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Keyword: Longitudinal data; poverty persistence; affluence persistence; income mobility; Chile; Latin America.

JEL Cassification: D31, D63, I32

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Modelling the persistence of income position in Chile[1]

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1. Introduction

In the last two decades, inequality has been changing in different regions of the world. While most of the OECD countries have experienced an increase in income inequality, in regions such as Latin America, though the starting point was much higher than in the OECD, income inequality has decreased (Amarante & Colacce, 2018; OECD, 2015). These increases or decreases in inequality can occur in different income mobility contexts. For example, a country may have a simple stretch or shrinkage of the ends of the income distribution where households remain in the same position within the distribution. However, longitudinal data have shown that changes in inequality are explained, in relative terms, by the movement of households up and down within the income distribution (Fields, 2008; Jäntti & Jenkins, 2015).

Although this high mobility of income may be associated with greater economic insecurity (Jarvis & Jenkins, 1998), for any society a desirable objective is to prevent poor households from remaining stuck in their condition over time. The aim is for a type of income mobility that will allow these households to stay out of poverty for long periods. Conversely, a society may want to prevent those households at the top of the income distribution from remaining the same, generating barriers for others to move up as well. As Krugman (1992) puts it, "an increase in income mobility tends to make the distribution of lifetime income more equal, since those who are rich have nowhere to go but down, while those who are poor have nowhere to go but up".

A recent study used longitudinal household panel surveys from OECD countries to measure the intragenerational income mobility in the last two decades (OECD, 2018b). It found that there is currently a greater persistence in the income positions than what was found by the end of the nineties. However, it has not been studied in depth why individuals stay longer in the same position in the distribution of income. To answer this question, it is necessary to know if the income persistence is explained by the characteristics of the individual (observable and non-observable) or by the mere fact of being in a certain income position (state dependence). In other regions of the world, such as Latin America, the shortage of longitudinal household surveys has resulted in a lack of knowledge about income mobility levels. The exception that confirms the rule are the works that used the panel data from Chile with three waves over a decade (1996–2001–2006). These works show that the unequal income distribution in Chile contrasts with the high mobility of all but those at the high-end of the income distribution (Contreras, Cooper, Herman, & Neilson, 2005; Sapelli, 2013).

In this paper, I study one specific dimension of the intragenerational income mobility in Chile. It is known in the literature as 'positional movement', which measures the movement of individuals across different positions (quintiles, deciles, or ranks) in the income distribution. In particular, I analyse the 'origin independence', which measures whether an individual's position in the income distribution affects their chances of overcoming poverty or remaining at the top of the income distribution. To do that, I use four rounds of the Socioeconomic Household Panel Survey (P-CASEN) for the period between 2006 and 2009.

Based on this mobility concept, a most desirable type of society would be one where the income mobility is high and the current position of an individual in the income distribution does not depend on his/her previous position. It should be mentioned that when a society has high fluidity but inadequate or insufficient social protection, the well-being of the population can be affected by the stress or anxiety generated by economic uncertainty. However, this issue cannot be addressed just by looking into income mobility, it requires studying economic insecurity using a different empirical framework (Hacker, 2018).

Studying the 'positional movement' of mobility will enable me to: i) generate transition matrices of entry and exit of both poverty rates and affluence rates, and ii) understand the mechanisms that explain why households at the lower-end of the income distribution have a low probability of moving up, and those that at the higher-end of the income distribution have little chance of moving down. Therefore, the dual objective of this paper is to measure the persistence at the bottom and at the top of the income distribution, and to break down the persistence observed at both ends of the income distribution into the components that can be attributed to state dependence and non-observed heterogeneity as well as to the effects of the observed characteristics of individuals and households.

The contributions of this research are three. First, I use econometric strategies to model joint low-income persistence and high-income persistence. Existing studies have primarily focused on analysing only one end of the income distribution, estimating the state dependence effect in poverty persistence (e.g. Giarda & Moroni, 2018). For a review of these studies see Biewen (2014). I use a random effect dynamic ordered probit model that takes into account the state dependence of previous income position, individual heterogeneity, and unobserved heterogeneity. It also controls for the initial condition problem (Rabe-Hesketh & Skrondal, 2013; Wooldridge, 2005) and the possible correlation between random effects and time-varying explanatory variables (Chamberlain, 1984; Mundlak, 1978). Second, I provide an answer to the question on why people in Chile who have been on a low income or a high income are more likely to persist in the same position in the income distribution in the future. Until now, to the best of my knowledge, no studies in the literature have analysed the causes of the persistence both at the bottom and at the top of the income distribution in any Latin American country.

Third, I perform two robustness checks to validate the results concerning attrition bias. When I use the P-CASEN to analyse low-income/high-income persistence, there is a risk of getting biased results due to non-random attrition. Not considering attrition may result in misleading estimates of income position persistence. I test whether or not attrition is correlated with the dependent variables applying variable-addition tests proposed in Verbeek & Nijman (1992). Also, I use inverse probability weights to adjust for attrition to compare weighted estimates and unweighted estimates from the baseline model to determine whether attrition bias has a significant effect on the estimated coefficients of interest (Wooldridge, 2002b).

The remainder of this paper is organised as follows. In section 2, I provide an overview of the relevant literature about intragenerational income mobility and income position persistence. In Section 3, I describe the datasets and definitions. In section 4, I present the descriptive statistics and transition matrices. In section 5, I introduce the econometric model (REDOP) and estimation strategy that I followed. In section 6, I show and discuss the empirical results, and in section 7, I present the conclusions.

2. Background

The economic literature has debated for several decades whether or not greater income mobility represents a social improvement (Atkinson, Bourguignon, & Morrisson, 1992). The positive view understands high income mobility as a sign of dynamism, social mobility and equal opportunities compared to a more rigid society (Friedman, 1962). A critical interpretation of high income mobility is the economic insecurity that is generated in the households that are exposed to fluctuations in households' income (Jarvis & Jenkins, 1998).

This discussion is not foreign to emerging economies such as Chile. Two studies have analysed income mobility for the periods 1996-2001, and 1996-2006 in Chile using a panel survey of three rounds (Contreras et al., 2005; Sapelli, 2013). Both studies found high mobility, although they differ in their interpretation. While Sapelli (2013) considers that high levels of income mobility are desirable because they imply that the lowest income has a high probability of rising up the income ladder and episodes of income reduction are transitory, Contreras et al. (2005) relate this high mobility to greater vulnerability to poverty since the unanticipated income fluctuations or shocks are socially undesirable considering that the median income is not very far from the official poverty line in Chile.

The current debate about whether or not a society with high income mobility is desirable has incorporated the different dimensions of mobility in the discussion.[3] In this way, the answer to whether a fluid society is preferable to a rigid society will depend on the concept of income mobility that is being studied (Jäntti & Jenkins, 2015). For instance, when using inter-temporal dependency as a mobility concept, a society with high mobility is desirable, as individuals' current income does not depend on their previous income. From an intergenerational perspective, when measuring income mobility using the concept of positional movement, a more fluid society is also preferable. In this type of society, the richest can become less rich and the poorest can become less poor. When using the same concept in an intra-generational

[3] Since the concept of mobility has multiple dimensions several types of indicators are needed to measure it. This partly explains why, in the last 40 years, at least twenty indicators have been proposed to study income mobility (Atkinson, 1970; Chakravarty, Dutta, & Weymark, 1985; Fields, 2001; Fields & Ok, 1999; Hart, 1976; Shorrocks, 1978). The works of Jenkins (2011) and Fields (2008, 2010) have made an important contribution to organising the discussion and relating these indicators to different mobility dimensions such as positional change, individual income growth, reduction of longer-term inequality, and income risk.

analysis, this preference is not so clear because the mobility of income is also explained by the life cycle of individuals.

In this same line of argument, in which the preference regarding income mobility levels within a society depends on the concept used, it is possible to find that income mobility can reduce inequality in the long term, but from the perspective of mobility as income risk, that would not be socially beneficial. From the perspective of income risk, if mobility occurs in a context of economic shocks where income fluctuations cannot be predicted at the individual level, generating economic uncertainty (mobility as income risk), a high mobility of income would not be desirable. Additionally, applying different concepts of mobility to compare countries also gives us different answers about the level of income mobility. For example, income mobility is more rigid in the UK than in the U.S.A. if the dependence on current income from the past is used as a mobility concept, but the UK has more mobility than the U.S. if mobility is measured as changes in the individuals' position within the income distribution (Fields, 2008).

In order to analyse income persistence, I use the concept of income mobility known as positional income mobility, which takes into account the position in the previous period. A recent study that used this definition of mobility for country members of the OECD found that income persistence is stronger at the bottom and, in particular, the top of the income distribution, where respectively 60 per cent and 70 per cent of individuals stay over four years (OECD, 2018b). This translates into both lower chances of moving upwards for those at the bottom, and lower chances of moving down for those at the top. For emerging countries the lack of mobility is more pronounced at the bottom of the income distribution (OECD, 2018b).

There is extensive literature that has focused on the analysis of income mobility at the bottom of the income distribution. Individual persisting in their poverty situation, known as poverty traps, have been studied in developed countries (Andriopoulou & Tsakloglou, 2011; Ayllón, 2013; Biewen, 2014; Devicienti, 2011; Giarda & Moroni, 2018), as well as in developing countries (Alem, 2015; Bigsten & Shimeles, 2008; Thomas & Gaspart, 2014).[4] The empirical evidence from these studies, for both type of societies, shows that those who have been in poverty have a high probability of experiencing it again in future periods.

[4] Poverty persistence has also been studied for groups of the population as households with children (Bárcena-Martín, Blanco-Arana, & Perez-Moreno, 2017; Fabrizi & Mussida, 2020; Jenkins, Schluter, & Wagner, 2003).

Two mechanisms explain the influence of time on the persistence of poverty. First, the experience of poverty in one year *per se* raises the risk of being poor in the next year. This process is called true state dependence or the 'scarring effect'. In other words, the fact of experiencing poverty – independent of other factors – has a real causal impact on future poverty (Heckman, 1981). The literature suggests two possible explanations behind true state dependence in poverty. According to Biewen (2009), a low income may be associated with adverse incentives such as moral hazard (e.g. no willingness to search for jobs so to not lose the economic benefits of the unemployment insurance). In addition to these work disincentives, negative duration dependence in poverty can be explained by vicious circle processes, which make the search for a new job more complicated. For example, the absence of counselling and training or a demoralising attitude towards work explained by the habituation or stigmatisation of being jobless (Devicienti, 2011).

