to differ. Individuals in the society with higher mobility would enjoy greater incentives to exert effort and climb up the income distribution than individuals in the society with lower mobility. The aggregation of these individual incentives would in turn be translated into higher productivity in the overall economy, with subsequent beneficial outcomes.

Macroeconomic vulnerability, coupled with the lack of an effective social protection network in the Region, imposes a considerable risk for individuals to slip into poverty (as reported, for instance, in Argentina by Corbacho, García-Escribano and Incahuste, 2003). This form of individual vulnerability is associated with downward absolute mobility along the welfare distribution. Fields et al. (2005) have found that, in upper segments of the income distribution, there is no conclusive evidence that individuals either realize large gains during booms or experience large losses during recessions. That is to say that downward mobility might therefore

not take place equally across the whole income distribution or, if it does, it happens at different rates.

Exclusion implies an inherent difficulty for individuals who want to move out of dire conditions by neglecting them access to services, consumption goods and assets. Societies with a higher incidence of exclusion should then report lower upward mobility than societies with more equal opportunities (as reported for Chile by Scott, 2000). Along similar lines, high and persistent inequality is consistent with lower mobility, although the causal relationship still requires an empirical investigation.

The analysis of mobility and the mechanisms through which it operates constitute important tools for policymaking. When governments know the details about the most effective ways of moving people up or preventing them from falling down the income ladder, the design of policies becomes more effective. Also, when governments better understand the tools to cope with downward mobility, the welfare losses associated can be at least ameliorated. That is, an understanding of the factors behind mobility becomes a must.

This paper is a contribution to the limited literature on regional income mobility. There are several reasons for choosing a regional focus, but the most important one, from a policymaking stance, is that it allows for country-specific effects to be compared with sub-regional and Region-wide effects. Of course, the analysis of regional mobility has shortcomings of its own, such as the need to exclude countries and periods from the analysis due to data limitations, as explained below. After this introduction, Section 2 defines mobility along the lines of the categorization in Fields (2005) and discusses the methodology used to estimate *absolute* income mobility, *conditional* mobility (after controlling for personal, socioeconomic and geographical features of households), country-specific income mobility and poverty mobility (defined as slipping into or moving out of a poverty threshold). Section 3 describes the construction of a pseudo-panel composed of 14 Latin American countries for the period 1992-2003. The section also describes income and poverty trends for the constructed cohorts, which are innovatively constructed as biannual averages. This strategy ensures a pseudo-panel balance and avoids estimation caveats faced by unbalanced panels. Section 4 discusses the results and Section 5 provides concluding remarks.

[1] See, among others, Vos et al. (2006), World Bank (2003) and IDB (1998).

2. The Estimation of Mobility

The measurement of income mobility started with Lillard and Willis (1978). It basically involves the establishment of a relationship between past and present income:

$$y_{i,t} = \beta y_{i,t-1} + \mu_{i,t} \qquad (1)$$

where $y_{i,t}$ is the total income for household i at time t, μ_{it} is a disturbance term and the parameter β, the coefficient of the slope in a regression of the income over its lagged value, is the measure of mobility. Fields (2005)[2] refers to this as *time-dependence* mobility and it will be the focus of our paper. A value of β equal to 1 represents a situation with no income convergence; a value of β below 1 corresponds to a situation in which there is convergence, while zero represents an extreme case in which mobility would be total (as there would be no relationship between past and present incomes). Although there are no ex-ante restrictions on the range of values that β should take, they are regularly within the [0,1] interval. Additionally, the mobility estimator obtained from (1) is called *unconditional* in the sense that it does not take into account the presence of covariates (other than past income) that may explain present income. When the estimation is performed with additional controls, we have the time-dependence conditional estimation of mobility:

$$y_{i,t} = \beta y_{i,t-1} + \delta X_{i,t} + \mu_{i,t} \qquad (2)$$

where X is a vector of covariates and δ is intended to measure the impact of those covariates on income. Given that this sort of analysis attempts to follow individuals (or households) over time, the quintessential data tool has been panel data. Unfortunately, such data have only recently become available in in Latin America, and the few data panels presently in existence cover only short periods.[3] This has constituted an important barrier to the analysis of mobility in the Region. The development of pseudo-panel techniques that was initiated by Deaton (1985) has been an

[2] Fields (2005) also summarizes other definitions of mobility: positional movement (a measure of individual's changes in economic positions); share movement (a measure of changes in individual's shares of incomes); income flux (size of the fluctuations in individual's incomes but not their sign); directional income movement (how many people move up or down and by how many dollars); mobility as an equalizer of longer-term incomes (a comparison of the inequality of income at one point in time with the inequality of income over a longer period). Time-dependence mobility is the definition most vastly used.

[3] This is the case of a two-period Chilean panel available in the CASEN survey of 1996-1998 or a two-period panel in El Salvador, for rural areas. A panel can also be constructed for Mexico, using the Encuesta Nacional de Empleo Urbano (ENEU), which has a rotating panel, with households followed for five consecutive quarters. Also Argentina

interesting alternative to overcome this data limitation. A pseudo-panel is formed creating synthetic observations obtained from averaging real observations with similar characteristics (regularly, birth year) in a sequence of repeated cross sectional data sets. In this way, the synthetic units of observations can be thought as being "followed" over time. The model then requires an appropriate modification:

$$\bar{y}_{c(t),t} = \beta_c \bar{y}_{c(t-1),t-1} + \delta_c \bar{X}_{c(t),t} + \mu_{c(t),t} \qquad (3)$$

where the individual index, *i*, has been replaced by a cohort index, $c_{(t)}$, that is time-dependent. Analogously to equation (1), the slope β_c is the parameter of interest. The literature has then focused on exploring the conditions under which such a parameter can be consistently estimated, provided the data limitations imposed by a set of repeated cross-sections (instead of real panel data). The works of Browning, Deaton and Irish (1985), Moffit (1993), Collado (1997), Girma (2000), McKenzie (2004), Verbeek and Vella (2005) and Antman and McKenzie (2005), among others, have provided sets of conditions that the interested reader can explore.

Not surprisingly, there are pros and cons about the use of pseudo-panels for the analysis of mobility. At least three arguments may be cited in its favor. The first is that they suffer less from problems related to sample attrition (because the samples are renewed at every period). The second is that, being constructed by averaging groups of individual observations, they also suffer less from problems related to measurement error (at least at the individual level). A third argument in favor of the use of pseudo-panels, a more practical one, is that because of the wide availability of cross-sectional data it is possible to construct pseudo-panels that are appropriately representative, covering long periods back in time, substantially more than what can be covered by real panels. The main argument against its use has to do with the fact that the decision about the clustering of observations in cohorts depends on a trade-off (number of cohorts vs. number of observations in each cohort) on which the literature has not yet been conclusive. The larger the number of cohorts, the smaller the number of individuals per cohort. On the one hand, one would like to have a large number of cohorts so that the regressions performed with the resulting pseudo-panels suffer less from small sample problems. On the other hand, however, if the number of observations per cohort were not large enough, the average characteristics per cohort

(1988 to date), Brazil (1980 to date), Peru (1991-1997), and Venezuela (1994-1999) have household surveys with similar design. See Fields et al. (2006) for additional details.

would fail to be good estimates for the population cohort means. In addition, Antman and McKenzie (2005) note two caveats from the use of pseudo-panels. They may introduce biases if the average cohort household fails to account for changing trends in household dissolution and creation (such as migration, for instance[4]). Also, intra-cohort mobility is utterly ignored. In this vein, Girma (2000) indicates that intra-cohort homogeneity in pseudo-panels (consistent with the notion of "representative" agents) is too strong an assumption.[5]

