London School of Economics and Political Science

New approaches to measuring economic and social well-being in Chile

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A thesis submitted to the Department of Social Policy at
the London School of Economics for the degree of Doctor of Philosophy,
London, November 2020

Declaration of authorship

I certify that the thesis I have presented for examination for the PhD degree of the London School of Economics and Political Science is solely my own work other than where I have clearly indicated that it is the work of others.

I warrant that this authorisation does not, to the best of my belief, infringe the rights of any third party.

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I can confirm that my thesis was copy edited for conventions of language, spelling and grammar by Clare Sandford.

Joaquín Prieto

London, November 2020

Acknowledgements

Studying the changes that homes experience over time has not exempted my own family. In 2012 we left Chile with my wife Isabel for postgraduate studies. At that time, we were four. Now we are five. While finishing writing this thesis, Ramón, our third child, started his school life, Julia her last year in primary school, and Blanca her second year in secondary school. I will remember the year 2019 as the year where everyone in my family was a student.

Having completed a doctorate accompanied by my family has been a privilege. I feel very fortunate to have had the time to study in-depth the topics that interest me and at the same time enjoy everyday life with my children and wife in a fascinating city like London. My family and I will cherish these years with much affection.

Being able to balance my doctoral studies with my family life properly has been possible, thanks to the support of several people and institutions. First of all, I want to thank my supervisors. The guidance I received from Stephen and Grace during the doctorate has been vital for my research to come to a successful conclusion. Each meeting we had to discuss my progress undoubtedly served to improve the chapters of this thesis substantially. I have also learned from their rigorous and critical work style that I will apply in my future projects. In particular, I would like to thank Stephen for helping me build my knowledge puzzle about wellness measures from a longitudinal perspective.

I thank the Department of Social Policy -all the academic and administrative team- for their support in these four years. Especially to the cohort that started their PhD projects with me in 2015. I also want to thank the households that answered the surveys I have used in my research, and the Chilean Ministry of Social Development and the Central Bank of Chile for granting public access to these databases to be analysed by those who wish to do so. I thank the Chilean people for funding my postgraduate studies through the Becas Chile Scholarship, and both the Financial Support Office and Social Policy Department of LSE for sponsoring my participation in conferences.

Finally, I would like to thank Isabel. Her example and unconditional support have been fundamental in all my projects.

Abstract

I propose three new measures of social and economic well-being using different approaches. These measures are applied to Chile using two household surveys: the Panel CASEN and the Financial Survey.

First, I use an income positions persistence approach to estimate the persistence of households in different positions of the income distribution. The application of this measure enables us to understand the mechanisms that explain why those at the lower end of the income distribution have a low probability of moving up (sticky floor), and those at the higher end of the income distribution have less chance of moving down (glass floor). The results show that income mobility is particularly high for all groups in the income distribution.

Second, I use a low-income dynamic approach to estimate degrees of vulnerability to poverty. This measure enables us to obtain two vulnerability lines that measure the risk of non-poor households falling into poverty in the next period. This enables the identification of three types of households: those with high, moderate and low vulnerability. The latter corresponds to the income-secure middle class. The results show that vulnerability to poverty affects a significant part of the population that exited poverty in the last decade.

Third, I use a multidimensional approach to measure economic insecurity at the household level. I build an index that combines four indicators of economic insecurity that cause stress and anxiety: unexpected economic shocks, unprotected employment, over-indebtedness and asset poverty. In this way, the index offers a measure that directly relates economic uncertainty to stress due to the lack of social protection and household buffers to face an unexpected economic shock. The results show that households in the entire income distribution, even in the highest income deciles groups, are affected by economic insecurity.

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List of Acronyms

APE	Average Partial Effect
BHPS	British Household Panel Survey
BLI	Better Life Index
CASEN	*Encuesta de Caracterización Socioeconómica de Hogares*
CLP	*Chilean Pesos*
DINA	Distributional National Accounts
ECLAC	Economic Commission for Latin America and the Caribbean
EG DNA	Expert Group on Disparities in National Accounts
EPSEM	Equal Probability Selection Method
FHS	Financial Household Survey
GDP	Gross Domestic Product
GIC	Growth Incidence Curve
GNP	Gross National Product
HDI	Human Development Index
HDR	Human Development Report
IEII	Integrated Economic Insecurity Index
IGE	Intergenerational elasticity
IOp	Inequality of Opportunity
LAC	Latin America and the Caribbean
MDS	*Chilean Ministry of Social Development*
MEII	Multidimensional Economic Insecurity Index
OECD	Organisation for Economic Co-Operation and Development
P-CASEN	Panel CASEN
PISA	Programme for International Student Assessment
PPP	Purchasing Power Parity
pppd	per person per day
REDOP	Random Effect Dynamic Ordered Probit Model
SII	Servicio de Impuestos Internos
UNESCO	United Nations Educational, Scientific and Cultural Organization
USD	United States Dollars
VAT	Value-added tax
VEP	Vulnerability as Expected Poverty

Chapter 1

Introduction

1.1 Motivation

Most Latin American countries have been hit by the Covid-19 crisis in the context of high levels of income inequality combined with weak social security systems that fail to offer protection to those most at risk of falling back into poverty. Despite the efforts of governments to support the most vulnerable families, workers and firms, poverty is expected to increase again in the region after two decades of continuous decline. Besides, the pandemic came just after a year of social unrest in democratic countries that have had socio-economic progress such as Chile and Colombia. Large-scale uprisings and massive street protests show that the progress of these countries has been severely incomplete and insufficient (Ferreira & Schoch, 2020).

The aftermath of this crisis could help to make a case for the need to redefine a new social contract based on a stronger social protection system centred on people's well-being (OECD, 2020). This will require new measures of progress and well-being so to design better policies that could lead Latin American countries towards more inclusive and sustainable development (OECD, CAF, ECLAC, & EU, 2019). However, how to measure progress differently than the Gross Domestic Product (GDP) per capita or the Human Development Index (HDI) remains a pending strategic and methodological challenge, particularly in regions such as Latin America (Barcena, Manservisi, & Pezzini, 2017).

During my PhD, I studied new approaches to measure economic and social well-being using longitudinal survey data. My contribution to this topic has been to propose three measures of well-being, adapted for and applicable to middle-income countries with fast-growing economies in the Global South, particularly in regions such as Latin America and the Caribbean.[1] The first is a measure of income mobility that shows the persistence of poverty and prosperity, defined

[1] The Global South considers four macro regions: Latin America, Africa, Asia and Oceania. This phrase works as a way to differentiate it from the North Atlantic countries, namely, Canada, the U.S.A. and Europe, referred to as the Global North. Initially used in political science and sociology to mark the North-South power relationship, it is now broadly used in developmental and economic studies as well (Dados & Connell, 2012).

as the probability that households have to remain at the extremes of the income distribution (Chapter 2). The second is a measure of vulnerability to poverty that corresponds to the risk that non-poor households have of falling into poverty (Chapter 3). The third is a measure of economic insecurity defined as the anxiety and stress that households experience when they are not capable of facing an unexpected economic shock (Chapter 4).