The second mechanism is known as individual heterogeneity. This means that people who remain in poverty for longer may possess similar characteristics that hinder their exit of the poverty spell. These features may be observable (e.g. educational level, unemployment, health problems) or unobservable (e.g. lack of cognitive skills, low motivation). Therefore, being poor with these characteristics over time increases the risk of being poor in the future. In other words, poverty is unrelated to the duration of the poverty spell.

Although high-income persistence has not been studied as much as the persistence of poverty, there are authors who argue that the high end of the income distribution can show even more persistence (Solon, 2017). Affluence shields have the same effect as poverty traps, this is, an individual's current position in the highest income group increases their probability of remaining in the same position in the future. There is extensive sociological literature on the barriers to entry to the upper classes (e.g. the professionals and managers' class, to use Erikson and Goldthorpe's (1992) definition). Some barriers emerge from the ownership of different types of assets, such as property, sectoral barriers, or authority in the workplace (Torche, 2015). Other mechanisms that reproduce the upper classes are mediated by getting educational credentials (Ishida, Muller, & Ridge, 1995) or their peers and social network (DiMaggio & Garip, 2012).

Reeves (2017) calls this process opportunity hoarding among the top of the income distribution. He argues that the parents of the upper middle class of the United States (the top 20 percent on the income distribution) have successfully managed to ensure that their children maintain the same status and position in the income distribution, which has resulted in a reduction in the overall intergenerational mobility. According to Reeves, mechanisms such as zoning laws and schooling, occupational licensing, college application procedures, and the allocation of internships have allowed the highest quintile of American society to build a glass floor that not only protects their children from falling in the income distribution when they are older but also prevents others who were born in a lower position from crossing the glass roof that has been built, thus generating a society with less social mobility.

There are several modelling approaches to studying the persistence of someone's income position. In general, these methods have focused on studying only low income and not the upper part of the income distribution. See Aassve et al. (2006) for a complete review. Each approach is associated with a specific methodology, as they rely on different definitions of income mobility related to the poverty line. Some of these are, for instance, chronic versus transient poverty, consecutive periods in poverty, or years in poverty during a fixed timeframe (Jenkins, 2011). One of these approaches is known as the components of variance model. It focuses on estimating the permanent and transitory components of poverty as well as the determinants of both types of deprivation. One of the first works in this line of research was carried out by Lillard and Willis (1978), in which they captured the dynamics of income through a complex structure of the error term. Once the dynamic model has been estimated, the frequency and duration of periods of poverty are calculated.

A disadvantage of the component approach is that all of the deviations that are captured by transitory poverty are considered as if they were random and therefore equivalent. However, as Bane and Ellwood (1986) observed, the changes in income over time neither lead to the same long-term dynamics, nor are they random. For example, the trajectories of future income of a person that falls into poverty due to a job loss may not be equivalent to the income trajectory of a person suffering due to a negative health shock. These authors propose a different approach known as hazard rate models. These consist in analysing on their own merit the deviations or changes in income over time, by examining the duration of the periods in poverty, the odds of exiting and re-entering this state and the events associated with these transitions (Bane & Ellwood, 1986; Stevens, 1994). One of the main contributions of this approach to the study of poverty dynamics is that it shows that the longer people persist on a low income the lower their chances of exiting poverty (Arranz & Cantó, 2012; Biewen, 2009; Cellini, McKernan, & Ratcliffe, 2008; Jenkins, 2011).

However, the problem with these models is that they do not consider the fact that individuals in poverty in the first interview, as well as in the sample attrition, are not randomly distributed. Markov models of transition to poverty – first-order models – do control the initial conditions of individuals and the attrition, allowing for predicting rates of poverty, rates of escaping and entering poverty, and the length of time of remaining in poverty for individuals with different characteristics (Cappellari & Jenkins, 2004).

There is a fourth methodology that can be used to analyse poverty dynamics, which has some overlapping features with the others; it is known as dynamic discrete choice models. These models are designed to measure the two mechanisms that explain the influence of time on the persistence of poverty: i) the true state dependence, and ii) the observed and unobserved individual heterogeneity. These models assume that poverty follows a first order Markov process. This means that if an individual remains for two consecutive years below the poverty line then it is possible to confirm that there is poverty persistence. To do that, the models have to distinguish the true state dependence captured by the impact of the lagged dependent variable from the spurious state dependence caused by the presence of time-invariant unobserved heterogeneity.

This last approach is the one that I use here. However, since the outcome in this research is not a poor/non-poor dichotomous category but rather considers the categories for poor/middle class/affluent in the income distribution, it requires working with Random Effect Dynamic Ordered Probit (REDOP) models. In doing so I have to deal with three issues: i) the correlated individual effects (persistence may be partially explained as being due to individual observed and unobserved heterogeneity rather than true state dependence), ii) the initial conditions problem (the observed start of the Markov process does not coincide with the true start of the process) and iii) the attrition bias (the variables affecting attrition might be correlated with the underlying income mobility process under study). To deal with the correlated individual effects and the initial condition problem, I adopt the approach suggested by Wooldridge (2005) and modified by Rabe-Hesketh & Skrondal (2013). And, to assess whether attrition bias is a problem in my REDOP models, I apply variable addition tests (Verbeek & Nijman, 1992) and I compare estimated coefficients of interest variables between pooled model with inverse probability weights and without weights (Wooldridge, 2002b). Further details on the methodological strategy I used are explained in section 5.

3. Data and definitions

The dataset I use is the Chilean Socioeconomic Household Panel Survey (P-CASEN) for the years 2006, 2007, 2008 and 2009.[5] The P-CASEN provides longitudinal data on the socioeconomic conditions of the Chilean population at a household and individual level (Observatorio Social, 2011).

The final national sample consists of 8,079 households, comprising a total of 30,104 individuals. Each person in the original sample was followed and re-interviewed consecutively at a time interval of about one year. In the analyses I used both a balanced sample that contains information about the individuals that were interviewed in the four rounds, and an unbalanced sample that takes advantage of all available observations. The response rate between wave 1 and wave 2 was 73 percent, and for the following waves the attrition was 11 and 10 percent respectively. The balanced database has 18,065 individuals (adults and children) present in each of the four waves. The attrition of the sample will be discussed in more detail later.

The P-CASEN contains a wide range of economic and sociodemographic variables, which are available for each round. I use characteristics of the head of household and characteristics of the household in the multivariate analysis. The head of the household is defined as the person in the household who contributes the most with her salary to the household income. In the case of a workless household, the household head is the self-reported household head in the survey. In keeping with previous studies on income distribution that use household survey data, the covariates are defined at the level of the head of household. Therefore, in the analysis I use a sample of households. The methodological reason for not including children is that they do not make decisions that cause changes to the household's income mobility. In the case of adults, the reason is not to replicate the information of the head of household in the econometric models.

I use an income perspective to study the income position persistence of poor and affluent populations, which means that people's well-being is captured in terms of income. I construct post-transfer monthly household income based on the sum of income from labour, assets,

[5] For more information on the Panel CASEN, see:
http://observatorio.ministeriodesarrollosocial.gob.cl/enc_panel.php

imputed rent, private transfers and public transfers.[6] It is worth noting that November was the reference month for income questions in each wave. In general, household surveys in Latin American countries, including Chile, collect income for official poverty and inequality measures using a monthly reference period to build these measures (e.g. ECLAC, 2019). All income has been converted to November 2009 prices to compare with real income.

Recognizing that there is no single way to define low income or poverty nor to define high income or affluence, I use both relative and absolute cut-offs to identify both groups at the extremes of the income distribution. First, for the relative measure, to identify the poverty line I use the threshold that determines the first income quintile group for each wave, and for the affluence line, I use the cut-off that identifies the fifth income quintile group. These types of thresholds capture relative poverty and affluence. I applied both cut-offs to the equivalised total household income. Equivalization allows for comparison between individuals from different sized households. To equivalise incomes I use the scale that divides total household income by the square root of household size (Buhmann, Rainwater, Schmaus, & Smeeding, 1988). This equivalization allows me to compare some of the results I obtained with those from studies that also use these relative income cut-offs to analyse OECD countries (CASE & III, 2018; OECD, 2018a).

Second, for the absolute cut-offs, to identify poor households, I use the international poverty line suggested by the World Bank for upper-middle-income countries in Latin America (US $ 5.5 per person per day in 2011 PPP). To identify the affluent group, I use the ninetieth percentile of the income distribution in wave one following the conventional approach to building an affluence line in Latin American countries (e.g. Birdsall, 2007). Since the international poverty line makes a per-capita adjustment within the household's income, I follow the same equivalization procedure.

Following the argument of Jarvis & Jenkins (1998), there are conceptual and empirical advantages that justify the use of absolute and relative cut-offs in parallel in order to identify groups in the income distribution. Conceptually, this strategy constitutes a midpoint between

[6] Differently from the procedure of income construction in industrialised countries, I did not extract taxes from disposable income, which is obtained through socioeconomic surveys because in the case of Chile the survey asks respondents for their net income.

two different views. On the one hand, some advocate a fixed real income cut-off because poverty should decrease as real income goes up (Ferreira et al., 2013). On the other hand, others prefer to study changes in income positions by defining thresholds that depend on the distribution of income itself (OECD, 2018a). From an empirical point of view, the use of absolute and relative thresholds allows for a sensitivity analysis of outcomes based on the differences between thresholds. For example, the cut-off from the lower quintile is higher than the international poverty line used.

The two dependent variables that I use in the empirical models developed in Section 5 are income quintile groups (IQGs) and welfare level both in the current year. Regarding IQG variable, the relative cut-offs allow me to group the data in three categories: low income (IQG1), middle income (IQG2+ IQG3+ IQG4), high income (IQG5). Concerning the welfare level variable, the absolute thresholds identify: poor, middle class and rich. It is important to say that the middle-income group and the middle class are presented as a broad group in the income distribution. However, I do not make categorizations within these middle-groups because, as I have explained before, I focus on the positional change of the extremes of the income distribution. A similar argument is also valid to explain why I do not work with the continuous income distribution. Since my objective is to model the joint persistence of households in both high income and low income, as well as the poverty persistence and affluence persistence, I have to work with intrinsically discrete data.

The explanatory variables included in the models are the income quintile groups and the welfare level in the previous year (the lagged dependent variable), and three sets of variables related to the composition of each household, the different assets that the household owns, and the household's environment (location of the house). In the literature, these three vectors are described as the main determinants of the income mobility and poverty dynamics of a household (Galster, 2012; Jenkins, 2011).

Household composition is summarised in terms of the household size, the number of children in the household, whether the household has a female head or not, and the age of the household head in the first wave. In order to estimate the effect of different types of family structures on the probability of moving in the distribution of income (Wiepking & Maas, 2005), I have also included a family typology that distinguishes between households with and without children, that have a single parent with children, and that comprise a lone person.