The pseudo-panel approach has been recently undertaken in the Region to estimate mobility as defined above, at least by Navarro (2006) for Argentina and by Calónico (2006) for a set of eight countries (Argentina, Brazil, Chile, Colombia, Costa Rica, Mexico, Uruguay and Venezuela).[6] The latter found low patterns of mobility for all these countries during the period 1992-2002. When trying to compare the results from both papers for Argentina we still found some differences. First, the papers use different time spans. While Navarro computed mobility for the period 1985-2004, Calónico did so for 1992-2003. Second, the studies differ in the concept of income that is used. While Calónico uses monthly labor incomes, Navarro based her analysis on hourly wages received by individuals in their main occupation. Third, Navarro narrows her estimations to the conglomerate of Gran Buenos Aires in Argentina in order to construct a much larger pseudo-panel. All in all, Navarro (2006) presents a higher degree of income mobility than Calónico (2006), a result supported by Albornoz and Menendez (2004) and Fields and Sánchez-Puerta (2005) using panel data for Argentina. Likewise, Antman and McKenzie (2005) report for specific age-education cohorts in Mexico between 1987 and 2001 little mobility between the earnings of rich and poor households but rapid convergence in the average household's earnings, suggesting higher levels of conditional mobility.

Other studies have explored income (earnings) mobility in the context of pro-poor growth, typically using panel data. Gottschalk (1997), Fields and Ok (1999), Ravallion and Chen

[4] There is, however, no easy way to measure the impact of migration in the observed mobility. One of the possible options would be to measure mobility only for locals. However, this may introduce additional undesired complications. It is not clear what would be the role of incoming remittances on the measurement of mobility (i.e., what kind of endogeneity problem may occur). But remittance are also likely to affect other income-generating decisions such as whether to work and, if so, how much. .

[5] Girma's proposed method, a pair-wise quasi-differencing approach, allows for estimated parameters to vary freely across groups and allows for the presence of unobserved individual specific heterogeneity within each cohort. However, it imposes an equicorrelation structure within a group-time cell. In other words, it also imposes some degree of homogeneity within groups.

[6] Also, the study of mobility using real panels has been undertaken in Fields et al. (2006) for Argentina, Mexico and Venezuela; and Albornoz and Menendez (2004) for Argentina.

(2003), Grim (2007), among others, explore whether economic growth has favoured the poor in the United States, the United Kingdom and other OECD countries, as well as China, Peru and Indonesia. They typically find different growth rates of earnings among the poor and the non-poor. Increasing mean individual and family earnings consistent with decreasing poverty coexist with increasing inequality and limited mobility. Interestingly, in Peru and Indonesia, Grim (2006) underscores the relevance of transfer policies as he observes significant mobility among originally poor households moving out of poverty and non-poor households moving into poverty despite low or negligible economic growth rates. In contrast, Gottschalk (1997) reports that despite an increase of 27 percent in per capita incomes, poverty in the US between 1973 and 1994 increased from 11.1 percent to 14.5 percent.[7]

Our study complements previous work in both scale and scope. We examine 14 countries during the period 1992 to 2003, analyzing not only the mobility estimator, β , but also changes in the "poverty incidence" for the pseudo-individuals, analyzing the determinants of them. For that purpose, for each cohort we compute the percentage of individuals whose income is below a "poverty threshold" (poverty incidence within the cohort) and then, denoting that percentage by *p*, we estimate the determinants of the changes in poverty incidence in the cohorts:

$$\Delta p_{c(t),t} = \delta_c \overline{X}_{c(t),t} + \mu_{c(t),t} \qquad (4)$$

In this way we are able to provide estimators of the role of initial conditions on income mobility and the transitions up and down poverty lines.

3. Data

The raw data for this study comes from national household surveys of 14 Latin American countries in the Region.[8] These surveys have been harmonized by the Research Department of the Inter-American Development Bank to ensure a comparable definition of variables and household incomes across countries. Countries included in the pseudo-panel share the same sources of labor incomes: labor (approximately 75 percent of the Region's average household

[7] The author indicates that the United States is the only OECD country OECD countries where family earnings inequality was larger than individual earnings inequality: labor decisions, taxes and transfers did not reduce inequalities in the US during that period.

[8] The countries are the following: Argentina, Brazil, Bolivia, Chile, Colombia, Costa Rica, Honduras, Mexico, Panama, Paraguay, Peru, El Salvador, Uruguay and Venezuela

incomes) and non-labor incomes (accounting for the remaining 25 percent). Countries that fail to report non-labor incomes in any of their household surveys were excluded from the pseudo-panel; this was the case of Dominican Republic, Guatemala, Nicaragua and Ecuador. Due to problems in the income variables, we also excluded from the analysis data from Brazil and Mexico for the year 1992.[9] All incomes were deflated using the Consumer Price Index of each country and year, and we further adjusted incomes using Purchasing Power Parity,[10] as reported in the World Development Indicators, to make them comparable across countries.

We construct the pseudo-panel with data from these 14 countries using surveys between 1992 and 2003 and focusing on household heads aged 21 to 65. Countries collect their surveys in different seasons, different years, with different frequencies and coverage (urban or national). Table 1 in Annex 1 details these features for the countries in our pseudo-panel. Our strategy in constructing the pseudo-panel consisted of maximizing the number of homogenous observations, which meant restricting the panel to one survey round (or sub-period) per country and period, as well as considering two-year periods instead of annual periods. We would typically select the latest available round in a given year for those countries with multiple annual sub-periods.[11] Interestingly enough, countries in this pseudo-panel collect their surveys typically in the second half of the year, with 11 out of 14 countries collecting surveys during the fourth quarter of the year. It would be therefore expected that seasonality effects, if present, are similarly distributed in the pseudo-panel.[12] We also select the survey collected in the even year in the two-year period (that is, 1992 in the 1992-1993 period). We respect the coverage of the surveys and do not exclude countries with sub-national coverage (only Argentina and Uruguay have sub-national coverage).[13] Although this design entailed a loss of information from available surveys in some countries, it allowed us to consider the highest possible number of countries with information

[9] We observed that even after adjusting for consumer price index, incomes presented dramatic fluctuations. The high inflation rates (and currency changes in Brazil) explain these inconsistencies in the evolution of incomes variables.
[10] The purchasing power parity (PPP) conversion factor is the number of units of a country's currency required to buy the same amounts of goods and services in the domestic market as U.S. dollars would buy in the United States.
[11] Only four of the 14 countries had multiple rounds in any given year: Argentina, Colombia, Peru and Venezuela.
[12] In any case, we ensured that the income variable referred to the same reference period, that is, the previous month to the collection of the survey. Other variables used in the analysis such as gender, sex, age, household position, household number are either unchangeable or subject to little (and presumably unbiased) change regardless of the choice of the survey round. It is unlikely that the selection of even years instead of odd years introduces any biases into our estimates. One would not argue that election years, or domestic and international shocks, for example, take place disproportionately in either odd or even years.
[13] In addition, the 1992 survey in Colombia was urban. In Argentina and Uruguay, the urban population covered in the survey represented 62 percent and 80 percent, respectively, of the total population in 2003.

available for the largest number of periods, in this case, six.[14] This was also a preferred option over "averaging" pairs of years or sub-periods within the same year: shocks would have been smoothed out, biasing the probability of income mobility. In other words, we dismiss the "excess" of information for some countries in favor of more countries and a lengthier pseudo-panel. Nonetheless, this implies that our interpretation of the dynamics is no longer tied to the customary annual period but to a two-year period.

