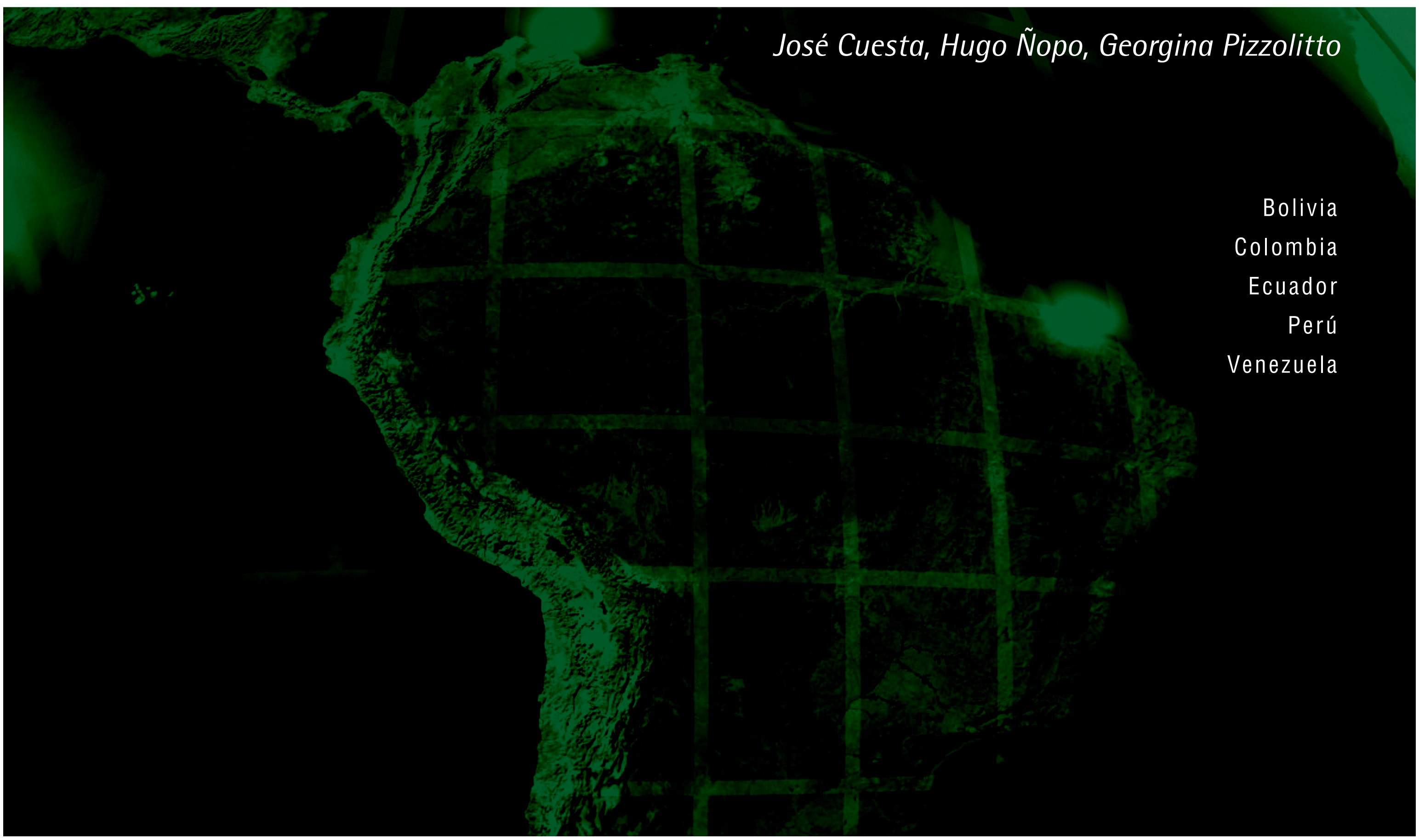
Country Department Andean Group

Income Mobility in Latin America



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Foreword

Latin America is the most unequal region in the world. High levels of inequality are pervasive in spite of recent economic growth, institutional development and deliberate targeted social interventions. Critical for the effective combat of inequality is the realization that its resilience is not a static phenomenon. Instead, inequality is dynamic, affected by structural and transitory components, region-wide and country specific drivers. Understanding its dynamics is an important tool for policy-making. When governments know the details about the most effective ways of moving people up or prevent them from falling down along the income ladder, the design of policies becomes more effective. Also, when governments understand better the tools to cope with downward mobility, the welfare losses associated could be at least ameliorated, social investment and social protection interventions better conceived.

Although the term 'pro-poor growth' has been only recently coined, the Bank has been working since its inception in fostering a regional development that creates economic growth, protection for the most vulnerable in periods of crisis and opportunities for a permanent graduation from poverty. Analytically, the Bank has contributed to unveil the taxonomy and evolution of inequality, its determinants and causes. The current study constitutes a comprehensive attempt to understand the dynamics of incomes in the region. The number of countries analyzed, the time span covered, the number of cohorts followed over time and the represented population are unprecedented. Interestingly, the study confirms the previous finding of very limited income mobility in the region. However, it shows that a large part of that regional immobility is not necessarily permanent but depends on factors susceptible to improvement under effective interventions. Country-specific results substantiate this finding, showing wide variations of mobility by country. One-size-fits-all interventions will not bring about uniform reductions of inequality across the region.

This study is the result of inter-agency and inter-division work by a team consisting of José Cuesta (SCL/SPH), Hugo Ñopo (RES) and Georgina Pizzolitto (World Bank). The authors thank Sebastián Calónico, participants at the 12th LACEA meetings and an anonymous referee for valuable comments; Michael Jacobs, Division Chief (SCL/SPH) and Fidel Jaramillo (CAN/CAN) for their material support and Francesca Castellani (CAN/CAN) and Leticia Recalt (CAN/CAN) for the preparation of the publication.