Human capital, household labour market attachment and physical assets are used to measure household assets. Human capital is proxied by the education of the household head and the household head's partner. Household labour market attachment is summarised by the employment status of the household head and the household head's partner, and the number of workers in the household. When information on households' financial or physical assets is not available, the house ownership information is used as a proxy for physical assets (Neilson, Contreras, Cooper, & Hermann, 2008).

Regarding the location variables, I include the variable zone (urban or rural) and region. As will be explained in section 5, for the advanced modelling of Wooldridge's model, I include additional time-invariant variables to solve both the unobserved heterogeneity and initial conditions problems.

I do not include among explanatory variables those variables related to income shocks or trigger events, such as losing a job, having a separation or suffering from a disease (DiPrete & McManus, 2000). There are two reasons for not including this type of variable in regressions of positional income dynamics. The first reason is the difficulty of identifying the influence of the trigger-event variables on the transitions from one position to another in the income distribution if one also controls for characteristics measured at a particular point in time (Stevens, 1999).

Second, variable trigger-events cannot be treated as exogenous variables. A change in the entry position and a trigger-event can be determined by a common factor that is not observable and the inclusion of the variable trigger-event could bias the estimated parameters. Biewen (2009) shows that this endogeneity situation can also occur for other point-in-time variables and, emphasises that caution should be exercised in regard to including explanatory variables in models that can generate biased estimates. See Jenkins (2011) for a detailed discussion of this.

4. Persistence at the extremes of the income distribution in Chile: a description

In this section I briefly describe the transitions of those in the two extremes of the income distribution in Chile during the analysed period for the balanced sample. Table 1 provides descriptive information of the variables for four subsamples. These subsamples are constructed using the persistence-at income-position indicator. This is defined as individuals living in households in a specific extreme income position in the current year and at least in two of the preceding three years.[7] The first column of the table presents information for those who persist in the first income quintile group, while the second column corresponds to those who were in the fifth quintile in 2009 and were in that quintile at least twice between 2006 and 2008. The third and fourth columns present the persistence results for the poor and the affluent categories for the absolute thresholds. These represent the two extremes of the categories that measure income position in terms of welfare. The comparison between the columns in Table 1 allows for observing that certain variables are correlated with the extremes of the income position for both dependent variables.

Regarding the relative cut-offs to identify the income position on both extremes of the income distribution, the results show that those who persisted in quintile group 1 show a higher proportion of women as head of household compared to those who remained in quintile group 5. Also, more than a third of those who remained in the highest income quintile group had a university education level compared to less than zero percent in the lowest quintile. Formal work and the number of workers per household show a significantly higher proportion in quintile group 5. The average number of couples with children is higher in quintile group 1. The same is true for the number of children per household. Income quintile group 1 also shows a higher proportion of households in rural areas whose housing is either subsidised or rent free. All in all, most of the differences between the averages of the variables mentioned above are accentuated when the comparison is made for absolute poverty persistence and affluence persistence.

[7] The statistics are based on the balanced sample weighted using the P-CASEN wave 4 enumerated individual weights.

Table 1: Descriptive statistics of the variables by subsample (persistence-at income-position)

Variables	Relative thresholds				Absolute thresholds			
	Persistence at bottom quintile		Persistence at top quintile		Poverty persistence		Affluence persistence	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Household head characteristics								
Female	0.361	(0.018)	0.315	(0.024)	0.332	(0.030)	0.370	(0.043)
Age	46.5	(0.617)	48.6	(0.726)	41.5	(0.685)	50.0	(1.536)
Education: Primary school	0.508	(0.021)	0.059	(0.010)	0.506	(0.036)	0.034	(0.012)
Education: Secondary school	0.425	(0.021)	0.416	(0.028)	0.400	(0.036)	0.327	(0.047)
Education: University degree	0.016	(0.006)	0.525	(0.029)	0.030	(0.015)	0.639	(0.048)
Labour status: Formal employed	0.496	(0.016)	0.839	(0.018)	0.496	(0.025)	0.786	(0.037)
Labour status: Informal employed	0.199	(0.011)	0.076	(0.011)	0.262	(0.022)	0.095	(0.022)
Labour status: Unemployed	0.050	(0.005)	0.005	(0.002)	0.065	(0.011)	0.003	(0.002)
Labour status: Inactive	0.254	(0.015)	0.080	(0.014)	0.177	(0.021)	0.116	(0.029)
HH head's partner characteristics								
Age	39.3	(0.567)	47.4	(0.764)	37.5	(0.713)	47.7	(1.799)
Education: Primary school	0.562	(0.030)	0.065	(0.013)	0.624	(0.047)	0.038	(0.019)
Education: Secondary school	0.420	(0.030)	0.551	(0.035)	0.362	(0.047)	0.478	(0.076)
Education: University degree	0.000	(0.000)	0.380	(0.035)	0.000	(0.000)	0.484	(0.076)
Labour status: Formal employed	0.087	(0.011)	0.504	(0.030)	0.075	(0.017)	0.576	(0.067)
Labour status: Informal employed	0.078	(0.011)	0.060	(0.010)	0.073	(0.016)	0.021	(0.010)
Labour status: Unemployed	0.063	(0.010)	0.027	(0.007)	0.064	(0.015)	0.006	(0.004)
Labour status: Inactive	0.772	(0.018)	0.408	(0.030)	0.788	(0.027)	0.397	(0.067)
Household characteristics								
Equivalised total household income	96,334	(1,212)	828,461	(35,081)	82,730	(2,164)	1,096,466	(69,300)
Household type: Couple without children	0.134	(0.012)	0.399	(0.026)	0.054	(0.014)	0.394	(0.048)
Household type: Single without children	0.100	(0.011)	0.140	(0.022)	0.063	(0.015)	0.155	(0.032)
Household type: Couple with children	0.458	(0.020)	0.322	(0.024)	0.622	(0.033)	0.186	(0.039)
Household type: Single with children	0.192	(0.016)	0.060	(0.011)	0.241	(0.029)	0.040	(0.016)
Household type: Lone person	0.117	(0.013)	0.079	(0.017)	0.020	(0.010)	0.224	(0.041)
Number of persons	3.7	(0.070)	3.6	(0.088)	5.0	(0.137)	2.7	(0.125)
Number of children < 15	1.241	(0.051)	0.580	(0.043)	2.091	(0.099)	0.329	(0.062)
Number of workers	0.751	(0.020)	1.653	(0.045)	0.844	(0.036)	1.372	(0.072)
Housing: Own housing (no mortgage)	0.449	(0.021)	0.448	(0.028)	0.406	(0.035)	0.413	(0.049)
Housing: Own housing, mortgage	0.041	(0.008)	0.262	(0.023)	0.031	(0.013)	0.246	(0.039)
Housing: Rent	0.141	(0.017)	0.228	(0.033)	0.133	(0.029)	0.271	(0.061)
Housing: Subsidized or rent free	0.369	(0.021)	0.062	(0.011)	0.430	(0.036)	0.070	(0.022)
Rural	0.239	(0.017)	0.036	(0.008)	0.261	(0.030)	0.026	(0.012)
Regions: 1st, 2nd, 3rd and 4th	0.095	(0.012)	0.104	(0.014)	0.092	(0.020)	0.069	(0.019)
Regions: 5th, 6th, 7th, 8th, 9th and 10th	0.648	(0.021)	0.362	(0.026)	0.614	(0.036)	0.316	(0.044)
Regions: 11th and 12th	0.006	(0.002)	0.019	(0.005)	0.008	(0.005)	0.017	(0.009)
Regions: 13th	0.251	(0.020)	0.515	(0.029)	0.285	(0.034)	0.598	(0.048)

Source: Author's calculations from the P-CASEN 2006-2009 (balanced sample with longitudinal weights are used).

Notes: Maximum number of observations: 18,772 household-year observations. All results are rates (%) unless stated otherwise. The equivalised total household income is valued in terms of 2009 Chilean pesos.

The descriptive analysis is complemented by showing the changes in the individuals in the two ends of the income distribution taking into account the central question of this investigation, which is: how does the position in the income distribution in the previous period affects the probability of being in the current position? I use transition matrices to analyse the state dependence. In Table 2 the rows indicate the previous position of the individual in the income distribution while the columns indicate the current position of the individual. For example, the elements of the first row provide information on the conditional distribution of the ranking of individuals in the income quintiles at time *t* since the individuals had been in the lowest quintile group. Transitions by quintiles are also shown for transitions between welfare measures.

Table 2: Annual income position at *t* conditional on income position at *t* -1

(A) Income quintile groups (IQGs): relative thresholds

IQGs, year *t* -1	IQGs, year *t* (row %)		
	IQG 1	IQGs 2-3-4	IQG 5
IQG 1	49.6	47.2	3.2
IQGs 2-3-4	14.7	73.7	11.6
IQG 5	3.7	32.1	64.2
Total	19.2	59.6	21.3

(B) Welfare level: absolute thresholds

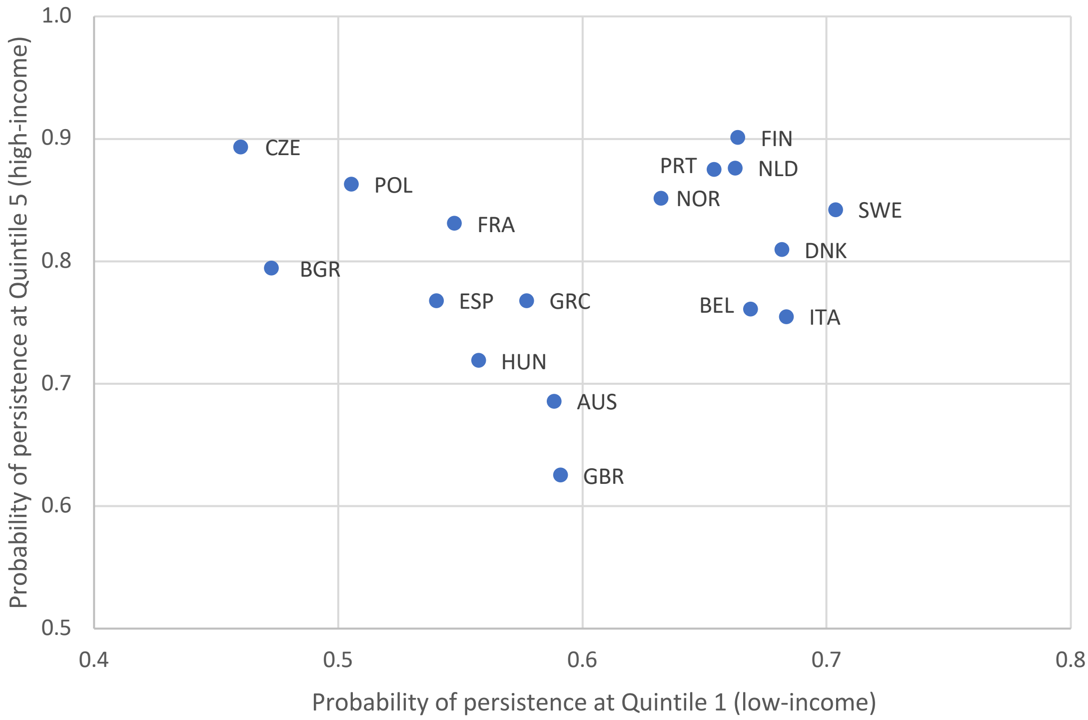
Welfare year *t* -1	Welfare, year *t* (row %)		
	Poor	Middle Class	Affluent
Poor	36.1	62.9	1.0
Middle class	7.4	88.2	4.4
Affluent	1.8	37.3	60.8
Total	9.8	81.0	9.2

Source: Author's calculations from the P-CASEN 2006-2009 (balanced sample with longitudinal weights are used).