Birth cohorts include household heads born in seven-year spans, starting with those born between 1927 and 1933 and ending with those born between 1976 and 1982. Alternative cohort lengths were also attempted without significant changes in the estimated results.[15] (See Annex 2.) Cohorts are constructed based on year of birth, country of residence and gender. Although cohorts could also have been defined by urban/rural area, place of residence is a decision that may be affected by income dynamics through the mechanism of internal migration: that is, it is endogenous to the economic phenomenon of analysis. Our pseudo-panel averages observations pertaining to the same cohort that appear in subsequent household surveys (each observation is appropriately weighted by the sample expansion factors). In the face of substantive differences in size cohorts across countries, cohort averages are weighted by the expansion factors in each survey, which means that a cohort average from Brazil will have a different weight than the same cohort from El Salvador, for example.

As a result, the constructed pseudo-panel follows eight birth cohorts over six periods. This comprises a total of 139,132 individual observations collapsed into 1,024 synthetic observations that constitute a representative sample of household heads for the 14 countries under consideration. That number of observations is the result of collapsing the dataset by country (14 countries), gender (1 for men and 0 for women) and the eight birth cohorts (from 1927-33 to 1976-82), for the six periods of analysis. That would imply a total of 14x2x8x6=1,344 synthetic observations. However, some countries had missing household surveys for some years (especially the earlier ones), and others were not usable due to the lack of

[14] In fact, there is not a period of time between 1990 and 2006 for which all 14 countries in our sample collected their household survey. Only Argentina, Costa Rica and Venezuela collected household surveys between 1992 and 2003 without interruption.

[15] In particular, four and six-year spans were attempted and the estimates of the time-dependence mobility did not change substantively. Tables 1 and 2 in Annex 2 report these estimates. Neither the magnitude of the parameters, the significance of the controls or the R^2 of each specification change substantively with four and six year cohorts.

a possibility to harmonize variables, as mentioned earlier. As a result the number of synthetic observations was reduced to 1,024. Table 1 below reports cohorts' sizes.[16]

This pseudo-panel exceeds both the depth and breath of other pseudo-panels for the Latin American region. Also, it strikes a balance between a relevant number of cohorts and a meaningful size of cohort. An insufficiently large number of cohorts causes pseudo-panel estimations to suffer from small sample problems, while an insufficiently large cohort size diminishes the quality of estimates for population cohort characteristics (McKenzie, 2004).

Table 1. Cohort Sizes

	Period						
	T1	T2	T3	T4	T5	T6	Total
Year Birth Cohort	1992-3	1994-5	1996-7	1998-9	2000-1	2002-3	
1927-33	2,055	1,284	851	303	…	…	4,493
1934-40	2,554	2,513	2,296	2,339	1,639	1,468	12,809
1941-47	3,084	3,098	2,845	2,879	2,768	3,121	17,795
1948-54	4,030	4,035	3,727	3,867	3,701	4,190	23,550
1955-61	4,516	4,585	4,171	4,519	4,570	5,166	27,527
1962-68	3,901	4,281	3,949	4,434	4,856	5,565	26,986
1969-75	934	2,319	2,411	3,182	3,968	4,858	17,672
1976-82	…	…	1,837	1,544	2,144	2,775	8,300
Total	21,074	22,115	22,087	23,067	23,646	27,143	139,132

Source: Authors' calculations based on IDB Research Department Harmonized Household Surveys.

Table 2 provides the basic descriptive statistics of the pseudo-panel: socioeconomic and geographical characteristics of synthetic household heads of the constructed cohorts. The average per capita household income in the pseudo-panel is about US$456 per month with a standard deviation of US$419 in PPP-adjusted real terms. The average household head is 43 years old and has seven years of education. Regarding attainment, 10 percent of household heads have no education; 44 percent have primary education (either incomplete or complete); and 33 percent have started or completed secondary education. The remaining 14 percent have college education. The average household has almost two children. Table 2 also reports the distribution of observations by sub-regions.[17] The two measures of poverty incidence, also reported in Table 2, deserve special mention. They capture the fraction of households (or, equivalently, household

[16] See Table 1 in Annex 1 for details on the number of periods available per country.

[17] The Southern Cone includes Argentina, Brazil, Chile, Uruguay and Paraguay; the Andean Region includes Bolivia, Colombia, Peru and Venezuela; Central America includes Costa Rica, El Salvador, Honduras, Mexico and Panama.

heads) within each cohort whose per-capita household income falls below the two most common internationally utilized thresholds of 1 and 2 dollars a day.

Table 2. Data Descriptive Statistics

Variable	Number of observations (in pseudo-panel)	Mean	Standard Deviation	Average inter-period variation (%)
Log Per Capita Household Incomes	1,024	5.36	0.68	-3.64%
% Female-headed households	1,024	0.50	0.50	0.11%
Age	1,024	43.22	13.84	0.02%
Years of Education	1,010	7.15	2.26	0.89%
No Education	1,024	0.10	0.11	-10.10%
Primary incomplete	1,024	0.23	0.13	-6.56%
Primary complete	1,024	0.21	0.09	-4.37%
Secondary incomplete	1,024	0.19	0.10	3.97%
Secondary complete	1,024	0.13	0.07	3.99%
Tertiary incomplete	1,024	0.07	0.07	2.37%
Tertiary complete	1,024	0.07	0.05	-0.31%
Number of Children aged 0 to 16 years	1,024	1.84	0.69	0.75%
Number of other relatives living in the household	1,024	0.60	0.40	-2.29%
Southern Cone	1,024	0.38	0.49	---
Andean Region	1,024	0.38	0.46	---
Mexico and Central America	1,024	0.33	0.47	---

Source: Authors' calculations based on IDB Research Department Harmonized Household Surveys.

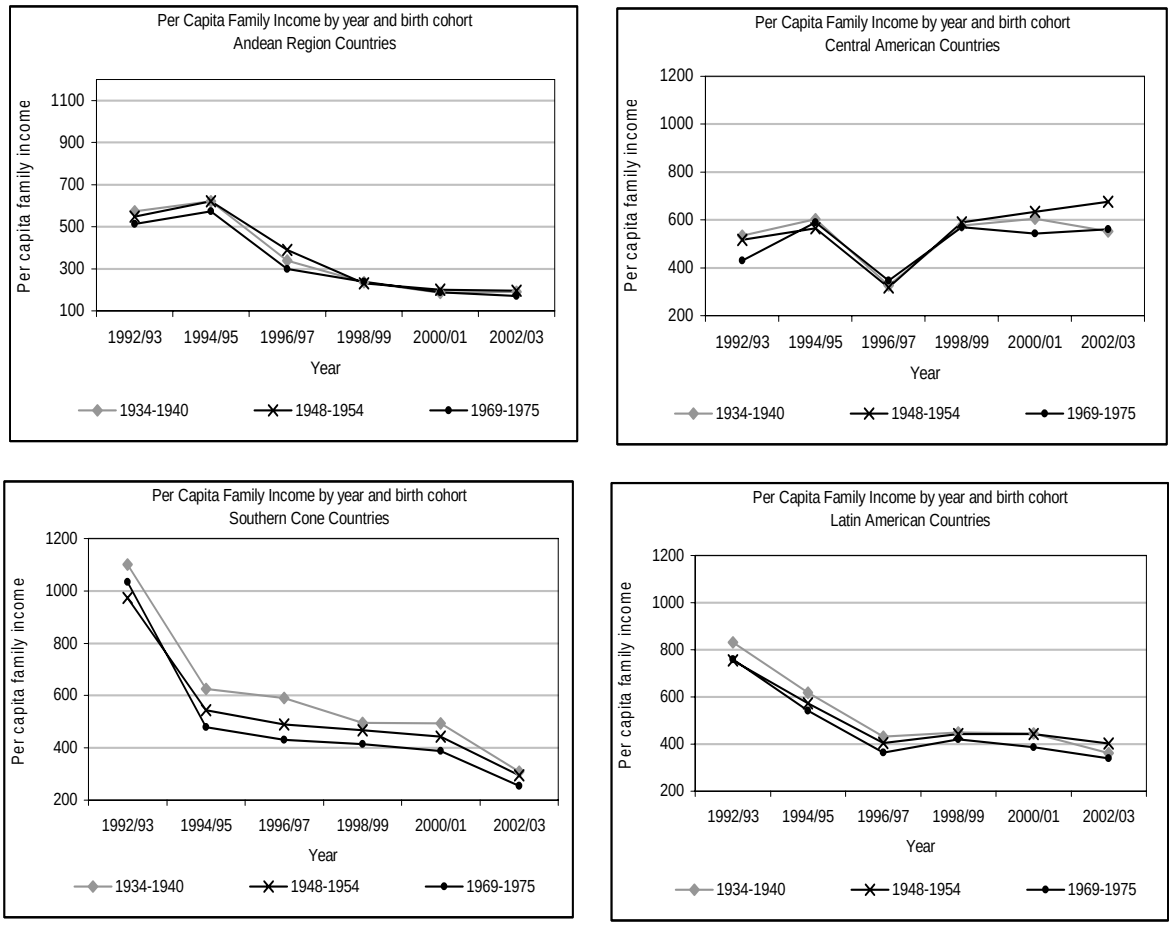
Interestingly, the variable measuring dwelling characteristics captures the quality of the living conditions of the households. The variable is computed using information about the quality of the materials used for the walls, the number of rooms, whether the household has a bathroom connected to a sewerage system inside the house or not, and access to a source of safe water and electricity. This variable, which we refer to as the Dwelling Characteristics Index, is constructed as the first principal component that explains most of the variance of the characteristics mentioned above. By construction, it has a zero-mean and a symmetric distribution around it. Because of this feature we are not reporting it on the descriptive statistics of Table 2, but we will use the index as a control in the mobility regressions. Table 2 also reports the distribution of observations by sub-regions[18] and the average inter-period changes of the