Chile is the country that I have used to illustrate all three measures. From a social and economic perspective, Chile is an interesting case study. Its significant economic growth has gone hand-in-hand with high levels of income inequality and a social security system that is still unable to offer adequate protection to those who are vulnerable to poverty and economically insecure. Additionally, Chile is the only country in the LAC region that has conducted longitudinal household surveys with more than three waves, enabling to build the measures a propose.

The three approaches that I propose contribute to improve the measures on economic well-being that have been developed so far. Separately, each one improves the existing measures and, when analysed together, they complement each other, providing a deeper understanding of the levels of well-being of the population. In the case of Chile, income mobility is highly correlated with both vulnerability to poverty and economic insecurity. My results show that vulnerability to poverty affects a significant part of the population that exited poverty. I thus argue that previous research has underestimated the size of the population that is vulnerable to falling into poverty and overestimated the growth of the middle class. The results also show that more than half of the Chilean population experienced economic insecurity during the last decade, increasing between 2014 and 2017, affecting even the highest income groups.

Measures of vulnerability to poverty and economic insecurity allow for a better understanding of the implications of high mobility in an unequal country in terms of income. Households' income mobility in Chile is far from positive. There is no evidence that this dynamism is associated with an improvement in people's life prospects, as suggested in the debates on intragenerational mobility (e.g. Sapelli, 2013). The high mobility of income presents a rather negative aspect since a significant proportion of households are exposed to fluctuations in their income, lacking minimum social protections that would help them to better face situations of economic loss.

Conventional measures of well-being and progress in Chile depict a country with low poverty and high GDP per capita, with a slight decline in income inequality and a high level of human development. Instead, when using the alternative measures of progress I propose, the reality appears quite different. They show that in Chile the high levels of income mobility are associated with economic instability, that a large -and growing- proportion of the population is vulnerable to poverty, and that the population is exposed to high levels of economic insecurity (also on the rise in the recent years). These well-being measures unveil the limits of the current model of social protection, which focuses on targeting poor people and offers limited social security to satisfy the need for economic stability by the new social group that has emerged in the recent years; the vulnerable-to-poverty.

The COVID-19 crisis has exposed the weakness of the current social protection system that provides few benefits to low-wage workers facing illness, layoffs or retirements and leaves a significant group of workers unprotected (e.g. Maldonado, Prieto, & Feres, 2019; Sehnbruch, Carranza, & Prieto, 2019). The new look at the population's well-being that the three measures I propose offer contribute to deepening the understanding of the massive social unrest in Chile that started in Chile few months before the COVID-19 pandemic. Incorporating this type of measures to monitor the countries' progress and well-being implies, from a public policy perspective, going beyond the extension of the subsidiary state exploring the possibility of moving towards a universal security model.

The structure of this introductory chapter is as follows. In section 2, I describe the progress in welfare measurements that go beyond GDP, showing the concepts that are relevant to my research. In section 3, I describe the political, economic and social background of Chile, incorporating the social policy context. In section 4, I describe the data sources I use in each chapter. Finally, in section 5, I present an outline of my thesis, including the most important findings, contributions and implications.

1.2 Measuring progress and well-being beyond GDP

Until now, Gross Domestic Product (GDP) has been the main measure used to monitor the transition to development of countries in the Global South. Indeed, the increase in GDP in recent decades has shown two concrete improvements in welfare in these countries: i) the real possibility of ending extreme poverty across the globe in the near future (World Bank, 2018b), and ii) a decrease in the inequality of aggregate indicators of human development between countries in the South and the North of the world (UNDP, 2013).

However, GDP as an indicator of progress and well-being has limitations in terms of adequately reflecting the current reality in the Global South regions. For example, although Latin America and the Caribbean (LAC) experienced a remarkable economic growth in the periods 2002-2008, and 2010-2014, changes in well-being of its population show mixed results. On the one hand, significant improvements were achieved in some indicators such as life expectancy, unemployment rates, health services and general satisfaction with life. Further, considering the GDP reached, these changes even surpassed what was expected (OECD et al., 2019).

On the other hand, key aspects of well-being within the LAC region advanced at a much slower pace, showing apparent deficiencies concerning GDP growth as a measure of well-being. Low quality education, high labour informality, and distrust in institutions are persistent problems in these countries. Particularly worrying are the high levels of income inequality and weak social security systems that fail to offer adequate protection to those at risk of falling back into poverty (Levy, 2018). Comparing two countries within LAC such as Chile and El Salvador helps to illustrate this point. According to the World Bank's measures, Chile is classified as a high-income country, and its income inequality, measured by the Gini index, is 0.47. El Salvador is classified as a medium-low income country, and its income inequality is lower (0.38). Despite these differences, in both countries, a third of the population is classified vulnerable to poverty using the World Bank vulnerability line (OECD et al., 2019).

Therefore, while the GDP growth in Latin America has generated improvements in many important areas of development, in areas such as inequality and social vulnerability, limited progress has been achieved. GDP as an indicator of progress and well-being hides the reality of some crucial dimensions of development. Someway, as a measurement tool, it can distort or mislead the formulation of policies aimed at supporting countries' transition to development (Stiglitz, Sen, & Fitoussi, 2009).

The need to use better development and welfare measures is not only of interest to countries in the Global South. In north-western countries, the financial crisis (2007-2008) and the increase in income inequality pressured governments, researchers and foundations to propose new measures of progress and well-being that go beyond GDP. The theoretical and empirical discussion of concepts such as economic insecurity, inequality of opportunities, vulnerability to poverty, subjective well-being, sustainability and horizontal inequality, has grown exponentially during the last decade. See Stiglitz et al. (2018) and D'Ambrosio (2018) for a comprehensive review.

Some of these measures are summaries of changes in each households' income over time (e.g. economic insecurity and income position persistence), requiring longitudinal data for their implementation (Cantó, García-Pérez, & Romaguera de la Cruz, 2019a; OECD, 2018a). Others require the consideration of specific dimensions of well-being that are not adequately covered by surveys or for which there is simply no such information (Balestra, Boarini, & Ruiz, 2018). In this way, together with the theoretical and conceptual discussion on how to satisfactorily measure social and economic well-being, the methodological and statistical challenges of its implementation are part of the development of these new measures (OECD, 2011, 2013a). The experience accumulated in the last decade mostly from developed countries should be considered in the discussion on how to measure the transition to development with equity and sustainability in the Global South.