In this way, the elements of Table 2 can be interpreted as the conditional probability under a Markov model. The persistence of the initial position in the distribution of income is observed, again, when considering the relative magnitudes of the elements of the diagonal and the elements close to it, in comparison to those that are far from the diagonal. When focusing on the two ends of the income distribution, I observe that staying in the highest quintile group (persistence at the top of the income distribution) has a probability of 0.64, while the probability of remaining in the lowest quintile group is 0.5 (persistence at the bottom of the income distribution). In regard to welfare levels, persistence in the affluent category has a probability of 0.61, and persistence in poverty has a probability of 0.36.

Regarding the issue of whether the sample retention is exogenous or endogenous to income position at *t*-1, Table A.2 (in the appendix) shows that the same calculations are made for both the balanced sample and the unbalanced sample, but without calculating the longitudinal weights. The proportion of missing income data is shown in the unbalanced sample. The results show the biggest problem is not the level of attrition of the sample but the proportion of missing income data, which is significantly different for income positions at *t*-1. As a result of this, provide evidence of attrition bias in the econometric strategy for modelling low-income/high-income persistence takes on real importance. In the next section, this point is explained in more detail.

Figure 1: Probability of persistence in the bottom and top income quintile group in European countries during the period 2006-2009



Sources: EU-SILC 2006-2009, values taken from Rendtel (2015).

Finally, to complement the descriptive analysis, I compare the indicators shown by the transition matrix of the income quintiles in Chile with other countries. To make this comparison, I use the Rendtel (2015) results, who uses the longitudinal component of the EU-SILC to compare income quintile groups transitions of European countries between 2006-2009. Two precautions must be taken when making this comparison. First, Rendelt (2015) did not use the current scale suggested by the OECD to equivalise incomes of each country. Therefore, these results may vary slightly because I use the last scale suggested, which is the square root of household size. Second, I calculated an equivalised total household monthly income for Chile while Rendelt (2015) uses an annual income measure.[8] Since changes in annual income are smoother than

[8] The reason for not using annual equivalised income in my work is because the official measures of income inequality and poverty in Chile have a monthly period of reference. Therefore, the design of the P-CASEN 2006-2009 focuses on obtaining a monthly income household making it challenging to build annual measures. For example, the first wave does not have the last year employment history of its interviewees.

changes in monthly income, the comparison could be not adequate. However, despite these limitations, the information is useful as a reference of persistence in the bottom and top income quintile group in European countries during the same period analysed in Chile.

Figure 1 shows the probability that individuals remain in the highest income quintile group during the period analysed together with the probability that individuals continue in the lowest quintile group. The persistence in low income is known as the sticky floor phenomenon due to the difficulty that households face to exit low income. In contrast, the glass floor image refers to the idea of high income people who observe others move along the income distribution without themselves falling from their current high-income position (OECD, 2018b).

Overall, all countries show high mobility in terms of income position, though there are interesting specific differences when comparing them. Taking into account the precautions mentioned above to make the comparison, Chile could be included in the lower-left position in Figure 1 because it shows a lower recurrence of both high-income spells and low-income spells. Conversely, the European countries that show more evidence of the existence of a glass floor and a sticky floor (top-right position in Figure 1), are Finland (FIN), Holland (NLD), Sweden (SWE), Portugal (PRT), Norway (NOR) and Denmark (DNK). For this group of countries, the probability of persisting in the highest quintile group is 0.8 and the probability of persisting in the lowest quintile group is 0.6. during the period between 2006 and 2009. The Czech Republic (CZE), Poland (POL) and Bulgaria (BGR) show less persistence in the lowest quintile group but high persistence in the highest quintile group (top-left position in Figure 1). The rest of the countries are in the centre of the figure.

The results obtained from the descriptive analysis provide interesting elements for the discussion of individuals' mobility within the income distribution in Chile. In the first place, there is the indisputable fact that in Chile, as in the rest of the OECD countries, a high persistence in terms of positions within the income distribution occurs at the two extremes of high- and low-income groups, both for the measure that uses relative cut-offs (income quintile groups) and the measure that uses absolute cuts (level of welfare).

However, this is not particularly novel since all OECD countries follow a similar trend. What is new in the case of Chile is that the proportion of the population that persists at the extremes of the income distribution is significantly lower when compared with the group of Europeans

OECD countries. Somehow, neither the sticky floor nor glass floor appear to be clearly displayed for the Chilean case. Comparing the results of Panel A in Table 2 with Figure 1, Chile shows not only the lowest probability of persistence in low incomes but also, and to a greater extent, in high incomes.

These results are quite counterintuitive since, among all of the OECD countries, Chile has the weakest social protection system and the highest levels of inequality, where the redistribution mechanisms make little difference in the levels of inequality before and after they are implemented. Therefore, one would have expected to see that those in poverty would have less capacity to get out of that situation and that the more affluent ones would not easily move from their position, generating strategies to keep their privileges and advantages with respect to the rest of the society. As I mentioned earlier, the greater mobility at the extremes of the income distribution in Chile may be explained by the fact that I use the monthly disposable income for Chile, while Rendelt (2015) uses the annual disposable income. However, these results are consistent with other approaches on this topic in Chile.

The high mobility at the bottom of the income distribution is probably related to Chile's high income inequality. As it is well known, the inequality in Chile is mainly explained by the high concentration at the top (first income decile group) (Torche, 2005). Thus, for the case of the relative measure, the cut-offs between quintile groups 1 to 4 are not too far from each other (Chauvel, 2018). This means that changes in the positions in the income distribution do not necessarily represent significant changes in the individuals' income. And, from the point of view of the absolute measures, the fact that poor individuals move up is what would explain the slight improvement in the levels of inequality in Chile.

These results are in line with the qualitative work of Araujo & Marticcelli (2011) who found that there is a 'positional inconsistency' shared by households in all positions in the income distribution, particularly in high income position. The authors define 'positional inconsistency' as the existence of a feeling that all income and class positions are permeable to change in Chile, which entails living with permanent insecurity. In advanced societies, this feeling of anxiety or stress among individuals due to economic problems in the future is known as economic insecurity, which has been studied with greater intensity since the economic crisis of 2007–2008 (Hacker, 2018; Osberg, 2018; Rohde & Tang, 2018).

5. The econometric strategy

Modelling joint low-income and high-income persistence

Poverty and affluence persistence of individuals in the income distribution can be explained not only by the characteristics of the population but also by the previous poverty/affluence state that they had. One of the objectives of my research is to test the presence of poverty traps and affluence shields.[9] That is, I study whether and to what extent the earlier welfare state affects the current probability of being poor and affluent. In other words, I test whether low-income persistence and high-income persistence are explained by the true or genuine state dependence (known as own-state traps/shields) and not by other observable and non-observable determinants.

To model, simultaneously, the income persistence at the bottom and at the top of the income distribution I used random effect dynamic ordered probit (REDOP) models. Using REDOP models, it is possible to distinguish true state dependence captured by the impact of the lagged income position from spurious state dependence caused by the presence of time-invariant unobserved heterogeneity. Thus, persistence may be partially due to individuals observed and unobserved heterogeneity rather than true state dependence. The general dynamic specification of the REDOP model is presented in Wooldridge(2005, p. 48). Applications of REDOP models to other outcomes such as health indicators and credit ratings are shown in Contoyannis, Jones and Rice (2004) and Mizen & Tsoukas (2009).

As I pointed out in the previous section, I build the observed dependent variable in my model using both relative and absolute income cut-offs to identify low-income households and high-income households along the income distribution in each round. In the case of the two relative thresholds, the outcome has three categories: the lowest income quintile group, the highest income quintile group and the other groups. For the two absolute thresholds, the dependent variable also has three categories: poor, middle-class and affluent. By doing so, I can specify a dynamic model of the position of an individual i in the income distribution at the interview date at time t as follows:

$$y_{it}^{*} = f(y_{it-1}, hc_{it}, ha_{it}) \qquad (1)$$

[9] See discussion in section 2 of both poverty traps and affluence shields.

where y_{it}^{*} is a latent variable of the individual position in the income distribution as a function of lagged observed annual income position (y_{it-1}), household composition (hc_{it}), and household assets (ha_{it}).

I used REDOP models on both the balanced and unbalanced samples of the P-CASEN for the period 2006-2009. The REDOP considers categorical variables in which the order from the lowest to the highest is not indifferent. Therefore, the values for the lowest income quintile, the highest quintile group, and the other groups are 1, 3 and 2, respectively. For poor, middle-class and affluent, the values are 1, 2 and 3. Also, the REDOP allows for including among the regressors the position in the previous states in the model in order to capture the state dependence and the variables related to the individual that change (and do not change) over time. In this way, the model assumes that the positional persistence follows a first-order Markov model. In other words, positional persistence is identified by two consecutive years in the same position in the income distribution.

The general dynamic model in equation (1) can be rewritten as a REDOP model:

$$y_{it}^{*} = \gamma' y_{it-1} + \beta' X_{it} + \upsilon_{it} \tag{2}$$

$$y_{it} = j \quad \text{if} \quad k_{j-1} < y_{it}^{*} < k_j \qquad j = 1, \dots, m \tag{3}$$

Here the subscript $i = 1, \dots, N$ denotes the individuals, the subscript $t = 2, \dots, T_i$ indicates the time period, T_i is the number of time periods observed for the ith individual.[10] X_{it} are the observed explanatory variables, and y_{it-1} is an indicator of the position of the individual in the distribution of income in the previous year. γ is the state dependence parameter to be estimated and υ_{it} is the unobservable error term.