[18] Southern Cone includes: Argentina, Brazil, Chile, Uruguay and Paraguay. Andean Region includes: Bolivia, Colombia, Perú and Venezuela. Central América includes: Costa Rica, El Salvador, Honduras, México and Panamá.

incumbent variables used in the analysis. Inter-period changes show that despite the number of years of education have only slightly increased on average, there are important changes in terms of educational attainment: sizeable decreases in the proportion of household heads with low education (primary or less) and significant increases in the proportion of secondary education household heads. Other demographic and personal characteristics have changed little. Living conditions (approximated by the Dwelling Characteristics Index) have improved substantially, even though their improvement does not follow a similar trend to that of per capita household incomes. These trends of decreasing aggregated or average incomes may conceal diverging trends indifferent regions of the income distribution, as reported by Gottschalk (1997) in the United States (see previous section). If that is the case, the incidence of poverty may not necessarily follow the same trend as that of average incomes, as is the case in Latin America during the 1990s (as indicated by trends in poverty and per capita GDP reported in CEPAL, 2007).

Figure 1 below depicts regional and sub-regional trends of per capita monthly household incomes, PPP-adjusted, for selected birth cohorts. Even when trends differ across sub-regions, within each of them the cohorts of young adults, prime-age and retirees follow similar patterns. This constitutes, although rudimentary, a prima facie evidence of low patterns of mobility in the region, along the lines of what Calónico (2006) found.

Figure 1. Income Trends by Sub-Region



Source: Authors' calculations based on IDB Research Department Harmonized Household Surveys.

Interestingly, these trends differ from nominal per capita household incomes and even PPP-adjusted national per capita GDP. For all the sub-regions and the Region as a whole, per capita income and GDP increased in the 1990s, as reported by CEPAL (2007), and were accompanied by a substantive decrease in poverty during the same period from 48 percent in 1990 to 39 percent in 2005. There are at least two reasons why these trends may differ. First, the latter trends refer to the average per capita income and inform little on the income trends of poor households. What we know about such changes (as reported below in Table 3) is that sizeable and symmetric movements take place into and out of poverty in the Region for the period considered. As a result, even if the incidence of poverty is to change, large overall change should should not be expected, as there are substantive composition effects from both households leaving and entering poverty. This evidence in Latin America confirms evidence reported in the

United States pointing to diverging trends in GDP growth, mean earnings and poverty incidence (see Gottschalk, 1997). Second, while Figure 1 reports PPP-adjusted real trends, GDP trends refer to the nominal purchasing power of each national currency in its respective country. That is, Figure 1 reports the real purchasing power of local currencies in the international economy or, more specifically, how the purchasing power of a Chilean peso or a Venezuelan Bolivar, for instance, would fare in the US over time. That purchasing power has typically declined over time, partly due to the increasing inflationary trend in the US in the same period. Of course, this deterioration of international purchasing power of a household in a given country should not necessarily bear comparable effects in terms of its domestic purchasing power and, ultimately, poverty status.

4. Estimations of Income Mobility and the Determinants of Poverty Changes

In this section we provide estimates of income mobility (equation 3) and the determinants of changes on poverty incidence within the cohorts (equation 4). The observational unit is the household, with additional variables capturing the personal characteristics of the household head. The dependent variable used in our estimates is the log of per capita household incomes for the period under consideration, which Fields and Ok (1999) demonstrate to be the only measure of income movement to have a set of desired properties (scale invariance, symmetry, multiplicability and additive separability). Our variable results from the sum of labor and non-labor incomes of all household members divided by the total household size as reported by the household survey selected in each two-year period. Table 3 below reports estimates of time-dependence income mobility, measured as the elasticity of current incomes with respect to past incomes. The results are reported for the whole Region without any further controls, with sub-region specific controls (three sub-regions: Southern Cone, Andean Region and Mexico and Central America) and with country-specific controls. These correspond to the columns of Model I, Model II and Model III, respectively. To the extent that these models are controlling for intra-regional variability but not for individuals' characteristics, we consider these estimators as "unconditional" according to the terminology introduced in Section 2. The results confirm a very low degree of income mobility for Latin America, as previously found in the literature. The estimate of the unconditional mobility indicator, β, is as high as 0.966 (when no control is considered).

Table 3. Estimates of Time-Dependence Income Mobility in Latin America, Unconditional Mobility

Dependent variable: log of real per capita household income (PPP) at time t	Model I	Model II	Model III
Estimated Income Mobility - Equation (3)			
β	0.966 [645.45]***	0.946 [342.54]***	0.949 [199.03]***
R-squared	0.9981	0.9983	0.9986
Controlling for			
Sub-Regional Dummies	No	Yes	No
Country Dummies	No	No	Yes
Observations	800	800	800

Absolute value of t statistics in brackets
* significant at 10%; ** significant at 5%; *** significant at 1%
Source: Authors' calculations based on IDB Research Department Harmonized Household Surveys.

The estimated mobility changes substantially after controls are introduced. Taking Model III as a point of departure and gradually adding controls for characteristics of the household head (age, gender and educational attainment), number of children 16 years old or less living at home and the dwelling characteristics index described above, the estimated mobility falls to almost two-thirds of its unconditional value.[19] This evidence suggests that a misleading attribution of demographic and socioeconomic impacts to past incomes may well generate a false sense of limited time-dependence income mobility.

[19] Note that adding the dwelling characteristics index reduces the number of observations from 800 to 500. To discard the possibility of sample composition effects driving the results, we also estimated Models IV and V using only the 500 observations included in Model VI. The results are almost identical. The estimation of Model IV using the same sample as in model VI delivers β=0.632 [42.19]***, R^2=0.9994, while for Model V β=0.605 [41.95]***, R^2=0.9995.