Below, I elaborate further on the paradigm shift when analysing transition to development in the Global South towards the notion of well-being and the challenges involved in measuring it. Also, I briefly present some of the theoretical concepts used to support the need for going beyond GDP and the most relevant initiatives taken in the field of national welfare measurements during the last decade.

Global convergence and the challenges that entail measuring progress and well-being

Several pieces of research suggest that we are currently witnessing a deep and continuous redesign of the global development map (Bourguignon, 2015; Horner & Hulme, 2019; Sumner, 2019). Reports show that the world's middle class has grown in importance (Kharas, 2017) while the proportion of the population living in extreme poverty has fallen dramatically worldwide (World Bank, 2018b). At the same time, there has been remarkable progress in economic growth, education, and health in the Global South (UNDP, 2013). The rise of the South has led authors to suggest that countries are moving towards a global convergence in terms of aggregate development indicators (Baldwin, 2016; Mahbubani, 2013). This new way of understanding the transition to development has had distinct implications for the agenda of multilateral agencies. The World Bank (2016) affirmed that it will no longer distinguish between developed and developing countries in its annual development indicators. This decision means that the Sustainable Development Goals (2015) are formulated not only for 'developing' countries but also for countries in the Global North (OECD et al., 2019).

However, some scholars have realised that the idea of 'global convergence' does not adequately capture the change that has caused the new prosperity generated by economic growth (Bourguignon, 2015; Horner & Hulme, 2019; Sumner, 2019). Horner & Hulme (2019) say we are facing a 'converging divergence'. This concept refers to the idea that while inequalities between countries have decreased ('converging' referring to the North-South pattern), inequalities within-country have remained high and even grown in some cases. This 'divergence' in inequality within countries is observed in aspects of economic development, human development and the environment in both the Global North and Global South.

Concerning economic development, while the globalisation process has drastically reduced income differences between Northern and Southern countries, the inequality in the living standards within countries has increased (Bourguignon, 2015). In North Atlantic countries, a significant proportion of the population has remained outside of the economic growth since the 1990s (Milanovic, 2016). This explains why 17 out of the 22 OECD countries experienced an increase in their income inequality between 1985 and 2013 (OECD, 2015a). Income inequality within Southern countries has been rising since the 1980s, though with considerable regional variation (Ravallion, 2014). Hence, while in countries such as China, India and Russia, income inequality has been steadily increasing in the last decades (ISCC, IDS, & UNESCO, 2016), in Latin America, a region with one of the highest levels of income inequality, several countries have managed to reduce their inequality in recent years (World Bank, 2016).

Another economic aspect that characterises this 'divergence' is the growth of the non-poor vulnerable group in both Southern and Northern countries. In the Global South, the divergence is explained by the large proportion of people who have escaped from absolute poverty but are not yet part of the income-secure middle class. This is because most are still living on relatively low incomes and are thus vulnerable to falling back into poverty (Birdsall, 2014). And in the countries from the Global North, the cause of the divergence is the increase in non-standard employment (e.g. fixed-term contracts and non-voluntary part-time work) in various sectors of the economy (ILO, 2016). Authors like Standing (2011) go further and suggest that a new global class has emerged: 'the precariat'. This class comprises people facing economic insecurity and moving in and out of jobs that offer no sense of secure occupational identity.

It is a fact that within-country inequalities in human development are substantial. In particular in some countries with low human development, inequalities in education and health are almost as large, or even greater, than income inequalities (Harttgen & Klasen, 2012). This is hardly surprising if we consider the high correlation between income inequality and non-income inequalities, such as health (Pickett & Wilkinson, 2015) and education (World Bank, 2016). Although there is little evidence of an increase in these inequalities given data availability issues (Bourguignon, 2015), there are some studies that have shown that in countries like the United States and in some cities in the UK life expectancy gaps have widened between people with higher incomes and those in the lower part of the income distribution during the last decades (Bosworth, Burtless, & Zhang, 2016; Chetty et al., 2016; CSDH, 2008).

In the case of education in the Global North, although there is no clarity about a tendency towards greater inequality, the results of PISA 2015 show significant within-country inequalities in educational attainment. For example, students who are in the lower part of the income distribution in OECD countries are almost three times more likely to fail to achieve the basic level of proficiency in science compared to students in the higher part of the income distribution (OECD, 2016). This gap in education inequality is much higher in low-income countries. For instance, for every 100 well-off youths who complete primary education, only 36 do so among the poorest (UNESCO, 2016).

The limited availability of and access to data on environmental inequalities makes it challenging to obtain a clear picture of trends within countries. However, recent studies have shown an apparent increase in within-country Green House Gas emission inequalities, in contrast with a decrease in between-country inequalities (Chancel & Piketty, 2015; Sauter, Grether, & Mathys, 2016). These within-country disparities are explained by differences between sectors of the economy, which, between 1970 and 2008, led to an increase in the gap between emission-producing areas and damage-exposed areas within countries (Sauter et al., 2016).

The evidence generated so far shows a complex reality: the economic growth of a country together with the progress in aspects of economic, human and environmental development do not necessarily go hand-in-hand with greater well-being for all of its households and individuals. Unless policies are implemented to counteract such trends, inequalities within countries can grow, even when countries become more prosperous. This reality is seen more clearly in regions such as Latin America, where, despite the steady economic growth in the last twenty years, all of the countries in the region still face severe social and developmental weaknesses, namely, high vulnerability to poverty, high income inequality, economic instability, unequal access to education and health services, and increase in the emissions that damage the environment (OECD et al., 2019). The transition of these countries to equitable and sustainable development will not be attainable as long as these vulnerabilities persist.

The road to development does not follow a linear path, and economic growth alone is not enough. Equally relevant is the progress in the well-being and equity in the economic, social and environmental development of the population. There is a consensus that the approaches that account for nations progress towards sustainable development should continually be rethought. This entails defining new ways to measure it in a context of globalisation where countries show new vulnerabilities, specific capacities and their own priorities (Barcena, Manservisi, & Pezzini, 2017). After the financial crisis of 2007-2008, the countries in the Global North agreed that it was necessary to measure their development and well-being using measures that go beyond the gross domestic product (European Commission, 2009; G20, 2009; OECD, 2011; Stiglitz et al., 2009). This explains the wide variety of social and economic welfare measures that have been proposed in the last decade (e.g. vertical and horizontal inequalities, inequality of opportunity, subjective well-being, vulnerability to poverty, economic security, sustainability, trust and social capital and so forth).[2] These new measures have enriched the existing multidimensional welfare

[2] For an extensive review of these alternative welfare measures that have emerged as part of national initiatives as well as in academic articles see Stiglitz et al. (2018) and D'Ambrosio (2018).

measures that were developed prior to the financial crisis (e.g. the Human Development Index (UNDP, 1990) and the Index of Economic Well-Being (Osberg & Sharpe, 2002).