In equation (3), an individual is observed to be in one of the m position categories in the income distribution when the latent variable of the income position (y_{it}^{*}) is between k_{j-1} and k_j. The threshold values k correspond to the cut-offs where an individual could move from one position category in the income distribution to another. This is because, even though the latent outcome,

[10] I estimated the dynamic models using data from waves 2-4 due to the use of lagged dependent variables.

y_{it}^*, is not observed, it is known in which category the latent variable falls (y_{it}). These models include in their estimations the cut-offs that separate one category from another.

Heckman and Borjas (1980) noted that equation (2), by not considering unobserved heterogeneity in the model, has the potential problem of biasing the estimates of the lagged variable, which might have a significant effect on the probability of the dependent variable. These authors propose that equation (2) should control for all observable and unobservable characteristics of individuals. In this way, the unobservable error term (v_{it}) could be decomposed into two terms ($v_{it} = \mu_i + \varepsilon_{it}$), where μ_i is a time-invariant individual specific effect, and ε_{it} is the remaining disturbance, which is assumed to follow a standard normal distribution with a zero mean and unit variance. Therefore, if I assume that ε_{it} is not related to the independent variables, equation (2) can be modified in the following way:

$$y_{it}^* = \gamma' y_{it-1} + \beta' X_{it} + \mu_i + \varepsilon_{it} \qquad (4)$$

Like the binary probit model, explanatory variables are introduced into the model by making the latent variable y_{it}^* a linear function of the X_{it}, and adding a normally distributed error term. This means that the probability of an individual reporting a particular value of $y_{it} = j$ is given by the difference between the probability of the respondent having a value of y_{it}^* less than k_j and the probability of having a value of y_{it}^* less than k_{j-1}. The probability that the observation i will select income position j at time t (y_{it}) conditioned to the independent variables and the individual effect can be expressed as follows:

$$P_{itj} = P(y_{it} = j) = \Phi(k_j - \gamma' y_{it-1} - \beta' X_{it} - \mu_i) - \Phi(k_{j-1} - \gamma' y_{it-1} - \beta' X_{it} - \mu_i) \qquad (5)$$

Where $\Phi(.)$ is the standard normal distribution function, which assumes that its density is $N(0, \sigma_\mu^2)$ and where j_0 is taken as $-\infty$ and j_m is taken as $+\infty$. Using these probabilities, it is possible to use maximum probability estimation to estimate the parameters of the model. These include the βs (the coefficients on the X variables) and the unknown cut-off values (the ks).

$$\ln L = \sum_{i=1}^{n} \left\{ ln \int_{-\infty}^{+\infty} \prod_{t=1}^{T} (P_{itj}) \left[\left(\frac{1}{\sqrt{2\pi\sigma_\mu^2}} \right) \exp\left(-\frac{\mu^2}{2\sigma_\mu^2} \right) \right] du \right\} \qquad (6)$$

The integral included in expression (6) can be approximated with M-point Gauss-Hermite quadrature. I use the mean-variance adaptive Gauss-Hermite quadrature to approximate the log likelihood. The REDOP models are estimated using the *meoprobit* command in Stata (Release 15.0, Stata Corporation). This command calculates the standard deviation for each parameter clustered at the house level in wave 1.

The initial conditions and correlated random effects problems in short-period panel data

When estimating the degree of state dependence of a condition (poverty or affluence) it is crucial to distinguish between true state dependence due to genuine causal effects of the past on current outcomes, and spurious state dependence, caused by the presence of time-invariant unobserved heterogeneity. This implies dealing with the initial conditions and unobserved heterogeneity.

The initial conditions problem appears when the observed start of the Markov model (y_{i1}) does not necessarily coincide with the true start of the process (Heckman, 1981). Given that I am estimating dynamic models I need to take into account whether the panel data shows a correlation between the initial position of the individuals in the income distribution (y_{i1}) and the individuals' unobserved heterogeneity. If the initial condition is not exogenous the estimate of the parameter of interest γ is biased upwards because part of the effect of the unobserved heterogeneity is captured by the coefficient on the lag dependent variable (Stewart, 2007).

I follow Wooldridge (2005) solution to solve the initial conditions problem.[11] Wooldridge's method allows individual effects to be correlated with explanatory variables, which partly controls for the endogeneity between the explanatory variables and the outcome. To do that, I model y_{it} at period $t = 2, \ldots, T$ conditional on the initial value of the dependent variable (y_{i1}) and exogenous variables (X_{it}). Then specify an approximation for the density of μ_i conditional on the initial value of the dependent variable (y_{i1}) and the period-specific versions of the time-varying explanatory variables starting from the second period of observations (X_i^+) as:

[11] In Heckman's solution, the initial conditions problem is solved by approximating the density function of the initial period using the same parametric form as conditional density for the rest of observations (Arulampalam & Stewart, 2009). Although the codes of its implementation are available, the computational implementation is hard because it requires separate programming owing to the absence of standard package. An alternative based on Heckman's proposal is the method of Orme (2001). The problem with Orme's solution is that it assumes a low correlation between the initial position of the individuals in the income distribution and individuals' unobserved effect, which is a strong assumption when using data from a short panel.

$$\mu_i = \mu_0 + \mu_1{}'y_{i1} + \mu_2{}'X_i^+ + e_i \quad (7)$$

Where $X_i^+ = (x_{i2}', \dots, x_{iT}')$ and e_i is a normal distribution that assumes $N(0, \sigma_e^2)$.

The second problem is the correlated random effects of dynamic panel model. Like the standard uncorrelated random effects probit models, so far, equation (4) is assuming that μ_i is uncorrelated with X_{it}. If this assumption is not met, then the maximum likelihood estimates are inconsistent. In order to deal with this issue, I could relax the assumption adding within-means of the explanatory variables into the main equation (Chamberlain, 1984; Mundlak, 1978). This allows for correlating the unobserved heterogeneity and the means of the observed independent variables. Following Wooldridge's approach, I could replace X_i^+ with the means of the time-varying explanatory variables of all time periods (Stewart, 2007).

However, this solution can present significant biases in longitudinal data with less than four rounds and a sample size of less than 800 cases per round (Akay, 2012; Arulampalam & Stewart, 2009). Even though the P-CASEN does not fit this description, since it has 4 rounds and a sample size exceeding the minimum recommended, in order to be on the safe side, I follow Rabe-Hesketh and Skrondal's (2013) proposal to deal with a short panel using the Wooldridge approach for correlated random effects. To do that, I replace X_i^+ in equation (7) by the mean $\overline{X_i^+} = (1/T - 1)\sum_{t=2}^{T} x_{it}$ that does not include the initial period explanatory variables.

Therefore, by parameterizing the unobserved heterogeneity distribution in this way, I address for short panels both the initial conditions problem and the correlated random effects problem. This assumes both the normality of μ_i and a zero-correlation between: i) the covariates, ii) the initial conditions and iii) the idiosyncratic error term (ε_{it}).[12] Thus, equation (4) is rewritten as follows:

$$y_{it}^* = \gamma' y_{it-1} + \beta' X_{it} + \mu_0 + \mu_1{}'y_{i1} + \mu_2{}'\overline{X_i^+} + e_i + \varepsilon_{it} \quad (8)$$

[12] These two strong assumptions require a certain amount of caution at the moment of interpreting the results of the REDOP models.

Rabe-Hesketh and Skrondal (2013)demonstrate that equation (8) will perform well as Heckman estimators for short-period of panel data. The parameters of equation (8) can be estimated following the process described in equations (5) and (6). The results from the implementation of this econometric strategy are presented in the next section.

6. Estimation results

Estimates of dynamic ordered probit models based on random effects specifications

The dynamic ordered probit models with Wooldridge's specification of correlated effects and initial conditions (Eq. 8) was estimated for the balanced sample. These models were estimated by maximum likelihood using Gauss-Hermite quadrature with 12 evaluation points. The balanced sample models use longitudinal survey weights. The results of the REDOP models are reported in Tables 3. In model 1, the low-income position and high-income position refer to the lowest income quintile group (IQG 1) and the highest income quintile group (IQG 5), respectively. Both groups are defined using relative thresholds. For model 2, the ends of the income distribution are defined as poor and affluent using absolute cut-offs.

The models were estimated for the household level to which the data on the characteristics of the head of household, head of household' partner, and characteristics of the household was assigned. The equation covers the years 2007-2009, while the initial conditions of the equation refer to the year 2006. Among the independent variables of the model is the lagged dependent variable, which captures the dynamic component of income position. In estimating the model, the head of the household used as the reference point is assumed to be a man, who completed secondary school, has a formal job, owns his house, has a couple without children and lives in an urban area in the capital city in Chile (region 13th).

Impact of explanatory variables

The parameters obtained after controlling for unobserved individual heterogeneity and initial conditions in the REDOP models are contained in Table 3. Before discussing the main parameters of interest, γ', which measures the extent of low-income persistence and high-income persistence, I briefly consider the estimates of the other parameters in both models, those relating to the explanatory variables.