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Income Mobility in Latin America: A Pseudo-Panel Approach

José Cuesta, Hugo Ñopo, Georgina Pizzolitto*

Abstract

This paper presents a comparative overview of income mobility patterns in Latin America. We construct a pseudo-panel for 14 Latin American countries between 1992 and 2003, unprecedented in the Region for its length and breadth. Estimates of time-dependence unconditional income mobility show that this is rather limited, as previously found in the scarce existing literature. However, after introducing personal, socioeconomic, demographic and geographical controls, conditional income mobility rises substantively for the Region. Also, unconditional and conditional income mobility show large variations across countries.

Keywords: Income Mobility, Poverty, Pseudo-Panels, Latin America

JEL Codes: D3 (distribution); I3 (welfare and poverty); O1 (economic development)

* Cuesta and Ñopo: Inter-American Development Bank; Pizzolitto: World Bank. The results and conclusions expressed in this research document are those of the authors and do not compromise the views of neither Bank nor their Boards of Directors.

1. Introduction

Latin America is the most unequal region in the world. The discussion behind this salient feature has agreed on some of its causes: pervasive levels of macro-economic vulnerability, inequality in political voice and problems of social exclusion that are rooted in history (Vos et al. (2006), World Bank (2003) and IADB (1998) among others). The role of mobility on the analysis of inequality has been emphasized only recently, however (see Fields (2005), Galiani (2006) for recent reviews). The static measures of inequality are not enough to picture the well being of individuals in a society, and so they need to be complemented by the dynamics of mobility. For example, societies with prevailing exclusion (that is, individuals or groups neglected of access to services, consumption goods and assets) should expectedly have low upward mobility. Instead, societies that have actively combated exclusion should reflect high upward mobility (as reported for Chile by Scott 2000). In societies vulnerable to macro-economic shocks and ineffective social protection mechanisms, individuals may face high levels of downward income mobility (as reported for Argentina by Corbacho et al 2003).

This study is a contribution to the limited literature on income mobility in Latin America.[1] The lack of analysis has been the result of data requirements that the Region has been unable to provide fully yet, that is, panel data. By constructing, alternatively, a pseudo-panel for 14 countries between 1992 and 2003, this regional study applies the new methodological developments on the analysis of mobility in an unprecedented number of countries and years. There are several reasons for choosing a regional focus, but the most important one, from a policy-making 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 on 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 *unconditional* income mobility and *conditional* mobility (after controlling for personal, socioeconomic demographic and geographical features). Section 3 describes the construction of the pseudo-panel used in this study and explores mobility trends for the Region. Section 4 discusses the main results of the analysis: one, unconditional mobility is very low but rises significantly when controls are introduced; two, country-specific income mobility varies largely. Section 5 provides concluding remarks.

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:

[1] However, this literature is recently growing with the use of several methods to analyze mobility from transition matrices to econometric techniques or by estimating measures of permanent income. These techniques may refer to panel data, pseudo-panel or longitudinal data. The unit of observation can also vary, from individuals to workers, districts within a city or cities and regions in a country. For a detailed description see Fields et al (2006).

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

Where $y_{i,t}$ is the total labor 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) refers to it as *time-dependence* mobility and it will be the focus of our paper.[2] 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 about 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. Provided that an analysis of mobility of this sort implies to follow individuals (or households) over time, the quintessential data tool has been panel data. Unfortunately the development of this kind of tool has been only recent in Latin America and the few panels of data available as of today 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 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 observation can be thought as being “followed” over time. The model then requires an appropriate modification:

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[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 individuals incomes but not their sign); directional income movement (how many people move up or down 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). By far, 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), that have a rotating panel, with household followed for five consecutive quarters. Also in Argentina (1988 to date), Brazil (1980 to date), Peru (1991-1997), and Venezuela (1994-1999) have household survey with the same design. See Fields et al (2006) for more details.

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

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 parameter can be consistently estimated in a context of repeated cross-section (instead of real panel data). The works of Browning et al. (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 under which β can be properly estimated.
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Not surprisingly, there are pros and cons about the use of pseudo-panels for the analysis of mobility. Among arguments in favor of it we can cite at least three. The first is that they suffer less from problems related to sample attrition (because the samples are renewed at every period). Other is that, being constructed averaging groups of individual observations, they also suffer less from problems related to measurement error (at least the individual-level one). A third argument in favor, more practical, 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) for which the literature has not been conclusive yet. The larger the number of cohorts, the smaller is the number of individuals per cohort. One the one hand, one would like to have a large number of cohort observations such that the regressions performed with the resulting pseudo panels suffer less from small sample problems. However, on the other hand, if the number of observations per cohort were not large enough, the average characteristics per cohort would fail to be good estimates for the population cohort means (McKenzie 2004). 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 pseudo-panels assume intra-cohort homogeneity (consistent with the notion of 'representative' agents) arguably 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, Antman and Mckenzie (2005) for Mexico and by Calónico (2006) for a set of 8 countries (Argentina,

[4] There is, however, no easy way to measure the impact of migration in the observed mobility. One of the obvious 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 generate). But they are also likely to affect other income-generating decisions such as whether to work or not and how hard to do it.

[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.

Brazil, Chile, Colombia, Costa Rica, Mexico, Uruguay and Venezuela). The latter found low patterns of mobility for all these countries during the 1992-2002 period. When trying to compare the results from both papers for Argentina we still found some differences. First, they use different time spans. Navarro computed mobility for the period 1985-2004, while Calónico did it for 1992-2003. Second, the studies differ in the concept of income used. While Calónico uses monthly labor incomes, Navarro based her analysis in hourly wages received by individual 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 Sanchez-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 (2003), Grimm (2007), among others, explore whether economic growth has favoured the poor in the US, UK and other OECD countries, 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 lots of 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% of per capita incomes, poverty in the US between 1973 and 1994 increased from 11.1% to 14.5%.[6]

Our study complements previous work both in scale and scope as it explores 14 countries during the period 1992 to 2003. On top of obtaining the cohort-mobility estimators (both unconditional and conditional β and β_c in Equations (2) and (3), respectively), we also explore the role of the initial level of income on the change observed in the incomes of the pseudo-individuals as well as other controls. This new estimator will tell the impact that the changes, rather levels, of initial income has on the variation of that income to be expected in the next period.

$$\Delta \overline{y}_{c(t),t} = \beta_c \overline{y}_{c(t-1),t-1} + \delta_c \Delta \overline{X}_{c(t),t} + \mu_{c(t),t} \qquad (4)$$

[6] The author indicates that US is the only country among OECD countries where family earnings inequality was larger than individual earnings inequality: labour decisions, taxes and transfers did not work out to reduce inequalities.