The new efforts to improve social and economic welfare measures, and thus design better policies in Northern countries, have occurred in the context of a paradigm shift in what the transition to development means. It is no longer possible to think of a world divided between industrialised and non-industrialised countries or First and Third World, as it used to be in the twentieth century. Now, we live in a world with significant inequalities where emerging countries are now economic powers, and the production, trade and financial systems of all countries are profoundly intertwined and globalised. Additionally, there is the indisputable fact that the distribution of natural resources and their future availability will affect all countries equally. For this reason, authors such as Giovannini & Rondinella (2018) have promoted the idea that the new welfare approaches (with a focus on equity along with multidimensional measures), should apply to both OECD and non-OECD countries.[3]

Nevertheless, this global agenda that aims to develop better measurements of welfare and progress of countries still has a long way to go. Well-being and development are complex concepts, and many of their economic, social and environmental dimensions are difficult to measure. And if this has been a statistical challenge for OECD member countries (OECD, 2011, 2013a), moving forward in others regions of the world such as Latin America entails even more difficulties. In effect, the very process of designing and implementing measures of progress and welfare faces multiple challenges. In first place, the political difficulty of raising the standard with which development and well-being are measured. In second place, the technical difficulty of agreeing on measures on which there is no consensus yet. In third place, dealing with the long-lasting problem of access to adequate data. In the case of Latin America, this is not only due to the difficulty of coordinating the countries' National Institutes of Statistics in homogenising and harmonising the data available to improve cross-country comparability, but also because in most of the countries the surveys and administrative data do not collect data on key aspects of well-being (e.g. subjective well-being and distribution of household wealth), let alone longitudinal data that would allow for the construction of intergenerational (e.g. inequality of opportunity) or intragenerational (e.g. vulnerability to poverty) welfare measures.

[3] For example, the equitable and sustainable well-being approach (Hall, Giovannini, & Ranuzzi, 2010) used as a theoretical framework for the construction of the Better Life index (OECD, 2011).

Moving towards broader metrics of well-being: the new consensus

Societies need to measure the progress they are making towards their economic and social goals. After World War II, Gross Domestic Product (GDP) was the key metric to monitor and compare economic performance and social progress among countries (Marcuss & Kane, 2007; McCulla & Smith, 2007). The general consensus was that economic development should provide the means to improve individual living standards and that GDP could adequately reflect it. The measurement of economic growth was clear and was implicitly linked to changes in direct welfare measures such as employment or household consumption. However, GDP is an economic indicator that measures market production – expressed in monetary units – and does not necessarily meet the objective of appropriately measuring economic welfare and the well-being of people. This issue was recognised by Kuznets himself, who developed the concept of GDP (Kuznets, 1934).

The first criticisms related to the use of GDP as a measure of well-being arose during the 1970s (Seers, 1969). Some authors evidenced the need to start using economic welfare measures that account for the sustainability of the economic growth of countries (Nordhaus & Tobin, 1973) together with welfare measures that incorporate economic and social dimensions of human progress (Christian, 1974) and distributional aspects such as income inequality (Sen, 1976).

It took two decades for official measures that go 'beyond GDP' to appear. In 1990 the United Nations Development Program launched the Human Development Index (HDI) as part of its first Human Development Report. Since then, the HDI, which combines GDP (well-being material) with health measures and educational achievements, has become the most successful index in the use of multiple dimensions that address economic development and social welfare. And yet, although several studies showed that the level of human development is inversely related to the level of inequality in health, education and income (Anand & Sen, 1993; Foster, Lopez-Calva, & Szekely, 2005; Grimm, Harttgen, Klasen, & Misselhorn, 2008; Hicks, 1997; Seth, 2009), it took another 20 years for the Human Development Report (2010) to include distributive considerations in the HDI.

The Great Recession, which began in 2007–2008, made manifest the limits of GDP as an indicator of both economic performance and well-being. The years before the financial crisis accounted for GDP growth that reaffirmed the widespread impression that everything was going in the right direction. The good performance of GDP did not allow to see the financial crisis that was coming. The key indicator of economic welfare was blind to the increase in inequality in advanced economies and to the accumulation of public and private debt in some of these countries (Atkinson & Morelli, 2011; Iacoviello, 2008).[4] Measuring development solely through GDP proved to be a flawed approach to guiding the political and economic leaders in the countries that triggered the banking crisis.

In the years since the financial crisis, policymakers and statistical offices in developed countries have recognised the importance of changing the emphasis of measuring economic production to measuring people's well-being (European Commission, 2009; G20, 2009; OECD, 2011; Stiglitz et al., 2009). One of the most distinctive documents of this renewed emphasis on individual and social well-being is the report by the Commission on the Measurement of Economic Performance and Social Progress (the Stiglitz-Sen-Fitoussi report) published in 2009 (Stiglitz et al., 2009). The report concludes that GDP as a single indicator fails to cover the multidimensionality of development, as well as the structural changes that have characterised the evolution of modern economies. Stiglitz et al. (2009) recommended combining the GDP measure with broader metrics of household economic well-being, considering: i) inequalities, ii) people's quality of life, and iii) the sustainability of these results over time. Since then a 'beyond GDP' movement has crystallised, resulting in an expansion of new statistics on economic welfare, well-being, and sustainability (Bleys, 2012; D'Ambrosio, 2018; ECLAC, 2012; OECD, 2017; Stiglitz et al., 2018; UNDP, 2018).