Table 3: Random effect dynamic ordered probit models

Variables	(1) Income quintile groups (IQGs) (Relative thresholds)			(2) Welfare level (Absolute thresholds)		
	Coefficient		Std. Dev.	Coefficient		Std. Dev.
Lagged dependent variable for models (1) and (2)						
Ref. (1) IQGs 2-3-4 / (2) Middle class at t-1						
(1) IQG 1 (lowest) / (2) Poor at t-1	-0.254	***	(0.052)	-0.174	**	(0.082)
(1) IQG 5 (highest) / (2) Affluent at t-1	0.358	***	(0.069)	0.803	***	(0.131)
Initial conditions for models (1) and (2)						
Ref. (1) IQGs 2-3-4 / (2) Middle class at t1						
(1) IQG 1 (lowest) / (2) Poor at t1	-0.555	***	(0.059)	-0.497	***	(0.096)
(1) IQG 5 (highest) / (2) Affluent at t1	1.149	***	(0.088)	1.099	***	(0.179)
Household head characteristics						
Female	-0.101	**	(0.047)	-0.037		(0.065)
Age	0.004	***	(0.002)	0.008	***	(0.002)
Ref. Education: Secondary school						
Education: Primary school	-0.248	***	(0.037)	-0.229	***	(0.042)
Education: University degree	0.719	***	(0.095)	0.635	***	(0.124)
Ref. Labour status: Formal employed						
Labour status: Informal employed	-0.116	*	(0.064)	-0.132		(0.097)
Labour status: Unemployed	-0.883	***	(0.188)	-0.902	***	(0.174)
Labour status: Inactive	-0.424	***	(0.114)	-0.632	***	(0.151)
HH head's partner characteristics						
Age	0.002		(0.003)	-0.005		(0.003)
Ref. Education: Secondary school						
Education: Primary school	-0.295	***	(0.046)	-0.214	***	(0.057)
Education: University degree	0.328	***	(0.118)	0.350	***	(0.128)
Ref. Labour status: Formal employed						
Labour status: Informal employed	-0.091		(0.092)	-0.045		(0.114)
Labour status: Unemployed	-0.168		(0.135)	0.069		(0.151)
Labour status: Inactive	-0.015		(0.068)	0.003		(0.096)
Household characteristics						
Ref. Household type: Couple without children						
Household type: Single without children	0.049		(0.144)	0.339	**	(0.169)
Household type: Couple with children	0.113		(0.103)	0.076		(0.124)
Household type: Single with children	0.068		(0.174)	-0.110		(0.207)
Household type: Lone person	-0.287		(0.205)	0.724	**	(0.235)
Number of persons	0.245	***	(0.028)	-0.338	***	(0.036)
Number of children < 15	-0.071		(0.058)	0.021		(0.071)
Number of workers	0.862	***	(0.034)	0.790	***	(0.049)
Ref. Housing: Own housing (no mortgage)						
Housing: Own housing, mortgage	0.126	**	(0.054)	0.169	***	(0.066)
Housing: Rent	-0.140	**	(0.067)	-0.147	*	(0.080)
Housing: Subsidized or rent free	-0.194	***	(0.050)	-0.347	***	(0.060)
Rural	-0.183	***	(0.045)	-0.165	***	(0.055)
Ref. Regions: 13th						
Regions: 1st, 2nd, 3rd and 4th	0.069		(0.055)	-0.011		(0.065)
Regions: 5th, 6th, 7th, 8th, 9th and 10th	-0.168	***	(0.041)	-0.218	***	(0.053)
Regions: 11th and 12th	0.108		(0.096)	0.071		(0.112)
Statistics						
Cut 1	-1.189		(0.144)	-2.565		(0.228)
Cut 2	1.917		(0.145)	1.921		(0.195)
Variance unobservable heterogeneity	0.435		(0.061)	0.333		(0.096)
Log pseudolikelihood	-7,703,729.3			-4,745,448.4		
Number of household-years	13,920			13,920		
Number of households	4,640			4,640		

Source: Author's calculations from the P-CASEN 2006-2009 (balanced sample with longitudinal weights are used).

Notes: Coefficients for year dummies and within means of demographics not reports for brevity. Models estimated using observation for t > 1. *** significance at 10 percent; ** significance at 5 percent; * significance at 1 percent.

Table 3 shows the coefficient of the explanatory variables on the probability of being low-income and high-income. Regarding the demographic characteristics of the head of household, age has a positive impact on the probability of being in the highest IQG and being affluent. While, a female head of household has a significant effect on the probability of being in the lowest IQG, and not on the probability of being poor.

As suggested by the human capital theory, household members who have a larger endowment of formal education increase the probability of their households being high income. Although having completed university-level education for the head household and head household's partner are statistically significant, the coefficients for the head household is double than his/her partner in both models.

The head household labour status is also important to explain whether the household is located at the extremes of the income distribution. As expected, being unemployed is the highest coefficient among the observable variables explaining the increase in the probability of being in the lowest quintile or being poor. However, for the household head's partner, it is not significant in either of the two models. The variable that does has the most significant positive effect on the probability of being in the highest IQG and being affluent is the number of workers.

Household size is a variable sensitive to the income thresholds used to define low-income and high-income in the income distribution. While in Model 1, this variable increases the probability of being in the highest IQG in model 2, the impact is also significant but increases the probability of being poor.

As to housing, those who do not own the house have a higher probability of low-income in both models. Regarding location, households that are both in rural areas and in intermediate regions (not including the metropolitan 13th Region) have a greater probability of being in the lowest quintile or being poor.

Finally, both models 1 and 2 introduce explicit unobserved individual heterogeneity into the dynamic ordered probit model by specifying random effects (last row of Table 3). The latent error variance attributable to unobserved heterogeneity is 43.5 per cent for the Model 1 and 33 per cent for the level of Model 2. This measure corresponds to the intra-class correlation coefficient (ICC).

Initial conditions and state dependence in both low-income and high income

As I explained above, the critical estimation problem of state dependence is the potential endogeneity of the initial conditions. Table 3 shows in rows (3) and (4) the parameter estimates for the initial condition variables are highly significant for both models (at 1 per cent or lower). The effect that is controlling for initial conditions has on the estimates of the magnitude of low-income persistence and high-income persistence I will be discussed below in Table 4.

The γ' coefficients are presented in the first two rows of Table 3. These values correspond to the true state dependence for both low-income and high-income positions. It is clear that after controlling for observed and unobserved heterogeneity, being low-income in period $t-1$ has a negative and statistically significant effect on the probability to move into a higher income position in period t while being in high-income in period t-1 has a positive and statistically significant effect on the probability to stay in the same income position. There is, therefore, a genuine state dependence in the ends of the income distribution. However, the magnitude of the coefficients varies between both models. The affluence persistence coefficient is more than double that of the IQG5 persistence, while the poverty persistence coefficient is lower than the IQG1 persistence.

Table 4: Alternative estimators of lagged dependent variable for IQG 1/poor and IQG 5/affluent

Lagged dependent variable	(1) Pooled ordered probit	(2) Random effect dynamic ordered probit	(3) REDOP with specifications of correlated effects and initial conditions
Income quintile groups (IQGs)			
IQG 1 (lowest) at t-1	-0.647	-0.522	-0.254
IQG 5 (highest) at t-1	1.102	0.971	0.358
Welfare level			
Poor at t-1	-0.572	-0.521	-0.174
Affluent at t-1	1.516	1.469	0.803

Source: Author's calculations from the P-CASEN 2006-2009 (balanced sample with longitudinal weights are used).

Notes: All coefficients for pooled ordered probit model (1) and REDOP without specifications (2) are significant at 1 per cent. Models estimated using observation for t > 1.

Table 4 provides further information on the extent of state dependence for low-income and high-income. The γ' coefficients from the first and second rows of Table 3 are reproduced in the third column while the first and second columns contain other measures of state dependence. There are coefficients on a lagged dependent variable for IQG 1/poor and IQG 5/affluent in a pooled ordered probit model and a dynamic ordered probit model assuming exogenous initial conditions (Eq. 4). In other words, Table 4 shows how I control models for observed and unobserved heterogeneity (column (2)) and heterogeneity and initial conditions (column (3)).

When I move the columns from left to right in Table 4, it is clear that the estimated extent of low-income and high-income decline as I control for more factors. In the model (1), between columns (1) and (3), the reduction of the coefficients for both IGQ 1 persistence and IQG 5 persistence is more than 60 per cent. In the model (3), the extent of poverty persistence coefficient estimated using REDOP with specifications of correlated effects and initial conditions is 70 per cent lower than from the pooled data. In the case of affluence persistence, it leads to a reduction of 47 per cent of the initial estimate. Therefore, controlling for heterogeneity and initial conditions is crucial when trying to establish the level of true state dependence in both low-income and high-income.

Average partial effect of the state dependence

The coefficients provided by the REDOP models for the previous income position ($t-1$) are arbitrary. For this reason, they do not allow us to identify the magnitude of the state dependence on the conditional probability of staying in low-income/high-income. In order to have an indicator of the weight of the state dependence in absolute terms, it is necessary to calculate the average partial effects (APEs). The APE for the state dependence shows the impact of the previous income position ($t-1$) in the current income position (t). The state dependence effect is calculated as the difference between the average probability of being in a certain income position at time t after being in the same income position at time $t-1$ over the sample of those who were in other entry positions at $t-1$ and the raw aggregate probability of being in that particular entry position at time t over the same sample (Wooldridge, 2005).

I compute APEs for each of the categories for both ends of the income quintile groups and welfare level measurements. The estimates in Table 5 indicate that the contribution of genuine state dependence in the estimated models is less than 10 per cent. When comparing the extremes of the income distribution for both measures, I found that 4.3 per cent of those in the lowest quintile group (IQG 1) and 5.4 per cent of those in the highest income quintile group (IQG 5) are explained by having been in the same income position at $t-1$, thereby holding fixed characteristics. For the welfare measure, the state dependence effect is 5.8 per cent for the poor and 9.2 per cent for the rich.

To put these results in context, it would be useful to compare them with those from other studies but, as I previously noted, there are no other studies of high-income persistence. Regarding research on low-income persistence, they use different definitions of low-income and different methodologies, and this should be taken into account when comparing with other countries. Giarda & Moroni (2018) exploits the longitudinal component of EU-SILC for the period 2009–2012 to estimate poverty persistence in four European countries using dynamic random effects probit models after controlling for individual heterogeneity and initial conditions. Their estimates show that Italy has the highest poverty persistence, with an APE of 0.159 compared to 0.110 in France, 0.126 in Spain and 0.045 in the UK. In the case that I had applied the poverty line used by Giarda & Moroni (2018) to the P-CASEN 2006-2009, its value would be close to the relative cut-off to identify the lowest income quintile group.[13] Therefore, it could be the case that being poor at time $t-1$ in Chile has a lower impact on the probability of being poor at time t than in the four countries compared.

[13] The poverty line used by these authors is fixed at the 60 percent of the national median equivalised disposable income.