Table 4. Estimates of Time-Dependence Income Mobility in Latin America, Conditional Mobility

Dependent variable: log of real per capita household income (PPP) at time *t*	Model IV	Model V	Model VI
Estimated Income Mobility - Equation (3)			
β	0.640	0.608	0.601
	[53.54]***	[52.47]***	[42.72]***
R-squared	0.999	0.999	0.999
Controlling for			
Characteristics of the household head (Age, gender and educational attainment)	Yes	Yes	Yes
Number of children (16 years old or less)	No	Yes	Yes
Dwelling Characteristics Index	No	No	Yes
Country dummies	Yes	Yes	Yes
Observations	800	800	500

Absolute value of *t*-statistics in brackets
* significant at 10%; ** significant at 5%; *** significant at 1%
Source: Authors' calculations based on IDB Research Department Harmonized Household Surveys.

A country-specific analysis of mobility should reveal the existing heterogeneity across the Region. Table 5 reports country-specific estimates of mobility for Models I, IV, V and VI. As in the aggregate, the sole introduction of household head characteristics notably reduces the measured mobility. The most notorious cases are Panama and Uruguay where the estimators of mobility were reduced to less than one-third of their unconditional values. The further introduction of controls for children (16 years old or less) at home and dwelling characteristics further reduced the estimated conditional mobility, but to a lesser extent, in most countries (Brazil, Colombia and Costa Rica being interesting exceptions).

The estimates of income mobility in Table 5 are expressed as elasticities, which allows for a meaning comparison across countries with different starting income levels. Estimated elasticities vary widely across country, as predicted. High levels of conditional time-dependence income immobility (β exceeding 0.75) are found only in Brazil, Colombia and Costa Rica, while the rest of the Region shows higher levels of mobility (lower β). Countries such as Chile or Argentina show moderate immobility (β between 0.6 and 0.75) compared with other "mobile" countries (β below 0.6). These results confirm that higher mobility is found across countries when countries are considered separately than when countries are being pooled regionally (as was the case with results for Argentina using the separate estimations of Navarro

(2006) separate and the pooled estimations of Calónico (2006)led estimations). Also, our results are consistent with the finding of restrained mobility in Chile reported by Contreras et al. (2004). Even though this limited evidence does not allow for generalizations, it may be that Region-pooled estimates average out different country-specific patterns of income mobility.

Table 5. Country-Specific Estimates of Unconditional and Conditional Time-Dependence, Income Mobility in Latin America

Dependent variable: log of real per capita household income (PPP) at time *t*	Unconditional	Conditional		
Country	Model I	Model IV	Model V	Model VI
	β	β	β	β
Argentina	0.975 [192.90]*** (N=70 : R^2=0.9981)	0.746 [2.84]*** (N=70 : R^2=0. 9980)	0.662 [2.40]** (N=70 : R^2=0. 999)	0.674 [1.96]* (N=70 : R^2=0. 999)
Bolivia	0.973 [125.66]*** (N=68 : R^2=0.9958)	0.423 [8.02]*** (N=68 : R^2=0. 9996)	0.289 [4.77]*** (N=68 R^2=0. 999)	0.244 [1.09] (N=26 R^2=0. 999)
Brazil	0.982 [840.59]*** (N=56 : R^2=0. 999)	0.803 [19.65]*** (N=56 : R^2=0. 9997)	0.829 [22.03]*** (N=56 R^2=0. 999)	0.855 [15.82]*** (N=56 : R^2=0. 999)
Chile	0.995 [333.34]*** (N=70 : R^2=0. 9994)	0.499 [4.65]*** (N=70 : R^2=0. 9998)	0.476 [4.35]*** (N=70 : R^2=0. 999)	0.605 [5.34]*** (N=56 : R^2=0. 999)
Colombia	0.964 [204.16]*** (N=70 : R^2=0.9983)	0.781 [19.11]*** (N=70 : R^2=0. 999)	0.822 [20.97]*** (N=70 : R^2=0. 999)	0.808 [22.41]*** (N=70 : R^2=0. 999)
Costa Rica	0.973 [238.98]*** (N=70 : R^2=0.9972)	0.689 [7.44]*** (N=70 : R^2=0. 9996)	0.693 [7.40]*** (N=70 : R^2=0. 999)	0.781 [5.52]*** (N=28 : R^2=0. 999)
Honduras	0.963 [123.32]*** (N=44 : R^2=0. 999)	0.482 [3.61]*** (N=44 : R^2=0. 9991)	0.187 [1.70]* (N=44 R^2=0. 999)	-- -- --
Mexico	0.945 [133.95]*** (N=56 : R^2=0.9969)	0.43 [14.29]*** (N=56 R^2=0. 9998)	0.432 [17.20]*** (N=56 R^2=0. 999)	0.431 [17.02]*** (N=56 : R^2=0. 999)

Table 5., continued

Dependent variable: log of real per capita household income (PPP) at time *t*	Unconditional	Conditional		
	[281.24]***	[2.46]**	0.079 [1.14]	--
	(N=58 : R^2=0.9993)	(N=58 R^2=0. 9998)	(N=58 R^2=0. 999)	--
Peru	0.996 [175.12]***	0.746 [7.58]***	0.060 [0.57]	-- --
	(N=44 : R^2=0.9986)	(N=44 R^2=0. 9997)	(N=44 R^2=0. 999)	--
Paraguay	0.955 [257.19]***	0.981 [9.30]***	0.904 [7.92]***	0.537 [6.50]***
	(N=42 : R^2=0.9994)	(N=42 R^2=0. 9995)	(N=42 R^2=0. 999)	(N=42 R^2=0. 999)
El Salvador	1.005 [306.65]***	0.941 [5.11]***	1.121 [4.64]***	0.525 [2.81]**
	(N=28 : R^2=0.9997)	(N=28 R^2=0. 999)	(N=28 R^2=0. 999)	(N=28 R^2=0. 999)
Uruguay	0.932 [136.44]***	0.270 [7.91]***	0.269 [7.84]***	-- --
	(N=70 : R^2=0.9963)	(N=70 R^2=0. 9991)	(N=70 : R^2=0. 999)	--
Venezuela	0.896 [151.62]***	0.582 [18.14]***	0.558 [15.52]***	0.484 [12.73]***
	(N=54 : R^2=0.9977)	(N=56 R^2=0. 9990)	(N=56 R^2=0. 999)	(N=54 R^2=0. 999)
Controlling by				
Characteristics of the household head	No	Yes	Yes	Yes
N. of children (16 years old or less)	No	No	Yes	Yes
Dwelling characteristics	No	No	No	Yes

Absolute value of t statistics in brackets
* significant at 10%; ** significant at 5%; *** significant at 1%
Source: Authors' calculations based on IDB Research Department Harmonized Household Surveys

Then, we develop an indicator that captures changes in poverty incidence within the cohorts over time, that is, mobility around a threshold that can be thought as a poverty line. We perform the exercise for the widely used international poverty cut-offs of US$1/day and US$2/day per person.[20] While some critiques view this methodology as either consistently underestimating the number of the poor (Reddy and Pogge, 2003) or grossly overestimating them

[20] World Bank (1990) introduced the use of these measures. The construction of the US$1/day line is based on an average of six country-specific extreme poverty lines (Bangladesh, Indonesia, Kenya, Morocco, Nepal and Tanzania) that are subsequently expressed in national 1985 PPP$ terms, and updated in 2000 to US$1.08 to reflect 1993 PPP$.