Measuring progress and well-being: from macro data to micro data sources

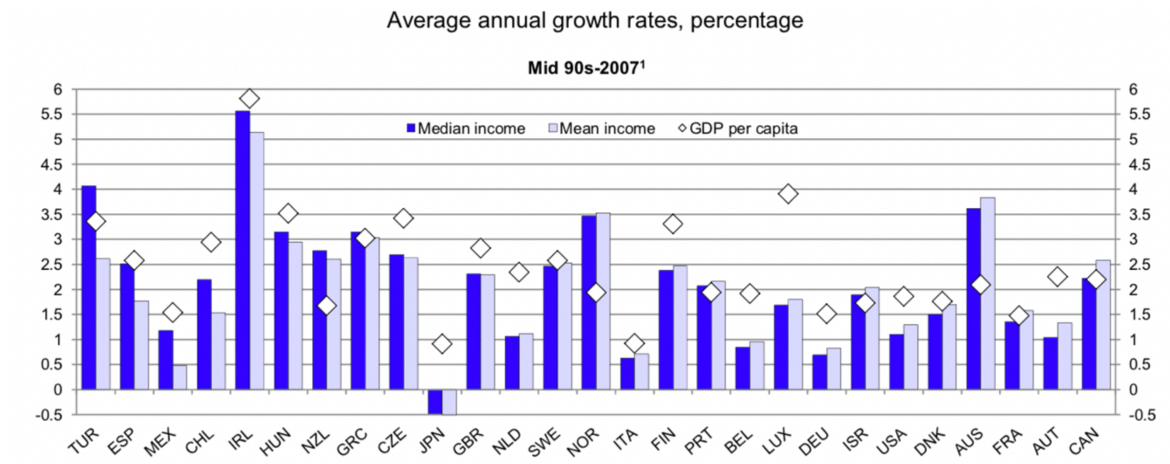
The first recommendation of the report by Stiglitz et al. (2009) was that the measurement of material well-being should assess individuals' economic situation instead of focusing on indicators for the entire economy. There are two main measures of material living standards

[4] There are two mechanisms that would explain the relationship between income inequality and the financial crash of 2007–2008: i) the income inequality led to a redistribution in the form of subsidised housing financing, which caused a boom in mortgages (Rajan, 2010), and ii) higher income inequality led to a higher level of bank loans to middle-income and poor households to maintain their rising standard of living due to real income drops (mechanism suggested by Stiglitz (2009) and theoretically developed by Kumhof et al. (2015).

that have followed this argument. The first privileges the household perspective obtained from the use of microdata sources, and the second incorporates distributional issues.[5]

The household perspective on measuring economic well-being is based on the idea that the average household's disposable income delivers the material standard of living of a 'typical' household in the country (Balestra et al., 2018). Two strategies stand out for the construction of such measures: i) calculating mean household disposable income using macro sources such as National Accounts, or ii) calculating mean or median household income using micro sources such as household surveys. Stiglitz et al. (2009) recommend the median income over the mean income as an adequate measure to represent the current material living standards of a 'typical' household because it provides a preliminary assessment of income inequality of the country.

Figure 1.1: Real annual growth rates of GDP, mean and median household disposable incomes



Source: OECD calculations based on OECD National Accounts and Income Distribution Databases. Figure appears on page 22 in OECD (2015a).

Note: For median and mean equivalised household disposable incomes, PPP are those for private consumptions of households. For GDP per capita, PPPs are those for the GDP deflator. Countries are sorted in ascending order according to the difference between the annual average growth rates of mean and median disposable incomes.

When comparing GDP growth among OECD member countries with the change in mean and median household disposable incomes (Figure 1.1), it is observed that, in many countries,

[5] There is a third measure that includes non-market activities. Under the premise that countries' economic activity entails more than just market production (GDP), measures have been proposed that come from i) services provided by the government, ii) unpaid work inside the home, and iii) those related to the 'third sector'. Access to better data has allowed for calculating household production satellite accounts that complement traditional estimates of economic activity by providing a better measure of the material well-being of households (Ahmad & Koh, 2011).

income inequality increased before the financial crisis (2007–2008), while the growth of household disposable income failed to match the earnings of GDP per capita.[6]

Figure 1.1 shows that between the mid-1990s and 2007, in more than half of the OECD countries, GDP per capita grew faster than the mean household disposable income. Also, in Canada, Austria, France, Australia, Denmark, United States, Israel, Germany, Luxembourg, Belgium, Portugal, Finland, Italy, Norway, Sweden and the Netherlands, the median income growth rate was lower than the average income. In these countries, the income of those in the middle of the income distribution increased less compared to those in the upper part of the distribution.

At the same time, in countries with high income inequality such as Turkey, Spain, Chile and Ireland, a substantial reduction in the gap between the mean and median incomes occurred. The increase of income in the lower part of the distribution occurred in a context where these countries had different annual GDP growth rates. Therefore, a linear relationship between economic growth and reduced inequality in these countries is not evident.

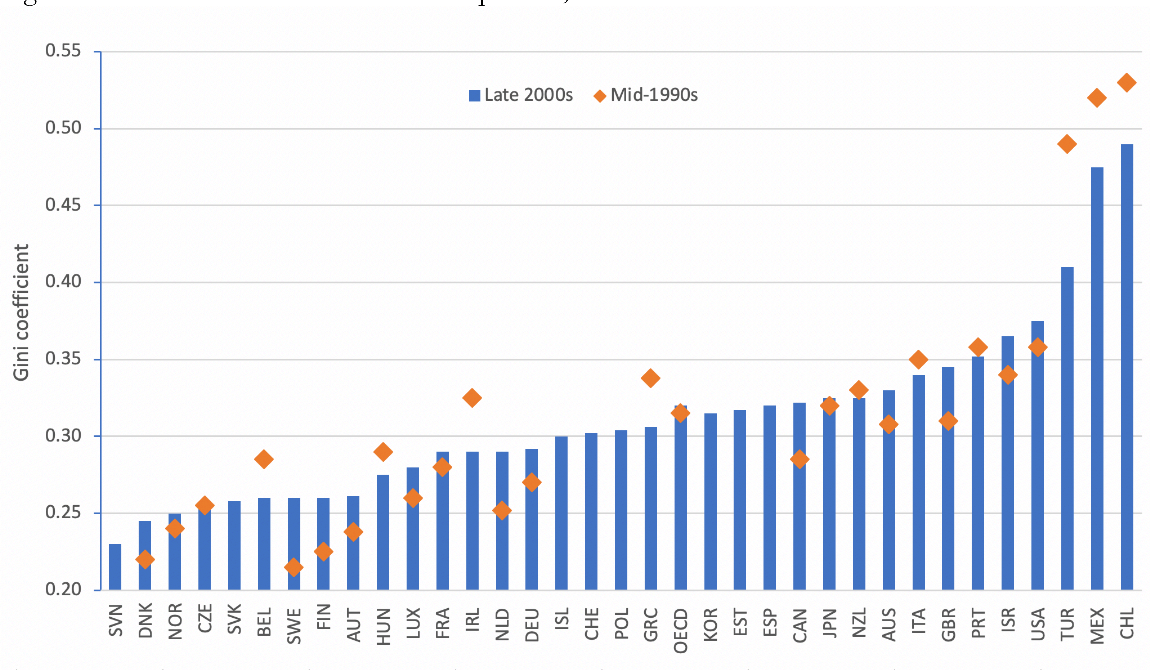
Although the median income provides a better measure of what is happening to a 'typical' household than the mean income, for policy purposes, it is also important to know what is happening at the bottom or/and top of the income distribution. For example, an increase in the average income of a country may hide the fact that the economic prosperity is distributed unevenly among different groups of society, leaving some groups relatively worse off than others (Stiglitz et al., 2009).