3. Data

The raw data for this study comes from national household surveys of 14 Latin American countries in the region.[7] These surveys have been harmonized to ensure a comparable definition of household incomes across countries. Countries included in the pseudo-panel share the same sources of labor incomes: labor –approximately 75% of the Region's average household incomes– and non-labor incomes –accounting for the remaining 25%. Countries that fail to report non-labor incomes in their household surveys were excluded of the pseudo-panel. That 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.[8] All incomes were deflated using the Consumer Price Index of each country and year. We also adjusted the incomes using the Purchasing Power Parity –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 at 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 to construct the pseudo-panel consisted of maximizing the number of homogenous observations. That meant to restrict the panel to one survey round (or sub-period) per country and period, and consider 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.[9] 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.[10] 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)[11]. Whether that means a loss of information from available surveys in some countries it allowed to have the highest number of countries with information

[7] The countries are: Argentina, Brasil, Bolivia, Chile, Colombia, Costa Rica, Honduras, México, Panamá, Paraguay, Perú, El Salvador, Uruguay and Venezuela

[8] 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.

[9] Only four of the 14 countries had multiple rounds in any given year: Argentina, Colombia, Peru and Venezuela.

[10] In any case, we ensured that the income variable referred to the same reference period, that is, the previous month. 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. Whether the selection of odd years instead of even years would introduce any biases to our estimates is unclear. One would not argue that election years, domestic and international shocks, for example, take place disproportionately on either odd or even years.

[11] In addition, the 1992 survey in Colombia was urban. In Argentina and Uruguay, urban population covered in the survey represents o62% and 80% of the total population for 2003, respectively.

available for the largest number of periods, in this case, six.[12] 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 not longer tied to the customary year logic but instead to two-year periods.

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.[13] See Annex 2. Cohorts are constructed based on year of birth, country of residence and gender. Urban/rural area could have been another possible candidate to define our cohorts. However, residence in urban or rural areas 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 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 representing household heads. 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 subject to analysis) and in others it was not possible to harmonize variables. As a result the number of synthetic observations was reduced to 1,024. Table 1 below reports cohorts' sizes (and Annex 1 reports the sources of information used to construct the cohorts in each country).

This pseudo-panel exceeds both the depth and breath of other pseudo-panels for the Latin American region. Also, this pseudo-panel strikes a balance between a relevant number of cohorts and a meaningful size of the cohort. An insufficiently large number of cohorts cause pseudo-panel estimations to suffer from small sample problems. An insufficiently large cohort size causes its averages not to be good estimates for the population cohort characteristics.

[12] In fact, there is not a period of time between 1990 and 2006 for which all fourteen countries in our sample collected their household survey. Only Argentina, Costa Rica and Venezuela collected uninterruptedly household surveys between 1992 and 2003.

[13] 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.

Table 1: Cohorts' sizes

	Period						
	T1	T2	T3	T4	T5	T6	Total
Year Birth Cohort	1992-3	1994-5	1996-7	1998-9	2000-1	2002-3	1993- 2002
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	9,34	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: Own calculations based on IDB Research Department Harmonized Household Surveys.

Table 2 provides the basic descriptive statistics of the pseudo-panel: personal, socioeconomic, demographic and geographical characteristics of synthetic household heads of the constructed cohorts. The average household per capita income, in the pseudo-panel earns about US$ 456 dollars 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% of the household heads have no education; 44% have primary education –either incomplete or complete–, while 33% have started or completed secondary education. The remaining 14% have college education. The average household has two children. We also construct an index of the dwelling characteristics to reflect the assets of the household. The index varies from zero to two and reflects the quality and availability of services in the dwelling.[14] The mean of the dwelling index is 1.27. Table 2 also reports the distribution of observations by sub-regions[15] and the average inter-period changes of the incumbent variables used in the analysis. Inter-period changes show that despite the number of years of education have 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 index– have increased substantially, even though their improvement does not follow a similar trend that that of per capita household incomes. Once again, these trends of decreasing aggregated or average incomes may conceal diverging trends at different regions of the income distribution. If that is the case, the incidence of poverty may not necessarily follow the same trend that

[14] The index takes into account the quality of the materials used for the walls, the number of rooms, if the household has a restroom with a toilet connected to a sewerage system or to a septic tank, the access to a source of safe water, and the possession of a phone, refrigerator and stove. The index is constructed taking the average of the selected dwelling characteristics.

[15] 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.

that of average incomes, as it is the case in the Latin American region during the Nineties (see recent trends on poverty and per capita GDP for the Region in CEPAL 2007).