Table 5: Average partial effects on probability of being on both low-income and high-income

Variables	Low-income						High income					
	(1) IQG 1 (lowest)			(2) Poor			(1) IQG 5 (highest)			(2) Affluent		
	dy/dx		Std. Dev.	dy/dx		Std. Dev.	dy/dx		Std. Dev.	dy/dx		Std. Dev.
Lagged dependent variable for models (1) and (2)												
Ref. (1) IQGs 2-3-4 / (2) Middle class at t-1												
(1) IQG 1 (lowest) / (2) Poor at t-1	0.043	***	(0.010)	0.019	*	(0.010)						
(1) IQG 5 (highest) / (2) Affluence at t-1							0.058	***	(0.013)	0.092	***	(0.022)
Household head characteristics												
Female	0.016	**	(0.008)	0.004		(0.007)	-0.014	**	(0.007)	-0.003		(0.005)
Age	-0.001	**	(0.000)	-0.001	***	(0.000)	0.001	**	(0.000)	0.001	***	(0.000)
Ref. Education: Secondary school												
Education: Primary school	0.040	***	(0.006)	0.024	***	(0.004)	-0.035	***	(0.005)	-0.018	***	(0.003)
Education: University degree	-0.095	***	(0.010)	-0.051	***	(0.007)	0.122	***	(0.017)	0.065	***	(0.014)
Ref. Labour status: Formal employed												
Labour status: Informal employed	0.019	*	(0.010)	0.014		(0.010)	-0.016	*	(0.009)	-0.010		(0.007)
Labour status: Unemployed	0.165	***	(0.039)	0.128	***	(0.031)	-0.104	***	(0.017)	-0.053	***	(0.007)
Labour status: Inactive	0.071	***	(0.021)	0.076	***	(0.023)	-0.058	***	(0.015)	-0.045	***	(0.011)
HH head's partner characteristics												
Ref. Education: Secondary school												
Education: Primary school	0.048	***	(0.008)	0.023	***	(0.006)	-0.041	***	(0.006)	-0.017	***	(0.004)
Education: University degree	-0.048	***	(0.016)	-0.031	***	(0.010)	0.051	***	(0.020)	0.033	**	(0.014)
Household characteristics												
Number of persons	-0.038	***	(0.004)	0.034	***	(0.003)	0.035	***	(0.004)	-0.028	***	(0.003)
Number of workers	-0.136	***	(0.005)	-0.080	***	(0.004)	0.124	***	(0.004)	0.066	***	(0.003)
Ref. Housing: Own housing (no mortgage)												
Housing: Own housing, mortgage	-0.019	**	(0.008)	-0.016	***	(0.006)	0.019		(0.008)	0.015	**	(0.006)
Housing: Rent	0.023	**	(0.011)	0.015	*	(0.009)	-0.020		(0.009)	-0.012	*	(0.006)
Housing: Subsidized or rent free	0.032	***	(0.008)	0.038	***	(0.007)	-0.027	***	(0.007)	-0.026	***	(0.004)
Rural	0.030	***	(0.008)	0.017	***	(0.006)	-0.026	***	(0.006)	-0.013	***	(0.004)
Ref. Regions: 13th												
Regions: 1st, 2nd, 3rd and 4th	-0.011		(0.008)	0.001		(0.007)	0.010		(0.008)	-0.001		(0.005)
Regions: 5th, 6th, 7th, 8th, 9th and 10th	0.027	***	(0.006)	0.022	***	(0.005)	-0.024	***	(0.006)	-0.018	***	(0.004)
Regions: 11th and 12th	-0.017		(0.014)	-0.007		(0.011)	0.016		(0.015)	0.006		(0.010)

Source: Author's calculations from the P-CASEN 2006-2009.

Notes: Models estimated using observation for t > 1. *** significance at 10 percent; ** significance at 5 percent; * significance at 1 percent.

Testing the attrition bias

I analyse the extent to which the results are robust to the possibility of selection bias due to no-random attrition from the household panel sample. The main problem associated with non-random attrition in the sample is when the variables affecting attrition might be correlated with the outcome variable of interest. In this situation, econometric estimates of key relationships will be biased.[14] In other words, attrition bias could occur if the error term in the equation of interest is correlated with the error term in the attrition equation (Wooldridge, 2002b).

To get an idea of the potential importance of non-random sample drop out in P-CASEN 2006-2009, Table A.1 (see appendix) reports the descriptive statistics for both balanced sample and unbalanced sample. The unbalanced sample contains all of the observations available in each round. The balanced sample uses all of the relevant variables that have information in the four rounds. When comparing the two samples, which do not use weights in the estimation of the means of the observable characteristics, it is possible to identify the impact of attrition. Results in Table A.1 suggest there is a relation between low-income/high-income and non-response. For example, small households, with less children and a higher level of schooling of its head −which on average are richer−, tended to be lost. The same is observed in households with better labour conditions and, accordingly, with higher incomes. Therefore, low-income households seem to be overrepresented and high-income ones underrepresented in the panel.[15]

As I said before, the problem arising from non-random selection is that it might lead to biased estimators. Therefore, the next step is to identify whether the non-randomness of the attrition bias the REDOP models. Testing whether or not there is attrition bias is not straightforward because the variables related to attriters are not observable in the year in which households stop participating in the panel sample. However, information is available on the observable variables of previous years for households that leave the panel. Verbeek and Nijman (1992) propose including in the main equation of the model indicators describing individuals' pattern of survey response (known as variable-addition tests). The intuition behind the test is that if the attrition is not random, the indicators of an individual's pattern of survey responses should be associated

[14] This is closely related to the general case that Heckman (1979) called sample selection bias, arising in situations where a sample is not drawn randomly from the population of interest.

[15] Nevertheless, when comparing the means of the variables after using longitudinal weights in the balanced sample, they appear similar to the means of the unbalanced sample. I will return to this point later.

with the dependent variables of the model after controlling for the independent variables. The test variables that I use are: a) an indicator summarising whether attrition occurred in the following wave (Next wave); b) the total number of waves in which the individual is observed (N waves); and c) an indicator of whether the individual is in the survey all the time (All waves). Each of these indicators is added to the dynamic correlated effects ordered probit model, given by equations (8) and estimated with the unbalanced sample. This gives three separate attrition bias tests. If the coefficients of the variables related to the test are zero ($H_0\colon \beta = 0$), then there will be no selection bias explained by the attrition.

Table 6: Variable-addition tests for attrition bias as proposed by Verbeek and Nijmand (1992)

Attrition indicators	REDOP with specifications of correlated effects and initial conditions				
	(1) Income quintile groups			(2) Welfare level	
	Coefficient		Std. Dev.	Coefficient	Std. Dev.
Next wave	0.194	**	(0.091)	0.123	(0.114)
N waves	0.036		(0.119)	-0.021	(0.141)
All waves	-0.197		(0.091)	-0.008	(0.124)

Source: Author's calculations from the P-CASEN 2006-2009 (unbalanced sample).
Notes: Models estimated using observation for t > 1. ** significance at 5 percent; * significance at 1 percent.

Table 6 shows the estimated coefficients on the additional variables using the dynamic ordered probit models for random effects specifications. I applied the tests for the two dependent variables: income quintile groups (1) and welfare measurement (2). In only one case of the model (1) the null hypothesis is rejected at the 5 per cent level. In other cases, the variable-addition tests are insignificant, and the evidence suggests that bias due to non-random attrition may not be a major problem. It is worth noticing that adding attrition indicators on the models is not intended to correct the estimates for attrition. Similar to other studies that have used variable-addition tests in their analyses, these are only informative for comparing estimates with the baseline models that do not include the test variable (Clark & Kanellopoulos, 2013; Contoyannis et al., 2004). Other limitations of these tests is that they may have low power, and also do not test selection on unobservable (correlation between the error terms), but only selection on observable (Nicoletti, 2006).

I provide additional evidence about whether selectivity bias is a problem by focusing on the difference between estimates from models that use weights to adjust for attrition and estimates from models without weights. To do the latter, I adopt an inverse probability weight (IPW) estimator for the unbalanced sample, and I use the longitudinal weights provided by the Chilean Ministry of Social Development for the balanced sample, which also adjusts for non-response over the period studied. I apply both of them to Wooldridge's pooled ordered probit model (2002b, 2002a).[16]

The idea behind the IPW estimator is the following: the weight adjustment associated with each observation is inversely proportional to the propensity to respond in each wave ($r_{it} = 1$ if observed; 0 otherwise) given a set of individual characteristics in the first wave (z_{i1}). An estimate of the response probability ($\hat{p}_{it}^{r}$) is derived from a statistical model (e.g., a probit regression). Therefore, individuals having characteristics such as a high $\hat{p}_{it}^{r}$ will have an adjustment factor close to 1, while individuals with characteristics associated with non-response (low $\hat{p}_{it}^{r}$) will have a higher factor. This approach requires z_{i1} to include the initial values of all of the regressors, as well as the initial income position states. Further, variables that predict attrition and are correlated with the outcome of interest, are deliberately excluded from Eq. (8).

I use as instrumental variables two dichotomous indicators related to the household's dwelling (whether the households resided on in a flat, whether the rent is more than 25 percent of the total household income) and a health indicator of the head household (whether during the last year he/she has received some outpatient or hospital care for chronic disease).

I estimate a probit model for response/non-response at each wave, from wave 2 to wave 4, using the full sample of households who are observed at wave 1. The inverse of the fitted probabilities from these models, $1/\hat{p}_{it}^{r}$, are then used to weight observations in the maximum likelihood estimation of the pooled ordered probit model in the objective function as follow:

$$\ln L = \sum_{i=1}^{n} \sum_{i=t}^{T} (r_{it}/\hat{p}_{it}^{r}) \ln L_{it}\,, \quad t = 2, \ldots, T \qquad (9)$$

[16] The estimator cannot be applied to the log-likelihood function for the random effects specification because it is restricted only to objective functions that are additive across observations (Contoyannis, Jones, & Rice, 2004).

IPW works to identify attrition problem for a simple reason. Under the ignorability non-response assumption, the conditional on observables in the first time period (z_{i1}) is independent of r_{it}:

$$P(r_{it} = 1|y_{it}, y_{it-1}, X_{it}, z_{i1}) = P(r_{it} = 1|\, z_{i1}), \qquad t = 2, \dots, T \tag{10}$$

Wooldridge (2002b) prove that the IPW produces a consistent $\sqrt{N}$- asymptotically normal estimator. Therefore, "the probability limit of the weighted objective function is identical to that of the unweighted function if we had no attrition problem" Wooldridge (2002a, p. 588). This IPW estimator is implemented for the unbalanced sample using the *pweights* option in Stata (Release 15.0, Stata Corporation). Also, longitudinal weights are used for the balance sample. The estimates from both weighted models are compared with the estimates from the unweighted models for both balanced and unbalanced samples to assess the attrition bias.

Table 7: Weighted and unweighted estimates from pooled dynamic ordered probit models

Lagged dependent and initial conditions variables for models (1) and (2)	Unbalanced panel				Balanced panel			
	Unweighted		IPW		Unweighted		Longitudinal weights	
	Coeff.	Std. Dev.	Coeff.	Std. Dev.	Coeff.	Std. Dev.	Coeff.	Std. Dev.
(1) Income quintile groups								
Lagged dependent variable								
IQG 1 (lowest) t-1	-0.576	(0.033)	-0.592	(0.039)	-0.575	(0.035)	-0.577	(0.036)
IQG 5 (highest) t-1	0.708	(0.045)	0.723	(0.059)	0.744	(0.048)	0.757	(0.054)
Initial conditions variable								
IQG 1 (lowest) t1	-0.313	(0.033)	-0.331	(0.040)	-0.310	(0.034)	-0.301	(0.040)
IQG 5 (highest) t1	0.618	(0.047)	0.671	(0.059)	0.655	(0.050)	0.690	(0.054)
(2) Welfare level								
Lagged dependent variable								
Poor t-1	-0.463	(0.047)	-0.500	(0.057)	-0.487	(0.050)	-0.479	(0.054)
Affluence t-1	1.023	(0.081)	1.057	(0.110)	1.084	(0.088)	1.142	(0.111)
Initial conditions								
Poor t1	-0.303	(0.051)	-0.278	(0.065)	-0.309	(0.054)	-0.287	(0.069)
Affluence t1	0.759	(0.082)	0.737	(0.105)	0.836	(0.089)	**0.679**	**(0.110)**

Source: Author's calculations from the P-CASEN 2006-2009

Notes: Models estimated using observation for t > 1. All coefficients are significant at 1 per cent. Bold indicates coefficient significantly at 10 per cent different from unweighted regression in the unbalanced panel.