The way to escape the 'tyranny of averages' is to use dispersion measures such as income inequality. These measures enable evaluating the distribution of income to account for the different challenges that countries face in moving towards more inclusive development. The

[6] There are discrepancies between the mean household disposable income obtained by National Accounts and the estimate using household surveys. See Balestra (2018, pp. 57–61) for a detailed account of the main differences and implications. In recent years, two projects have been developed to overcome these differences between micro and macro sources. To achieve this goal, these projects propose methodologies that compile the income distribution data available from micro sources with the totals of the national accounts in a systematic way. One of them is the EG DNA (Expert Group on Disparities in National Accounts), a project convened by the OECD and focused on income, consumption and savings distributions. The other is DINA (Distributional National Accounts). DINA project is focused on income and wealth and originates from the WID initiative developed by Piketty & Zucman (2014). More details of both research efforts can be found in Alvaredo et al. (2018).

three best-known income inequality measures that use cross-sectional data from micro sources are the Gini coefficient, the mean log deviation and the P90 / P10 inter-decile ratio.

Figure 1.2: Gini coefficient of income inequalities, mid-1990s and late 2000s



Source: OECD Income Distribution Databases. Figure appears on page 64 in Balestra et al. (2018).

Notes: Data refer to the mid-2000s instead of the late 2000s for Greece and Switzerland. For Austria, Belgium, the Czech Republic, Estonia, Finland, Iceland, Luxembourg, Poland, Portugal, the Slovak Republic, Slovenia, Spain and Switzerland, the values are provisional.

Measuring income inequality using the Gini coefficient enables for observing two characteristics of the distribution of household disposable income in OECD member countries. The first is that there is considerable variation in income inequality between countries. Figure 1.2 shows that the Nordic countries and the countries of Eastern Europe have a less unequal income distribution, while countries such as Chile, Mexico and Turkey as well as the United States and Israel, have high income inequality. The second feature is that income inequality increased in most OECD countries between the mid-1990 and late 2000s, although there were some countries where it declined, such as Turkey, Ireland, Belgium, Greece and Chile.

Measuring progress and well-being: from a static to a longitudinal perspective (the case of income inequality and economic growth)

Income inequality measures are static measures. They do not consider that people in the group of the rich and people in the group of the poor are not the same over time. The fact that individuals experience relative ups and downs in their economic well-being is relevant to understand the relationship between economic growth and income inequality. By using longitudinal data, it is possible to relate these three types of changes: i) in income inequality, ii) in aggregate economic growth, and iii) in the position of individuals in the income distribution (re-ranking).

The case of the United States illustrates the implications of analysing trends in income inequality, ignoring the existence of re-ranking in the income distribution over time. Figure 1.2 shows that not only is the United States the most unequal nation among the North-Atlantic countries, it also increased its inequality during the period studied. A plausible interpretation would be that the income growth in the United States between the mid-1990s and late 2000s was greater for the rich than for the poor. However, the reality is more complicated. Using methods to decompose changes in income inequality and longitudinal data, Jenkins & Van Kerm (2006) observed a paradox during the 1980s (when income inequality in the USA also grew substantially). Although the poor fared badly relative to the rich, income growth was pro-poor. This means that income growth was higher for those with lower incomes despite the increase in income inequality. Thus, measures of changes in inequality from a longitudinal perspective (or non-anonymous approach) provide more adequate information in assessing the impact of growth on poverty.[7]

The non-anonymous approach has also been implemented in 'inclusive economic growth' measurements (that is, growth that benefits all segments of society). Although the measure of the distributive impact of economic growth is not new (Kuznets, 1955), during the 2000s several authors made substantial theoretical, methodological and empirical contributions developing new methods for measuring pro-poor growth (Bourguignon, 2003; Essama-Nssah & Lambert, 2009; Ferreira, 2010; Ravallion & Chen, 2003; Son, 2004). This literature analyses growth by comparing pre-growth and post-growth distributions using a repeated cross-section perspective. Growth Incidence Curves (GICs)[8], introduced by Ravallion and Chen (2003), are the best-known measures to assess the implications of well-being in different distributional patterns of

[7] The non-anonymous approach (or longitudinal perspective) analyses distributional changes identifying individuals over time using panel data. The anonymous approach (or repeated cross-section perspective) compares the distribution of income at two points in time without identifying individuals between both distributions.

[8] GICs plot the change in mean income (in absolute or proportional terms) of each quantile of the income distribution.

economic growth. However, these measures ignore the non-anonymous income dynamics along with the distribution. Therefore, there is a problem of identification when extrapolating the results to particular individuals.

When assessing economic growth in terms of welfare (e.g. using a social welfare function) it is relevant to take into account how individuals move in the income distribution (Palmisano & Peragine, 2015). This information shows who are the winners and losers of growth. It allows concluding whether or not those who were initially poor were affected by income growth (Grimm, 2007).

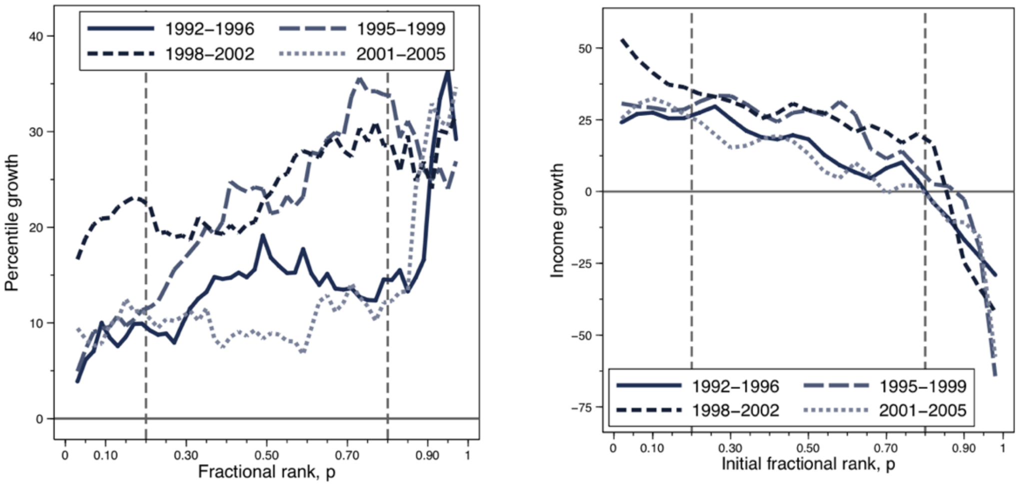
Recently, based on this longitudinal perspective, methods have been proposed to measure whether the type of 'economic growth' some countries are experiencing is progressive or regressive (see Bourguignon, 2011; Dhongde & Silber, 2016; Jenkins & Van Kerm, 2016; Palmisano & Peragine, 2015). These new measures come from the economic literature on income mobility, specifically, from the 'income movement' analysis, that focuses on summarising at a population level the changes in income over time of individuals within the population (Cowell, 1985; Fields & Ok, 1999). This approach uses non-anonymous GICs (or income mobility profiles – see Van Kerm (2006)) to illustrate individual income movements considering the initial status and different assumptions in the social welfare function.[9]