Table 2: Data Descriptive Statistics

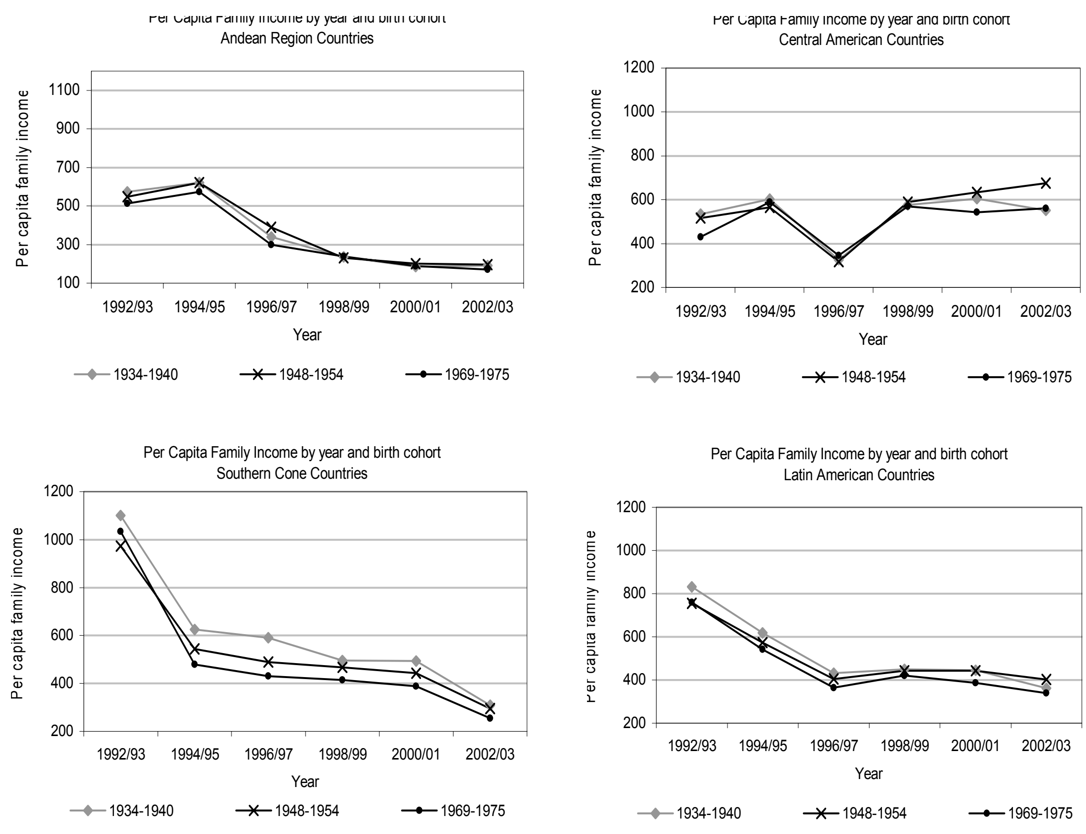
Variable	Number of observations (in pseudo panel)	Mean	Standard Deviation	Average inter-period variation (%)
Log Per Capita Household Incomes	1,024	5.36	0.68	-3.64%
% Female-headed households	1,024	0.50	0.50	0.11%
Age	1,024	43.22	13.84	0.02%
Years of Education	1,010	7.15	2.26	0.89%
No Education	1,024	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%
Dwelling Index	864	1.27	0.28	2.87%
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: Own calculations based on IDB Research Department Harmonized Household Surveys.

Figure 1 below depicts regional and sub-regional trends of per capita monthly household incomes for selected birth cohorts (results do not change for the rest of cohorts). These trends confirm previous evidence based on individual labor incomes pointing to limited mobility in the Region (see Calónico 2006). Even when trends differ among sub-regions, cohorts of young adults, prime-age and retirees follow similar patterns within each sub-region. 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 have increased in the Nineties, as reported by CEPAL (2007), and accompanied by a marked decrease in poverty during the same period from 48% in 1990 to 39% 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 considered period. As a result, if poverty incidence is to change, it should not be expected to do so largely as there are substantive composition effects from households leaving poverty and households slipping into it. This evidence in Latin America confirms evidence reported in the US pointing to diverging trends of GDP growth, mean earnings and poverty incidence (see Gottschalk 1997). Second, GDP trends refer to the nominal purchasing power of each national currency in its respective country, while Figure 1 reports the PPP-adjusted real trends. That is, Figure 1 reports the real purchasing power of local currencies in the international economy or, more specifically, how, for instance, the purchasing power of a Chilean peso or a Venezuelan Bolivar 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.

Figure 1: Income Trends by Sub-Region



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

When we analyze mobility with respect to poverty lines (using the international thresholds of US$1/day and US$2/day/person for extreme and total poverty, respectively), we also conclude that mobility is limited. Before discussing these results, it is worth noting that the US$1 /day and US$2/day per person are widely used international poverty lines accepted to estimate global poverty. World Bank (1990) introduced its use. 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$1.08 to reflect 1993 PPP$. Criticisms to this methodology argue that it either consistently underestimates the number of the poor (Reddy and Pogge, 2003) or grossly overestimates them (Sala-i-Martin 2006). 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's malnutrition and population 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 this paper. We follow the vast tradition of considering the US$2/day 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 using a US$1/day line)

Table 3, upper panel, reports that about 15% of the synthetic households (represented by their household heads) crossed the US$2/day/person threshold and less than 10% did so with respect to the US$ 1/day/person line. Interestingly, the numbers of households slipping into and moving out these thresholds are almost identical: 51% of these *mobile* households moved out of the threshold line; the remaining 49% slipped into poverty. In addition to describing its poverty dynamics, we can characterize the period in static terms. The lower panel in Table 3 shows that some 17% and 52% of all synthetic (or cohort representative) households were extremely poor or poor at some point between 1992 and 2003, respectively.

Table 3: Poverty Mobility

PERIOD	Mobility around the US$1/day threshold (% of synthetic households)		Mobility around the US$2/day threshold (% of synthetic households)	
t+1 t	Poor	Non Poor	Poor	Non Poor
Poor	11.72%	4.86%	36.74%	8.09%
Non Poor	4.61%	78.8%	7.60%	47.57%

	Incidence with respect to US$1/day threshold (distribution of synthetic households in each category)		Incidence with respect to US$2/day threshold (distribution of synthetic household in each category)	
N	178	846	536	488
%	17.38%	82.62%	52.34%	47.66%

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

Further analysis reveals that households moving in and out of extreme poverty (threshold of US$1/day/person) share more characteristics than those moving around the US$2/day/person poverty line. Table 4 shows that households pertaining to the two cohorts defined between 1955 and 1968 represent two thirds of the *mobile* households around the extreme poverty line. In contrast, those cohorts only explain 37% and 25% of the mobility out and into the US$2/day/person line, respectively. Households whose heads are aged 18 to 34 represent some 57% of those slipping into poverty but only 28% of those able to escape from poverty.