Table 7 reports some summary results from unweighted and weighted estimates. Most of the coefficients, on the lagged variables and initial conditions, are stable across the balanced and unbalanced samples without weights, as well as samples with IPW and longitudinal weights. In only one case – the affluents' initial conditions on the balanced sample with longitudinal sample -, the coefficient turns out to be statistically significant at 10 per cent. This may suggest that longitudinal non-response does not play a significant role and, as a result, the attrition bias does not seem to lead to biased results of the effect of previous low-income/high-income position and initial conditions. Again, it is important to note that IPW does not correct for attrition driven by shocks between wave $t-1$ and t that affect both low-income/high-income and survey participation and which are unobserved in the last wave of observation.

7. Conclusions

This paper studies the income position persistence in the extreme of the income distribution in Chile for the period 2006-2009 using the data from the P-CASEN. The models I have implemented allow the joint estimation of state dependence for low-income and high-income groups along the income distribution. It is the first time that both poverty persistence and affluence persistence are measured in a Latin American country.

The analysis I provide addresses all these limitations from previous studies that found that the unequal income distribution in Chile contrasts with a high mobility of all but those in the high-end of the income ladder (e.g. Contreras et al., 2005; Sapelli, 2013). These research not only used panel data considering only three waves over a decade (P-CASEN 1996-2001-2006), but also the analyses used simple empirical models and income mobility measures which have not fully exploited the longitudinal dimension of the data. They also did not consider the sample attrition problems which could have biased some of the findings obtained.

My analysis provides the following findings. First, the descriptive results show that the persistence at the two ends of the income distribution for the Chilean case exists but is lower than that found in previous research. The evidence to support the thesis of a sticky floor that prevents people from scaling the income ladder seems to be less convincing for Chile. The high mobility at the bottom of the income distribution is probably related to a right-skewed distribution. Since the boundaries between the income quintile groups 1 to 4 are close to each other, changes in the positions in the income distribution do not necessarily represent significant changes in individuals' income.

Likewise, the evidence to support the idea of affluence persistence, according to which high-income individuals stay put in their positions with no risk of falling, does not seem to be sufficiently strong in Chile either. The glass floor in Chile is much permeable than one would have initially thought. The turnover of this group occurs mainly between the middle-class and the affluent category. Again, the explanation can be found in the shape of the income distribution. In Chile, the right tail of the income distribution is so stretched that those in the highest decile group may be either too close or too far from the income decile boundary. Those close to the income cut-off might be exposed to greater fluidity with the decile groups below. This suggests that a glass floor might be in a higher income cut-off (e.g. the affluent 5 per cent of the population).

Second, the results from the econometric analysis suggest that both mechanisms true state dependence and heterogeneity (observable and unobservable) explain low-income persistence and high-income persistence. In the former mechanism, the contribution is more significant for the affluent than for the poor. While the poverty persistence has an APE of only 2 per cent, the APE in the affluence persistence is 9 percent. Therefore, past income position is more important in the richest groups than in the lowest part of the income distribution to explain current income position.

Moreover, the true state dependence impact on the current income position for low-income households appears to be low when compared to other explanatory variables. According to the models' outcomes, the unobservable heterogeneity accounts for between 33 and 44 per cent of the unexplained variation in income position changes. Furthermore, the models provide evidence that the effect of the observed characteristic in the current low-income position has a greater impact than the genuine state dependence.

For example, I found that the households' labour market conditions and the human capital of both the household head and the household head's partner are the variables on the models that have a higher APE in explaining both the lowest income quintile group persistence and poverty persistence. Since the inability to exit low-income is not the result of genuine dependence but reflects differences between the productive skills of households members, there is scope for policies that promote human capital to free households from low-income persistence.

Third, while descriptive evidence shows that there is income-related attrition in the data, with those in the high-income initial position more likely to drop out, both the variable-addition tests and comparison of estimates based on unweighted and weighted unbalanced samples show no evidence of attrition bias. This is, it does not influence the magnitude of the estimated effects of state dependence and initial conditions.

In summary, Chile appears to be a fluid society throughout its income distribution, even at both ends of the distribution. While all groups are likely to move upwards in the income ladder, this does not ensure the sustainability of those changes over time. This is because the income mobility is mostly bounded to short-range movements. It is thus evidencing that the entire population is vulnerable to experience a downward from their positions. In this scenario, income mobility seems to be more related to stress or anxiety generated by economic uncertainty than to an improvement in the well-being of individuals.

Finally, my approach to understanding the joint low-income and high-income persistence could offer a guide to further empirical work to other countries that have access to short-period panel data. Thus, new research could analyse poverty persistence and affluence persistence from a comparative and institutional perspective.

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Appendix

Table A.1: Descriptive statistics of the variables for both unbalanced and balanced samples (average values 2006-2006)

Variables	Unbalanced sample (Unweighted)		Balanced sample (Unweighted)		Balanced sample (Longitudinal weights)	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Household head characteristics						
Female	0.294	(0.002)	0.290	(0.003)	0.303	(0.007)
Age	47.8	(0.079)	48.9	(0.097)	48.3	(0.215)
Education: Primary school	0.309	(0.003)	0.373	(0.004)	0.311	(0.007)
Education: Secondary school	0.524	(0.003)	0.510	(0.004)	0.525	(0.008)
Education: University degree	0.143	(0.002)	0.087	(0.002)	0.140	(0.008)
Labour status: Formal employed	0.717	(0.002)	0.706	(0.003)	0.724	(0.006)
Labour status: Informal employed	0.110	(0.001)	0.112	(0.002)	0.107	(0.003)
Labour status: Unemployed	0.017	(0.001)	0.017	(0.001)	0.016	(0.001)
Labour status: Inactive	0.156	(0.002)	0.166	(0.002)	0.153	(0.005)
HH head's partner characteristics						
Age	44.6	(0.085)	46.1	(0.106)	45.4	(0.236)
Education: Primary school	0.316	(0.003)	0.387	(0.005)	0.331	(0.009)
Education: Secondary school	0.567	(0.004)	0.530	(0.005)	0.552	(0.011)
Education: University degree	0.102	(0.002)	0.064	(0.002)	0.102	(0.008)
Labour status: Formal employed	0.312	(0.003)	0.272	(0.003)	0.310	(0.009)
Labour status: Informal employed	0.093	(0.002)	0.087	(0.002)	0.084	(0.004)
Labour status: Unemployed	0.044	(0.001)	0.041	(0.001)	0.042	(0.003)
Labour status: Inactive	0.551	(0.003)	0.600	(0.004)	0.564	(0.009)
Household characteristics						
Equivalised total household income	351,788	(2,190)	279,176	(1,564)	331,364	(8,261)
Household type: Couple without children	0.278	(0.002)	0.282	(0.003)	0.277	(0.007)
Household type: Single without children	0.127	(0.002)	0.117	(0.002)	0.127	(0.005)
Household type: Couple with children	0.397	(0.003)	0.411	(0.003)	0.400	(0.007)
Household type: Single with children	0.106	(0.002)	0.114	(0.002)	0.111	(0.004)
Household type: Lone person	0.093	(0.002)	0.075	(0.002)	0.085	(0.005)
Number of persons	3.7	(0.009)	3.9	(0.012)	3.8	(0.027)
Number of children < 15	0.824	(0.005)	0.864	(0.007)	0.831	(0.015)
Number of workers	1.357	(0.005)	1.336	(0.006)	1.346	(0.013)
Housing: Own housing (no mortgage)	0.543	(0.003)	0.605	(0.004)	0.544	(0.008)
Housing: Own housing, mortgage	0.137	(0.002)	0.123	(0.002)	0.134	(0.006)
Housing: Rent	0.160	(0.002)	0.102	(0.002)	0.163	(0.008)
Housing: Subsidized or rent free	0.159	(0.002)	0.170	(0.003)	0.159	(0.006)
Rural	0.122	(0.002)	0.161	(0.003)	0.127	(0.004)
Regions: 1st, 2nd, 3rd and 4th	0.111	(0.002)	0.121	(0.002)	0.111	(0.005)
Regions: 5th, 6th, 7th, 8th, 9th and 10th	0.471	(0.003)	0.526	(0.004)	0.477	(0.008)
Regions: 11th and 12th	0.038	(0.001)	0.031	(0.001)	0.016	(0.001)
Regions: 13th	0.381	(0.003)	0.322	(0.003)	0.396	(0.008)
Nº individuals	30,196		18,076		18,076	
Nº households	8,079		4,693		4,693	

Source: Author's calculations from the P-CASEN 2006-2009.

Notes: All results are rates (%) unless stated otherwise. The equivalized total household income is valued in terms of 2009 Chilean pesos.

Table A.2: Annual income position at t conditional of income position at *t -1* for unbalanced and balanced samples

(1) Income quintile groups (IQGs): relative thresholds

IQGs, year *t* -1	IQGs, year *t* (row %)			
	IQG 1	IQGs 2-3-4	IQG 5	Missing
(1.a) Balanced sample				
IQG 1	50.0	47.4	2.6	-
IQGs 2-3-4	15.5	74.6	10.0	-
IQG 5	4.1	38.8	57.2	-
Total	21.3	63.1	15.5	
(1.b) Unbalanced sample				
IQG 1	43.3	40.9	1.9	13.88
IQGs 2-3-4	13.1	63.9	7.8	15.23
IQG 5	2.7	28.8	39.3	29.19
Total	14.0	42.3	9.8	33.9

(2) Welfare level: absolute thresholds

Welfare, year *t* -1	Welfare, year *t* (row %)			
	Poor	Middle Class	Affluent	Missing
(2.a) Balanced sample				
Poor	36.6	62.9	0.4	-
Middle class	7.9	89.0	3.1	-
Affluent	1.1	47.5	51.4	-
Total	10.9	83.9	5.3	
(2.b) Unbalanced sample				
Poor	31.8	54.6	0.4	13.26
Middle class	6.7	74.4	2.8	16.03
Affluent	0.9	27.8	33.6	37.79
Total	7.1	55.0	4.0	33.9

Source: Author's calculations from the P-CASEN 2006-2009.

Note: Statistics without weights.