Figure 1.3 shows that the implications for economic well-being of changes in the income distribution depend critically on whether a non-anonymous approach is taken. In Britain over the 1990s and 2000s, the anonymous GICs in Panel A show that economic growth over four-year periods was regressive in terms of changes in absolute income (change in real income). That is, income growth was lower for the poorest. This result was obtained using a repeated, cross-section perspective. When adopting a longitudinal perspective, the non-anonymous GICs or income growth profiles (Panel B), the image is different and shows that during the period studied the income growth was generally progressive (pro-poor).

[9] For example, Bourguignon (2011) adopts a social welfare function, which is sensitive to the horizontal and vertical inequality of growth, while Jenkins & Van Kerm (2016) adopt a rank dependent social welfare function, which is sensitive only to the vertical impact of growth. Palmisano & Peragine (2015) follow the proposal of Jenkins & Van Kerm (2016) but also focus on the horizontal inequality of growth.

Figure 1.3: Comparing anonymous GICs vs non-anonymous GICs in Britain: 1992-2005

(a) Absolute anonymous GICs (b) Absolute non-anonymous GICs



Source: Data from British Household Panel Survey. Both figures Panel A and Panel B appear on page 27 and 17 respectively in Jenkins & Van Kerm (2011).

It is worth mentioning that non-anonymous measures used to assess the economic growth have two limitations. The first is that they need longitudinal data for their implementation (most countries in the Global South lack this type of data). The second disadvantage is that their implementation and interpretation of the results require more effort compared to the analysis of trends in static measures of economic well-being. However, non-anonymous measures are crucial to assessing whether all groups in society benefit from the economic growth as well as the magnitude of those benefits. Besides, in economic crisis, these measures allow for identifying which groups have been most affected by economic losses.

Measuring progress and well-being: from a unidimensional to a multidimensional perspective

Both GDP and the welfare measures from household incomes reviewed so far provide a general idea of the levels of development of a country. In addition to being relatively easy to calculate, they are easy to understand and communicate. They also allow for comparisons to be made over time and between countries. However, they fail to capture the complexities of development or to obtain a more accurate picture of people's living conditions.

Besides economic resources, health, education, social relationships and subjective feelings are also constitutive elements of human life (Sen, 1987). These dimensions should not be ignored when assessing people's well-being. GDP per capita or household disposable income as welfare measures to compare countries, not only hide disparities in different aspects that are essential to people's lives, but also a high per capita income of a nation alone does not guarantee a better quality of life.

Table 1.1 presents the inconsistencies of a monetary measure, such as the Gross National Product (GNP), with some indicators of health and education well-being. These results first appeared in the Human Development Report (HDR) of 1990. The first group of three countries – Sri Lanka, Jamaica and Costa Rica – show high life expectancy and adult literacy rates and low infant mortality rates despite the low levels of GNP per capita. In contrast, the second group of three countries - Brazil, Oman and Saudi Arabia - show much lower life expectancy and adult literacy rates and higher infant mortality rates despite much higher levels of GNP per capita.[10]

Table 1.1: The gross national product (GNP) per capita versus other social indicators

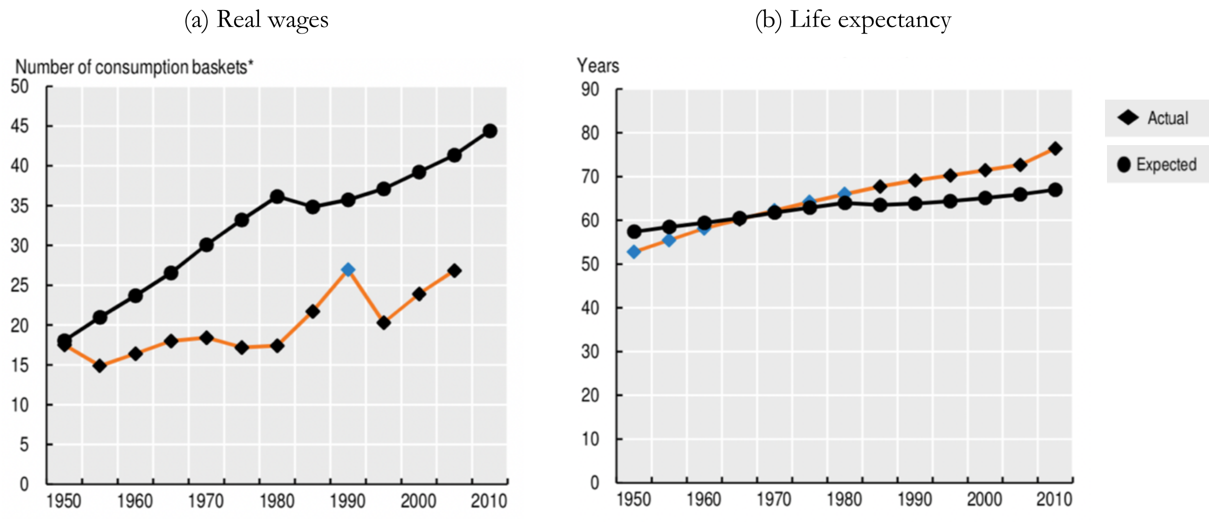
Country	GNP per capita (USD$) 1987	Life expectancy (years)	Adult literacy rate (%)	Infant mortality (per 1,000 live births)
Modest GNP per capita with high human development				
Sri Lanka	400	71	87	32
Jamaica	940	74	82	18
Costa Rica	1,610	75	93	18
High GNP per capita with modest human development				
Brazil	2,020	65	78	62
Oman	5,810	57	30	40
Saudi Arabia	6,200	64	55	70

Source: Figure appears on page 9 in UNDP (UNDP, 1990).