(Sala-i-Martin 2006),[21] Others consider that these income or consumption-based lines overlook other dimensions of poverty (UNDP 2006), and recommend the inclusion of early death, adult illiteracy, child malnutrition and the population's access to safe water in the calculation of poverty (which has, in effect, resulted in the construction of the Human Poverty Index). Notwithstanding the relevance of such criticisms, they are not the focus of the paper. We follow the vast tradition of considering the US$2/day per person international poverty line as an appropriate threshold for international comparisons across the typically middle-income economies in Latin America (and further compare them with estimates accruing from a US$1/day line). For the construction of such indicator we first compute the poverty incidence within each cohort or synthetic observation (that is, the percentage of households that have an average per capita income below the poverty cut-offs). Then, we subtract the poverty incidence of each synthetic observation in one period with the one observed in the previous period. With this procedure we obtain a measure of the changes in poverty incidence for each cohort. This way of constructing the variable implies that positive values for the change denote a reduction in poverty incidence within the cohort.

Having constructed the indicator of changes in poverty incidence for the pseudo-observations we then estimate the determinants of those changes using equation (4) in Section 2. Being the case that the dependent variable, by construction, is bounded between –1 and 1, the estimation is performed using a two-limit Tobit model with these two extremes as lower and upper limits respectively. The aggregate results are reported in Table 6.

[21] For a recent debate on the use of country-specific poverty lines and national accounts in the estimation of global poverty and inequality see Sala-i-Martin (2006) and Milanovic (2006).

Table 6. Determinants of Changes in Poverty Incidence in Latin America, Tobit Models, $1/Day and $2/Day

Dependent variable: Change in poverty incidence in the cohort	*1 U$S a day per person*			*2 U$S a day per person*		
	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
Age	-0.010	-0.011	-0.008	-0.008	-0.008	-0.006
	[4.11]***	[4.65]***	[3.28]***	[3.72]***	[4.07]***	[2.76]***
Age^2	9.37E-05	9.86E-05	5.57E-05	6.32E-05	6.75E-05	3.25E-05
	[3.14]***	[3.36]***	[1.84]*	[2.51]**	[2.71]***	[1.26]
Gender [=1 if male]	-0.007	-0.011	-0.011	-0.009	-0.011	-0.011
	[1.37]	[2.11]**	[2.04]**	[2.09]**	[2.59]***	[2.52]**
Primary incomplete or complete	0.157	0.153	-0.210	0.123	0.127	-0.154
	[2.48]**	[2.43]**	[1.94]*	[2.30]**	[2.38]**	[1.68]*
Secondary incomplete or complete	-0.004	-0.083	-0.307	-0.053	-0.086	-0.259
	[0.07]	[1.24]	[3.77]***	[1.08]	[1.52]	[3.73]***
Superior incomplete or complete	0.081	-0.006	-0.393	0.104	0.059	-0.245
	[1.41]	[0.10]	[3.84]***	[2.14]**	[1.11]	[2.81]***
Number of Children	0.008	0.018	0.014	0.006	0.013	0.009
	[1.03]	[2.38]**	[1.75]*	[1.04]	[2.07]**	[1.37]
Dwelling Characteristics Index	0.008	-0.002	0.012	0.007	0	0.012
	[3.48]***	[0.61]	[2.31]**	[3.76]***	[0.01]	[2.61]***
Constant	0.164	0.205	0.552	0.155	0.166	0.43
	[2.66]***	[3.13]***	[5.92]***	[2.98]***	[2.99]***	[5.41]***
Sub-Regional dummies	No	Yes	No	No	Yes	No
Country Dummies	No	No	Yes	No	No	Yes
LR chi2	49.95	70.00	101.96	62.06	75.14	104.30
Log Likelihood	534.79	544.81	560.79	619.22	625.76	640.34
Observations	500	500	500	500	500	500

Absolute value of *t* statistics in brackets
* significant at 10%; ** significant at 5%; *** significant at 1%
Source: Authors' calculations based on IDB Research Department Harmonized Household Surveys.

The most salient regularities on the estimations of the determinants of changes in poverty incidence are the role of age and gender of the household head. When estimating a quadratic impact of age, we found it to be statistically significant with the shape of an upward parabola. The age of the household head at which the changes in poverty of her/his household are minimal is around the late 50s. On the other hand, the estimates seem to suggest that being a female head of household represents a statistically significant limitation on the chances of moving out of poverty (or not falling into it), although the effect is small. To a lesser degree, we find a positive impact of dwelling characteristics on changes in poverty incidence.[22]

[22] As outlined above, the Dwelling Characteristics Index is constructed upon the basis of five observable (and comparable across countries) characteristics. When analyzing independently the role of those characteristics in

In theory, the role of number of children at home (or household size) in poverty mobility is unclear. A larger household size implies larger needs to cater for within the household, on the one hand, but also, typically, additional caretakers and higher incentives for adult members to work (as discussed in Cuesta, 2006). Which thrust dominates remains an empirical question. Interestingly, within this setup, we find only scattered evidence of a positive and significant effect of the number of children (16 years old or less) living at home.

The role of education of the household head deserves particular discussion. We found positive, statistically significant and economically relevant impacts of education on the changes in poverty incidence, especially among those with primary education (either complete or incomplete), for the specifications that did not make country distinctions (that is, for Models 1 and 2).[23] Interestingly, when introducing the set of country dummies the results reversed. In other words, the role of education on the chances of moving in and out of poverty seems to differ by country. An analysis of the same estimations at the country level promises to deliver interesting insights about it. Table 7 presents estimates of the determinants of poverty mobility at country level for the US$1/day poverty cut-off.

changes in poverty incidence we found that most of the effect of the aggregate index is driven by the quality of the walls of the dwellings. These results are available from the authors upon request.

[23] The base category is No Education.

Table 7. Determinants of the Changes in Poverty Incidence in Latin America Using $2/Day Poverty Line

Dependent variable: Change in poverty incidence in the cohort	*Country*									
	Argentina	Bolivia	Brazil	Chile	Colombia	Costa Rica	Mexico	Paraguay	El Salvador	Venezuela
Age	-0.023	-0.007	0.007	-0.055	-0.032	-0.029	-0.05	-0.021	-0.014	-0.014
	[1.64]	[0.27]	[1.65]	[3.58]***	[5.04]***	[1.81]*	[4.03]***	[1.68]	[1.73]*	[1.72]*
Age2	0.0003	0.00013	-0.0001	0.001	0.0002	0.0002	0.0005	0.002	0.0002	0.0001
	[2.02]**	[0.47]	[1.13]	[3.33]***	[3.35]***	[1.47]	[3.25]***	[1.38]	[2.44]**	[1.52]
Gender [=1 if male]	-0.029	-0.063	0.015	-0.058	-0.028	0.019	-0.074	0.013	0.01	-0.013
	[1.31]	[1.36]	[1.51]	[2.56]**	[3.37]***	[1.04]	[3.72]***	[0.52]	[0.38]	[0.95]
Primary incomplete or complete	-0.381	-0.012	-0.489	2.172	-0.996	-1.064	-0.093	-0.348	0.071	0.234
	[0.25]	[0.05]	[1.71]*	[2.98]***	[3.80]***	[2.19]**	[0.26]	[0.88]	[0.32]	[0.75]
Secondary incomplete or complete	0.777	0.721	-0.134	1.594	-1.148	-1.609	-0.464	-0.486	0.086	0.136
	[0.55]	[2.31]**	[0.52]	[2.22]**	[5.19]***	[3.06]***	[1.35]	[1.00]	[0.22]	[0.44]
Superior incomplete or complete	0.094	0.128	-0.529	1.34	-0.975	-0.038	-0.587	-0.536	0.034	0.089
	[0.07]	[0.41]	[1.92]*	[2.01]*	[4.14]***	[0.08]	[2.01]**	[1.27]	[0.11]	[0.37]
Number of Children	0.048	-0.015	0.032	-0.016	0.078	0.114	0.118	0.022	0.021	0.016
	[1.25]	[0.27]	[2.71]***	[0.34]	[3.48]***	[2.72]**	[3.57]***	[0.89]	[0.89]	[0.53]
Dwelling Characteristics Index	-0.015	0.007	-0.07	0.197	0.056	-0.111	-0.028	-0.01	0.053	0.014
	[0.36]	[0.25]	[1.81]*	[5.63]***	[8.48]***	[2.05]*	[1.95]*	[2.47]**	[3.07]***	[0.49]
Constant	0.129	-0.115	0.101	-0.295	1.766	1.469	1.175	0.88	0.231	0.139
	[0.09]	[0.20]	[0.40]	[0.40]	[8.53]***	[3.19]***	[3.60]***	[1.98]*	[0.59]	[0.50]
LR chi2	19.46	13.24	20.42	50.71	91.33	26.34	32.29	19.30	38.46	11.66
Log Likelihood	107.52	39.47	139.09	86.33	140.89	47.38	83.82	68.98	73.19	98.15
Observations	70	56	26	56	70	28	56	42	28	54