Table 4: Cohorts Mobility

Birth Cohort	Poor to Non Poor	Non Poor to Poor
US$1/day/person		
1927-1933	0.00	0.03
1934-1940	4.08	2.49
1941-1947	4.35	2.09
1948-1954	3.42	7.02
1955-1961	18.97	31.01
1962-1968	46.09	34.96
1969-1975	15.90	5.53
1976-1980	7.20	16.88
Total	100.0	100.0
US$2/day/ person		
1927-1933	1.80	0.55
1934-1940	7.43	5.56
1941-1947	10.01	2.74
1948-1954	15.19	9.92
1955-1961	23.91	9.98
1962-1968	13.50	14.31
1969-1975	26.05	36.61
1976-1980	2.10	20.33
Total	100.0	100.0

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

Table 5 confirms the existence of disparities between mobility around the US$1 and US$2/day/person lines. There are not statistically significant differences between households moving in and out of the US$1/day/person line in terms of gender and education of the household head, household size and dwelling characteristics. After all, these are variables whose changes throughout the period considered are either not substantial or, if so, subject to composite effects that reduce the total impact, as shown above in Table 2. Only age plays a role, with poor households able to move out of extreme poverty being older, on average, than other *mobile* households. In contrast, younger and more educated household heads in smaller households are more likely to slip into poverty than are such households to move out of poverty. This may simply reflect the different initial conditions of non-poor households before slipping into poverty rather than conditions that cause a household's slipping into poverty at any given time. In other words, mobility takes place among households whose heads have sufficient educational levels so as to escape poverty in the first place but not sufficiently high as to be permanently protected against shocks or other circumstances that may make their households slip into poverty. Instead, there are not significant educational differences among those who transit in and out of extreme poverty (that is, around the US$1/day/person), be it to leave it or plunge into it. In addition, it should be noted that these are cross-countries averages throughout a period of 12 years and different educational systems. For this reasons, these comparisons should be taken with great caution.

Table 5: Differences in Characteristics among Households

Characteristics	Poor to Non Poor	Non Poor to Poor	Remains Poor	Never Poor
US$1/day/ person				
Age	44.86	38.84	41.25	38.91
		[6.02]**	[3.61]	[5.95]***
Gender	0.23	0.25	0.41	0.48
		[-0.03]	[-0.18]**	[-0.25]***
Years of education	6.79	7.29	7.52	7.20
		[-0.50]	[-0.73]**	[-0.40]
Number of Children	2.01	2.10	2.42	1.83
		[-0.09]	[-0.40]***	[0.18]
Number of Other relatives	0.77	0.67	0.73	0.38
		[0.10]	[0.05]	[0.39]***
Dwelling Characteristics	1.18	1.13	1.22	1.35
		[0.05]	[-0.04]	[-0.17]***
US$2/day/ person				
Age	42.79	34.11	39.13	39.55
		[8.68]***	[3.66]**	[3.24]*
Gender	0.50	0.41	0.36	0.52

		[0.09]	[0.14]**	[-0.02]
Years of education	7.18	8.25	7.25	7.01
		[-1.08]***	[-0.07]	[0.17]
Number of Children	1.86	1.85	2.11	1.77
		[0.01]	[-0.24]***	[0.09]
Number of Other relatives	0.57	0.44	0.58	0.32
		[0.13]**	[0.00]	[0.25]***
Dwelling Characteristics	1.31	1.22	1.20	1.42
		[0.09]*	[0.11]***	[-0.11]***

Source: Own calculations based on IDB Research Department Harmonized Household Surveys. (***) statistical significance at 1%; (**) at 5%; (*) at 10%. Standard errors are presented in brackets. The variable 'gender' in here is interpreted as the proportion of households within each category that were female headed. Thus, only 23% of households moving from poverty to non-poverty are female-headed.

4. Estimation Results

In this section we provide estimates of income mobility. 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 over the total household size as reported by the household survey selected in each two-year period. Table 6 below reports estimates of time-dependence income mobility for Latin America as a region. Mobility is first reported as the elasticity of current incomes with respect to past incomes. As indicated in the Section 2, the inclusion of personal, socioeconomic, demographic and geographical controls determines several specifications of conditional mobility. In addition to specification I, the unconditional mobility model, specifications II to IX are constructed by introducing progressively such controls. The lower part of Table 6 reports the controls included in each specification. The sequential introduction of such controls allows us to better understand the marginal impact of socioeconomic and demographic factors versus geographical location. An additional time-dependence mobility indicator is also reported as the elasticity of future income changes with respect to initial incomes. This indicator differs from the former most traditional measure of time-dependence mobility in that captures how the magnitude of changes rather than levels of incomes affects the expected income mobility of that pseudo-individual.

Results confirm a very low degree of income mobility for Latin America as a region, as previously found in literature. The estimate of the unconditional mobility indicator, β , is as high as 0.996 (see specification I in the upper panel in Table 6). This changes substantially after controls are introduced. Specifications II to IV gradually introduce personal and socioeconomic controls such as age, gender, education, number of children and housing conditions (that is, the dwelling index acting as a proxy for satisfaction of basic needs). The estimated mobility indicator falls from 0.99 to 0.70. Furthermore, specifications V to VIII introduce regional controls. A meager additional 0.5% of inter-temporal income variation is captured when these regional controls are added to previous specifications. When country dummies are introduced instead of regional dummies (specification IX), they capture an additional 10% of the inter-temporal income variation. 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.