Absolute value of *t*-statistics in brackets.
* significant at 10%; ** significant at 5%; *** significant at 1%
Source: Authors' calculations based on IDB Research Department Harmonized Household Surveys.

The results suggest that education plays a statistical significant role on poverty mobility in Chile, Colombia and Costa Rica, although in different directions. The evidence seems to suggest that the possibilities of moving out of poverty (or not falling into it) for those with no education in Chile are substantially smaller than those of the educated (either at the primary, secondary or superior level). For Colombia and Costa Rica the results tell a story in which the uneducated have better prospects of upward (out of poverty) mobility.

5. Conclusions

Difficulties in the construction of panel-data have prevented a comprehensive analysis of mobility in Latin America and elsewhere in the developing world. This paper sheds some light on the implications of mobility in the Region by constructing, alternatively, a pseudo-panel for 14 countries over 11 years and eight birth cohorts. Our analysis focuses on the standard notion of income mobility and, in addition, explores a notion of "poverty mobility" around thresholds or poverty lines. We show that the Region as a whole is highly immobile both in income and poverty terms. However, a sizeable part of this immobility results from failing to account from the effects that personal and socioeconomic controls have on mobility (over 30 percent of the unconditional time-dependence mobility). Country-specific differences are also substantive and tend to cancel out when grouped into traditional sub-regions (Andes, Southern Cone, Central America). Current levels of incomes and poverty not explained by past levels of incomes or past poverty status may vary widely across countries, in some cases exceeding well over 50 percent of estimated changes. Specific to poverty mobility, we found statistically significant roles for age, gender and, to a lesser degree, education of the household head and dwelling characteristics.

Notwithstanding the limitations of the modeling, we reject as simplistic and misleading the widely accepted notion of a dominating socioeconomic immobility throughout the Region. This is a first step towards uncovering the underlying dynamics of poverty mobility. Further modeling efforts and the construction of appropriate panel data will be critical in providing further steps.

References

Albornoz, F., and M. Menéndez. 2004. “Income Dynamics in Argentina during the 1990s: ‘Mobiles’ Did Change over Time.” Washington, DC, United States: World Bank. Forthcoming.

Antman, F., and D. McKenzie. 2005. “Earnings Mobility and Measurement Error: A Pseudo-Panel Approach.” Stanford, United States: Stanford University. Mimeographed document.

Bourguignon, F., and C. Goh. 2004. “Estimating Individual Vulnerability to Poverty with Pseudo-Panel Data.” World Bank Policy Research Working Paper 3375. Washington, DC, United States: World Bank.

Browning, M., A. Deaton and M. Irish. 1985. “A Profitable Approach to Labor Supply and Commodity Demand over the Life-Cycle.” *Econometrica* 53(3): 503-544.

Calónico, S. 2006. “Pseudo-Panel Analysis of Earnings Dynamics and Mobility in Latin America.” Washington, DC, United States: Inter-American Development Bank, Research Department. Mimeographed document.

Comisión Económica para América Latina y el Caribe (CEPAL). 2007. *Panorama económico y social de América Latina y el Caribe*. Santiago, Chile: CEPAL. Santiago de Chile.

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

Contreras, D. et al. 2004. “Dinámica de la pobreza y movilidad social en Chile.” Santiago, Chile: Universidad de Chile. Mimeographed document.

Corbacho, A., M. García-Escribano and G. Inchauste. 2003. “Argentina: Macroeconomic Crisis and Household Vulnerability.” IMF Working Paper 03/89. Washington, DC, United States: International Monetary Fund.

Cuesta, J. 2006. “The Distributive Consequences of Machismo: A Simulation Analysis of Intra-Household Discrimination.” *Journal of International Development* 18: 1065-1080.

Deaton, A. 1985. “Panel Data from Time Series of Cross-Sections.” *Journal of Econometrics* (30): 109–126.

Fields, G. 2005. “The Many Facets of Economic Mobility.” Ithaca, United States: Cornell University, Department of Economics. Mimeographed document.

Fields, G., and F. A. Ok. 1999. “Measuring Movement of Incomes.” *Economica* 66: 455-71.

Fields, G., and M. Sánchez Puerta. 2005. “Earnings Mobility in Urban Argentina.” Background paper prepared for the World Bank. Washington, DC, United States: World Bank.

Fields, G. et al. 2006. “Inter-Generational Income Mobility in Latin America.” http://econ.ucsd.edu/%7Erduvalhe/research/Income%20Mobility%20LATAM%20Dec%2021%2006.pdf Forthcoming in *Economia*.

Galiani, S. 2006. “Notes on Social Mobility.” Buenos Aires, Argentina: Universidad de San Andrés. Mimeographed document.

Gaviria, A. 2006. “Movilidad social y preferencias por redistribución en América Latina.” Documentos CEDE 002678. Bogota, Colombia: Universidad de Los Andes-CEDE.

Girma, S. 2000. “A Quasi-Differencing Approach to Dynamic Modeling from a Time-Series of Independent Cross Sections.” *Journal of Econometrics* 98: 365-83.

Gottschalk, P. 1997. “Inequality, Income Growth and Mobility: The Basic Facts.” *Journal of Economic Perspectives* 11(2): 21-40.

Grim, M. 2007. “Removing the Anonymity Axiom in Assessing Pro-Poor Growth.” *Journal of Economic Inequality* 5(2): 179-97.

Huneeus, C., and A. Repetto. 2004. “The Dynamics of Earnings in Chile.” Documento de Trabajo 183. Santiago, Chile: Universidad de Chile, Centro de Economía Aplicada.

Inter-American Development Bank (IDB). 1998. *Facing Up to Inequality in Latin America*. Economic and Social Progress Report 1998/9. Washington, DC, United States: IDB.

Lillard, L., and R. Willis. 1978. “Dynamics Aspects of Earnings Mobility.” *Econometrica* 46(5): 985-1012.

McKenzie, D. 2004. “Asymptotic Theory for Heterogeneous Dynamic Pseudopanels.” *Journal of Econometrics* 120(2): 235-262.

Milanovic, B. 2006. “Global Income Inequality: What it is and Why it Matters.” World Bank Policy Research Working Paper 3865. Washington, DC, United States: World Bank. Moffit, R. 1993. “Identification and Estimation of Dynamic Models with a Time Series of Repeated Cross-Sections.” *Journal of Econometrics* 59: 99–124.