Table 6: Estimates of Unconditional and Conditional Time-Dependence Income Mobility in Latin America[16]

	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	0.966	0.744	0.707	0.704	0.949	0.723	0.69	0.693	0.588
	(645.45)**	(64.85)**	(55.59)**	(50.24)**	(199.03)**	(62.07)**	(55.40)**	(50.50)**	(46.91)**
R^2	0.998	0.997	0.998	0.999	0.999	0.997	0.999	0.999	0.999
N. observations	800	800	800	672	800	800	800	672	672
Estimated Income Mobility - Equation (4)	$\Delta\overline{\ln y}_{c(t),t} = \beta_c \overline{\ln y}_{c(t-1),t-1} + \delta_c \Delta\overline{X}_{c(t),t} + \mu_{c(t),t}$								
B	-0.034	-0.196	-0.184	-0.182	-0.051	-0.203	-0.196	-0.196	-0.202
	(22.41)**	(16.25)**	(15.75)**	(13.64)**	(10.65)**	(17.94)**	(18.16)**	(15.85)**	(16.76)**
R^2	0.390	0.520	0.550	0.560	0.550	0.590	0.620	0.630	0.720
N. observations	800	800	800	672	800	800	800	672	672
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

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

16 For presentation reasons, complete estimates for all specifications in this table and Table 7 are not reported in this paper. They are available upon request to the authors.

The impact of previous incomes on today's incomes is additionally explored by looking at how initial levels of income affect changes observed in the following period. See the middle panel in Table 6. Implicitly, the comparison on mobility results from both sets of equations informs on the additional information that brings the change in the levels of our control variables. Except for specifications I and V, [17] which lack of control, the rest of specifications indicate that changes are able to explain some 20% of the observed variation of incomes. We can also interpret this as an additional refinement of the attribution of the observed changes when we control for country-specific heterogeneity that is unlikely to change over time. That heterogeneity may have to do with labor institutions, business climate, cultural, demographic or geographic factors, among others, that vary across countries but are unlikely to change over time in a given country.

In any case, this alternative set of specifications confirms that the level of previous incomes plays a significant role in explaining today's incomes. The higher is the starting level of income, the lower its variation should be expected in a subsequent period. This can be interpreted as some form of diminishing returns law ruling the dynamics of income mobility. Its magnitude, however, varies according to the selected specification. Unsurprisingly, those with higher incomes are more capable of sustaining them, either because they possess larger stocks of human capital or have better access to insurance against shocks. When controls are introduced (specifications II to IX), this result becomes stronger, turning sizeable variations even less likely.

If initial levels of income play a significant role in explaining mobility, a country-specific analysis of mobility should reveal the heterogeneity of existing income levels across the Region. Table 7 reports country-specific estimates of mobility for the specification IV, which includes all personal, socioeconomic and demographic controls.

The estimates of income mobility in Table 7 are expressed as elasticities, which allows for a meaningful comparison across countries with different starting income levels. Estimated elasticities vary widely across country, as predicted. High levels of time-dependence income immobility (β exceeding 0.8) are only found in Brazil, Colombia and Paraguay, while the rest of the Region shows much higher levels of mobility (lower β). Countries such as Chile or Argentina show a moderate immobility (β between 0.66 and 0.79) compared with other *mobile* countries (β below 0.66). These results confirm that a higher mobility is found across countries when countries are considered separately than when countries are being pooled regionally, as it was the case with results for Argentina using Navarro (2006) and Calónico (2006). Also, our results are consistent with Contreras et al (2004)'s conclusion of restrained mobility in Chile. Even when this limited evidence does not allow for generalizations, it may be that region-pooled estimates average out different country-specific patterns of income mobility.

The above conclusion holds when country specific estimates of mobility are obtained using changes in income (equation 4) instead of levels of income (equation 3). The right

[17] Note that the β's for both specifications in the upper and middle panel add up to 1, that is, both β's provide exactly the same information in different units (levels and change).

hand side columns in Table 7 show that the level of past incomes may exert either a positive or negative impact in future incomes. Higher levels of past incomes are associated with larger increases in current incomes in Argentina, Chile and El Salvador, although it is only Chile (which managed to sustain its record of economic growth during the last 20 years) where such an impact is statistically significant. In the remaining countries, higher levels of previous incomes are associated with lower variations of future incomes: poorer countries exhibit larger time-dependence income mobility.

Table 7: Country-specific Estimates of Unconditional and Conditional Time-Dependence Income Mobility in Latin America

	Estimated Income Mobility Equation (3) $\overline{\ln y}_{c(t),t} = \beta_c \overline{\ln y}_{c(t-1),t-1} + \delta_c \overline{X}_{c(t),t} + \mu_{c(t),t}$		Estimated Income Mobility Equation (4) $\Delta \ln \overline{y}_{c(t),t} = \beta_c \overline{\ln y}_{c(t-1),t-1} + \delta_c \overline{\Delta X}_{c(t),t} + \mu_c$		
Country	Specification I (*)	Specification IV(*)	Specification IV		N
	β	β_c	β_c	R2	
Argentina	0.975	0.74	0.035	0.37	70
	192.20**	2.70**	0.44		
Bolivia	0.973	0.37	-0.026	0.47	40
	125.66**	5.24**	0.35		
Brazil	0.982	0.85	-0.051	0.95	56
	840.59**	20.14**	3.87**		
Chile	0.995	0.68	-0.068	0.89	56
	333.34**	7.60**	2.70*		
Colombia	0.964	0.81	-0.136	0.96	70
	204.16**	20.66**	7.80**		
Costa Rica	0.973	0.53	-0.472	0.85	28
	238.98**	2.59*	2.31*		
Honduras	0.96	0.09	-0.118	0.9	44
	123.32**	1.71*	2.27*		
Mexico	0.945	0.42	-0.32	0.9	56
	133.95**	12.54**	7.44**		
Panama	0.999	---	---		
	281.24**	---	---		
Peru	0.945	0.15	-0.056	0.87	44
	133.95**	17.1*	1.45		
Paraguay	0.996	0.88	-0.069	0.95	42
	175.12**	10.00**	2.69*		
El Salvador	0.955	0.47	0.017	0.53	28
	257.19**	2.86*	0.17		
Uruguay	1.005	0.3	-0.465	0.87	70
	306.65**	8.68**	10.11**		
Venezuela	0.896	0.4	-0.342	0.98	54
	151.62**	16.27**	15.08**		

Note: (*) R^2 for specification I in all countries revolves around 0.95 and for specification IV exceeds 0.99. Tables report t-statistics below each estimated β coefficient. Cohort averages are weighted by the expansion factors in each survey.
Source: Own calculations based on IDB Research Department Harmonized Household Surveys.

Next we disaggregate the sources of time-dependence income mobility by separating labor and non-labor incomes and estimating their respective parameter β. This exercise constitutes only a proxy to understand the role that social policies may have had in the Region in terms of enabling mobility. This analysis is a simple first step in that direction, since available data do not allow for singling out social incomes or public transfers from other non-labor incomes. Most countries did not simply report information precise enough to make this distinction. Also, none of the household surveys report in-kind transfers. Estimating such transfers is a demanding task on its own, as shown in Cuesta (2004) for Chile, and well beyond the scope of this paper. In addition, there are also issues of potential endogeneity between social and labor incomes that are not dealt with in this analysis. In as much as the reception and the level of pensions and social transfers are related to past and present labor incomes, endogeneity emerges as a problem. Only universal transfers may not face such biases, as they are not determined by labor incomes. Notwithstanding these caveats, Table 8 presents the Region-wide time-dependence mobility parameters for labor and non-labor incomes. Interestingly, estimates show that most of the *total* mobility phenomenon is explained by labor incomes. Even though non-labor incomes represent approximately 25% of total household incomes in Latin America, their contribution to the observed mobility rarely exceeds 10%. Having said that, non-labor incomes are statistically significant determinants of *total* income mobility. The $R^{2'}$s of the disaggregated estimations of mobility are above 0.99, as shown in the upper panel of Table 8. The middle panel in Table 8 shows that when considering the change and not the level of labor and non-labor incomes, the combined effects from both sources reassuringly add up to the aggregated estimated effect (as reported in Table 5). Interestingly, the estimated impacts for each source of incomes typically work in the same direction, which is consistent with financial and social incomes being cyclical to labor incomes, rather than counter-cyclical. However, they do not always work in the same direction. When no controls are introduced (specification I) or only country dummies are introduced (specification V), labor income impacts are not statistically significant to explain the observed change in *total* incomes. In other words, changes in non-labor incomes are fully responsible for inter-period changes in *total* incomes. In specifications XIII and IX, instead, when all controls are introduced, the impacts of changes in labor and non-labor incomes upon *total* incomes have the opposite effect. Whether there are biases (and if so, whether they are different in nature) between each source of incomes and controls is also beyond the scope of this paper, but it may well determine the discrepancies observed across these specifications.[18]

[18] The difference in those specifications and others in which changes in labor and non-labor work in the same direction (specifications II and III) is the inclusion of the dwelling characteristics dummy. It may be that changes in that dummy come from improved access to social services that may have little to do with changes in labor incomes but, rather, social interventions. Exploring further these or other possible factors would imply a further disaggregation of non-labor incomes into categories not systematically available in the existing household surveys across the Region.

Table 8: Estimates of Unconditional and Conditional Time-Dependence Income Mobility in Latin America by Sources of Income

	I	II	III	IV	V	VI	VII	VIII	IX
Estimated Income Mobility - Equation (3)									
$\overline{\ln y}_{c(t),t} = \beta_{1c}\overline{\ln ylab}_{c(t-1),t-1} + \beta_{2c}\overline{\ln ynolab}_{c(t-1),t-1} + \delta_c \overline{X}_{c(t),t} + \mu_{c(t),t}$									
B_1	0.962	0.687	0.626	0.594	0.868	0.646	0.617	0.59	0.547
	(80.58)**	(36.40)**	(31.65)**	(22.98)**	(57.39)**	(32.73)**	(30.62)**	(23.38)**	(24.23)**
B_2	0.034	0.039	0.059	0.089	0.104	0.053	0.053	0.082	0.03
	(2.35)*	(3.13)**	(4.51)**	(4.74)**	(6.59)**	(4.14)**	(4.01)**	(4.37)**	-1.58
R^2	0.995	0.998	0.999	0.999	0.999	0.998	0.999	0.998	0.999
N. observations	800	800	800	672	800	800	800	672	672
Estimated Income Mobility - Equation (4)									
$\Delta \ln \overline{y}_{c(t),t} = \beta_{1c}\overline{\ln ylab}_{c(t-1),t-1} + \beta_{2c}\overline{\ln ynolab}_{c(t-1),t-1} + \delta_c \Delta\overline{X}_{c(t),t} + \mu_{c(t),t}$									
B_1	0.018	-0.159	-0.151	-0.201	-0.012	-0.196	-0.193	-0.257	-0.289
	-1.83	(8.14)**	(7.94)**	(7.61)**	-0.88	(10.66)**	(10.82)**	(10.46)**	(10.22)**
B_2	-0.065	-0.037	-0.032	0.01	-0.045	-0.012	-0.008	0.043	0.062
	(5.35)**	(2.76)**	(2.45)*	-0.53	(3.32)**	-0.92	-0.69	(2.40)*	(2.84)**
R^2	0.41	0.53	0.56	0.57	0.56	0.6	0.63	0.65	0.73
N. observations	800	786	800	630	800	786	800	630	630
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
egional Dummies	No	No	No	No	No	Yes	No	Yes	No
Country Dummies	No	No	No	No	Yes	No	Yes	No	Yes

Source: Own calculations based on IDB Research Department Harmonized Household Surveys. T –Statistics between brackets

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 more light on the patterns and channels of mobility in the Region by constructing a pseudo-panel for 14 countries over 11 years and 8 birth cohorts. Our analysis focuses on the standard notion of income mobility and, in addition, explores a notion of mobility around poverty lines. We show that the Region as a whole is highly immobile in income terms.

However, a sizeable part of this immobility results from failing to account for the effects that personal and socioeconomic characteristics have on mobility (over 30% 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 not explained by past levels of incomes vary widely across countries, well exceeding in some cases 50% of estimated changes.