Navarro, A.I. 2006. “Estimating Income Mobility in Argentina with Pseudo-Panel Data.” Buenos Aires, Argentina: Universidad de San Andrés, Department of Economics. Mimeographed document.

Ravallion, M., and S. Chen. 2003. “Measuring Pro-Poor Growth.” *Economic Letters* 78: 93-8.

Reddy, S., and T. Pogge. 2003. "How Not to Count the Poor." Available at www.socialanalysis.org.

Sala-i-Martin, X. 2006."The World Distribution of Incomes: Falling Poverty and Convergence, Period." *Quarterly Journal of Economics* 121(2): 351-97.

Scott, C. 2000. "Mixed Fortunes: A Study of Poverty Mobility among Small Farm Households in Chile, 1968-86." *Journal of Development Studies* 36: 155-180.

United Nations Development Programme (UNDP). 2006. *Human Development Report*. New York: Oxford University Press.

Verbeek, M., and F. Vella. 2002. "Estimating Dynamic Models from Repeated Cross-Sections." Leuven, Belgium: K.U. Leuven Center for Economic Studies. Mimeographed document.

Vos, R. et al. 2006. *Who gains from Free Trade? Export-led Growth and Poverty in Latin* America, London: Routledge.

World Bank. 1990. *World Development Report 1990*. Washington, DC, United States: World Bank.

----. 2003. *Inequality in Latin America and the Caribbean: Breaking with History?* Washington, DC, United States: World Bank.

Annex 1. Data Sources

Table 1. Coverage of Data Sources

Country	Survey	Number of surveys per year	Chosen survey	Coverage
Argentina	Encuesta Permanente de Hogares (EPH)	May and October	October	Urban - 15 cities (1992-1998)
Brazil	Pesquisa Nacional por Amostra de Domicilios (PNAD)	Once a year	September	Urban - 28 cities (1999-2002)
Bolivia	Encuesta de Hogares	Once a year	October-November	National
Chile	Encuesta de Caracterización Socioeconómica Nacional (CASEN)	Once a year	November	National
Colombia	Encuesta Continua de Hogares	Once a year	Monthly	National
Costa Rica	Encuesta de Hogares de Propósitos Múltiples (EHPM)	Once a year	July	Urban (1992) National (1993-2002)
Honduras	Encuesta Permanente de Hogares de Propósitos Múltiples	May and September	September	National
Mexico	Encuesta Nacional de Ingreso y Gastos de los Hogares (ENIGH)	Once a year	August-November	National
Panama	Encuesta de Hogares	Once a year	August	National
Paraguay	Encuesta Permanente de Hogares	Once a year	August-December	National
Peru	Encuesta Nacional de Hogares sobre Medición de Niveles de Vida	Quarterly	IV quarter	National
El Salvador	Encuesta de Hogares de Propósitos Múltiples (EHPM)	Once a year	January-December	National
Uruguay	Encuesta Continua de Hogares	Once a year	XXX	National
Venezuela	Encuesta de Hogares por Muestreo	Twice a year	July-December	Urban

Source: Own calculations based on IDB Research Department Harmonized Household Surveys.

Annex 2. Sensitivity Analysis

Table 1. Estimates of Unconditional and Conditional Time-Dependence Income Mobility in Latin America Using Four-Year Cohorts

	I	II	III	IV	V	VI	VII	VIII	IX
Estimated Income Mobility - Equation (3)	$\overline{\ln y}_{c(t),t} = \beta_c \ln \overline{y}_{c(t-1),t-1} + \delta_c \overline{X}_{c(t),t} + \mu_{c(t),t}$								
B	0.966	0.736	0.696	0.693	0.949	0.716	0.68	0.681	0.582
	(807.29)**	(81.00)**	(69.91)**	(63.45)**	(248.57)**	(78.14)**	(69.60)**	(63.31)**	(59.62)**
R^2	0.995	0.998	0.999	0.999	0.999	0.998	0.999	0.998	0.999
N. observations	1320	1320	1320	1110	1320	1320	1320	1110	1110
Estimated Income Mobility - Equation (4)	$\Delta \ln \overline{y}_{c(t),t} = \beta_c \overline{\ln y}_{c(t-1),t-1} + \delta_c \Delta \overline{X}_{c(t),t} + \mu_{c(t),t}$								
B	-0.034	-0.192	-0.183	-0.181	-0.051	-0.2	-0.193	-0.192	-0.198
	(28.16)**	(20.08)**	(20.11)**	(17.47)**	(13.40)**	(22.39)**	(22.80)**	(19.91)**	(20.57)**
R^2	0.38	0.52	0.55	0.56	0.53	0.58	0.62	0.63	0.7
N. observations	1,320	1,296	1,320	1,044	1,320	1,296	1,320	1,044	1,044
Controlling By									
Age	No	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes
Age^2	No	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes
Gender	No	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes
Years of Education	No	Yes	No	No	No	Yes	No	No	No
Number of Children	No	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes
Number of Other relatives	No	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes
Educational Dummies	No	No	Yes	Yes	No	No	Yes	Yes	Yes
Dwelling Characteristics	No	No	No	Yes	No	No	No	Yes	Yes
Regional Dummies	No	No	No	No	No	Yes	No	Yes	No
Country Dummies	No	No	No	No	Yes	No	Yes	No	Yes

Absolute value of t statistics in brackets
* significant at 10%; ** significant at 5%; *** significant at 1%
Source: Own calculations based on IDB Research Department Harmonized Household Surveys.

Table 2. Estimates of Unconditional and Conditional Time-Dependence Income Mobility in Latin America Using Six-Year Cohorts

	I	II	III	IV	V	VI	VII	VIII	IX
Estimated Income Mobility - Equation (3)	$\overline{\ln y}_{c(t),t} = \beta_c \overline{\ln y}_{c(t-1),t-1} + \delta_c \overline{X}_{c(t),t} + \mu_{c(t),t}$								
B	0.967 (685.62)**	0.745 (67.94)**	0.703 (58.67)**	0.699 (53.09)**	0.95 (210.12)**	0.722 (65.18)**	0.685 (58.45)**	0.687 (53.18)**	0.582 (49.94)**
R^2	0.995	0.998	0.999	0.999	0.999	0.998	0.999	0.998	0.999
N. observations	912	912	912	768	912	912	912	768	768
Estimated Income Mobility - Equation (4)	$\Delta \ln \overline{y}_{c(t),t} = \beta_c \overline{\ln y}_{c(t-1),t-1} + \delta_c \Delta \overline{X}_{c(t),t} + \mu_{c(t),t}$								
B	-0.033 (23.56)**	-0.188 (16.07)**	-0.18 (16.23)**	-0.178 (13.91)**	-0.05 (11.14)**	-0.198 (18.01)**	-0.193 (18.72)**	-0.193 (16.25)**	-0.198 (16.81)**
R^2	0.38	0.51	0.55	0.56	0.54	0.58	0.62	0.63	0.7
N. observations	912	896	912	720	912	896	912	720	720
Controlling By									
Age	No	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes
Age^2	No	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes
Gender	No	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes
Years of Education	No	Yes	No	No	No	Yes	No	No	No
Number of Children	No	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes
Number of Other relatives	No	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes
Educational Dummies	No	No	Yes	Yes	No	No	Yes	Yes	Yes
Dwelling Characteristics	No	No	No	Yes	No	No	No	Yes	Yes
Regional Dummies	No	No	No	No	No	Yes	No	Yes	No
Country Dummies	No	No	No	No	Yes	No	Yes	No	Yes

Absolute value of *t*-statistics in brackets
* significant at 10%; ** significant at 5%; *** significant at 1%
Source: Authors' calculations based on IDB Research Department Harmonized Household Surveys.