Household mobility around poverty lines was found symmetrical in size: as many as those households moving into poverty, moved out of poverty. The analysis of the characteristics of *mobile* households shows interesting features, such that younger households being twice as likely to slip into poverty as to move out of it. Despite the limitations of the analysis (an econometric analysis of the effects of such controls on poverty mobility is also needed), we reject as simplistic and misleading the widely accepted notion of a dominating socioeconomic immobility throughout the Region. In addition, we found no conclusive evidence that social transfers favor mobility, especially among the poor. Indirect evidence, however, points to sources of incomes other than labor to bear relevant consequences in *total* income mobility. This is a first step towards uncovering the underlying dynamics of poverty mobility in a Region that for long has implemented one-size-fits-all economic reforms, poverty strategies and social interventions.

References

Albornoz, F. y Menéndez, M. (2004). "Income dynamics in Argentina during the 1990s: 'Mobiles' did change over time". World Bank, forthcoming.

Antman, F. and Mckenzie, D. (2005). "Earnings Mobility and Measurement Error: A Pseudo-Panel Approach", World Bank Policy Research Working Paper # 3745.
.

Bourguinon F. and Goh C. (2004). "Estimating individual vulnerability to poverty with pseudo-panel data". The World Bank, Washington DC.

Browning, M., Deaton, A. y Irish M. (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". Research Department, Inter-American Development Bank, Washington DC.

Collado, M.D. (1997). "Estimating dynamic models from time series of independent crosssections". Journal of Econometrics 82: 37–62.

Contreras, D., Cooper, R., Herman, J. and Neilson, C. (2004). "Dinámica de la pobreza y movilidad social en Chile".Universidad de Chile. Mimeo.

Corbacho, A., M. Garcia-Escribano, M. and G. Inchauste (2003) "Argentina: Macroeconomic Crisis and Household Vulnerability", IMF Working Paper.

Cuesta, J. (2004) "Social Transfers as a Determinant of Intrahousehold Allocation" Journal of Income Distribution, Volume 13, Number 1-2, pp. 76-104.

Deaton, A. (1985). "Panel data from times series of cross-sections". Journal of Econometrics (30): 109–126.

Fields, G. (2005) "The Many Facets of Economic Mobility" Dept. of Economics Mimeo, Cornell University.

Fields, G. and F. A. Ok (1999) "Measuring Movement of Incomes" Economica, 66, p. 455-71.

Fields, G. and Sánchez Puerta, M. (2005). "Earnings mobility in urban Argentina". Background Paper Prepared for the World Bank. World Bank, Washington DC.

Fields G., Duval R., Freije S. and Sánchez Puerta M. (2006). "Inter-generational income mobility in Latin America". Economia, forthcoming.

Galiani, Sebastián (2006). "Notes on Social Mobility." Mimeo. Universidad San Andrés.

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), pp. 21-40.

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

Inter-American Development Bank, IADB (1998).Economic and Social Progress Report 1998/9. IADB, Washington DC.

Lillard, L. y Willis, R. (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. World Bank, Washington DC.

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”. Department of Economics, Universidad de San Andres. Mimeo

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

Reddy, S. and Pogge T. (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, May 2006, 121 (2): 351-97.

Scott, C. (2000) “Mixed Fortunes: A Study of Poverty Mobility among Small Farm Household 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. y Vella, F. (2002). “Estimating dynamic models from repeated cross-sections”. Mimeo, K.U. Leuven Center for Economic Studies.

World Bank (2003) Inequality in Latin America and the Caribbean. Breaking with History? World Bank, Washington DC.

World Bank (1990). World Development Report 1990. World Bank, Washington DC.

Annex 1. Data Sources

Table A1.1. 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) Urban - 28 cities (1999-2002)
Brasil	Pesquisa Nacional por Amostra de Domicilios (PNAD)	Once a year	September	National
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	Urban (1992) National (1993-2002)
Costa Rica	Encuesta de Hogares de Propósitos Múltiples (EHPM)	Once a year	July	National
Honduras	Encuesta Permanente de Hogares de Propósitos Múltiples	May and September	September	National
México	Encuesta Nacional de Ingreso y Gastos de los Hogares (ENIGH)	Once a year	August-November	National
Panamá	Encuesta de Hogares	Once a year	August	National
Paraguay	Encuesta Permanente de Hogares	Once a year	August-December	National
Perú	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	Continuous	Urban
Venezuela	Encuesta de Hogares por Muestreo	Twice a year	July-December	National

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

Table A1.2: Household Surveys – and periods considered to construct the pseudo panels

Country	Period					
	T_1	T2	T3	T4	T5	T6
	992-1993	.994-1995	1996-1997	1998-199	2000-2001	2002-2003
Argentina	x	x	x	x	x	x
Brasil		x	x	x	x	x
Bolivia	x	x	x	x	x	x
Chile	x	x	x	x	x	x
Colombia	x	x	x	x	x	
Costa Rica	x	x	x	x	x	x
Honduras			x	x	x	x
México		x	x	x	x	x
Panamá		x	x	x	x	x
Paraguay			x	x	x	x
Perú			x	x	x	x
El Salvador				x	x	x
Uruguay	x	x	x	x	x	x
Venezuela		x	x	x	x	x

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

Annex 2 Sensitivity Analysis

Table A2.1: Estimates of Unconditional and Conditional Time-Dependence Income Mobility in Latin America using 4-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	1320	1296	1320	1044	1320	1296	1320	1044	1044
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

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

Table A2.2: Estimates of Unconditional and Conditional Time-Dependence Income Mobility in Latin America using 6-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	0.745	0.703	0.699	0.95	0.722	0.685	0.687	0.582
	(685.62)**	(67.94)**	(58.67)**	(53.09)**	(210.12)**	(65.18)**	(58.45)**	(53.18)**	(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	-0.188	-0.18	-0.178	-0.05	-0.198	-0.193	-0.193	-0.198
	(23.56)**	(16.07)**	(16.23)**	(13.91)**	(11.14)**	(18.01)**	(18.72)**	(16.25)**	(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

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