A more recent study in Latin America and the Caribbean (LAC) shows that different well-being outcomes diverge from the predictions that use GDP as an explanatory variable (OECD et al., 2019). While real wages in LAC have increased less than in other countries with a similar GDP growth per capita, the life expectancy exceeded the level expected for the economic growth achieved in the region (Figure 1.4).

[10] It is important to mention that the figures in Table 1.1 are not corrected for variations in purchasing power for the six countries. UNDP report (1990, p. 12) points out that doing so would not change the ranking among countries, but if distributional adjustments are made using each country's Gini coefficient, the original order reverses between countries such as Brazil and Costa Rica. Therefore, such distributional corrections can make a significant difference in evaluations of country performance.

Figure 1.4: Actual and expected performance for selected well-being outcomes in LAC over time



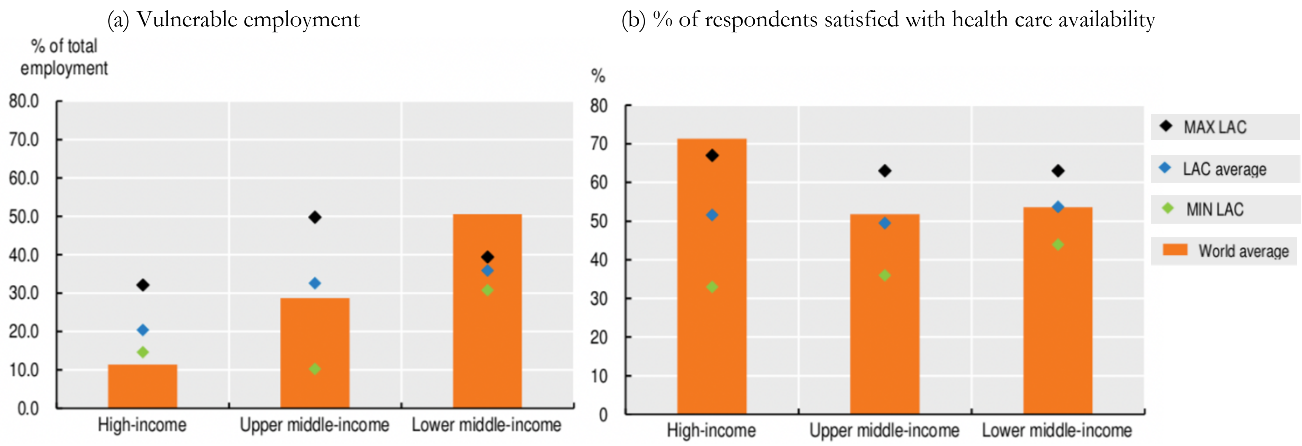
Source: Based on www.clio-infra.eu/ and CEPALSTAT. Figure appears on page 83 in ECLAC et al. (2019).

Notes: * Real wages are measured as the number of consumption baskets purchases with the real wages of a male unskilled worker in the building industry. Expected values are calculated with a panel dataset composed of 183 countries worldwide from 1900 to 2010. The LAC average includes all countries in the Americas except Canada and the United States.

In the same study (OECD et al., 2019), countries with similar per capita incomes are compared obtaining different outcomes. It shows that high-income countries within LAC have much worse development outcomes compared to countries in other regions of the world with the same classification. For example, Panel A in Figure 1.5 shows that vulnerable employment among high-income countries is 10 per cent across the globe, but, in Latin American high-income countries, the vulnerable employment is double (20 per cent). In the same Figure, Panel B shows that high-income countries in LAC have only 34 per cent of people satisfied with health care availability. In contrast, in similar-income countries in other regions, that figure reaches 70 per cent. This difference is also found among countries that belong to the same income group in LAC. For example, the proportion of people who are satisfied with the health system varies considerably among high-income countries within the region (from 67% in Uruguay to 33% in Chile).

These results show that the relationship between GDP and different dimensions of well-being is not linear. Therefore, a higher national income does not automatically lead to higher levels of well-being for all. Since there are relevant dimensions of well-being that economic resources alone cannot capture, it has become necessary to move from a money-based perspective to a multidimensional perspective. The focus is no longer on just one economic dimension, but on all of the aspects that constitute human life. This paradigm shift to measuring the social progress and well-being of countries has made a critical contribution to the design, implementation, monitoring and evaluation of policies that aim to improve people's life chances.

Figure 1.5: Selected development indicators by country income groups



Source: Based on World Bank (2018), UNODC (2018) and Gallup (2017). Figure appears on page 70 in ECLAC et al. (2019).

Notes: Simple averages are used both for LAC and world averages. LAC lower middle-income countries include Bolivia, El Salvador, Honduras and Nicaragua. LAC upper middle-income countries include Belize, Brazil, Colombia, Costa Rica, Cuba, Ecuador, Grenada, Guatemala, Guyana, Jamaica, Mexico, Paraguay and Peru. LAC high-income countries include Argentina, Bahamas, Barbados, Chile, Panama, Puerto Rico, Trinidad and Tobago and Uruguay.

The two best-known multidimensional welfare indices were developed by international agencies: the United Nations Development Program (UNDP) and the Organization for Economic Co-operation and Development (OECD). In 1990, the UNDP published the first "Human Development Report" (HDR) with its Human Development Index (HDI). Currently, more than 180 countries have incorporated the HDI into their official indicators and, as a result, it has become the welfare index with the greatest influence worldwide. The OECD proposed the Better Life Index (BLI). The BLI was first presented in 'How's life?' (2011), and since then it has been applied every two years in OECD and other partner countries (46 countries in total).

Measuring progress and well-being: from ex post to ex ante measures (the case of economic insecurity and vulnerability to poverty)

So far, I have presented measures of social progress and welfare that are alternative to GDP and are typically backwards looking. This means that they are ex-post measures based on household outcomes such as poverty or Gini coefficient after they have already occurred. The availability of household panel surveys has allowed the development of less traditional welfare measures such as economic insecurity and vulnerability to poverty. These measures have two shared characteristics. First, they focus on the anticipation of future events. Thus, allow ex-ante monitoring of: i) the anxiety and stress of individuals caused by a potential economic loss, and ii) the risk of a non-poor individual of falling into poverty.

Second, the two measures focus on the economic changes (e.g. income or earnings) of individuals from one period to another. This feature has been developed in-depth in the economic literature on income mobility (Jäntti & Jenkins, 2015), which has been crucial in the development of these concepts. In the case of economic insecurity and vulnerability to poverty the focus is on understanding changes in the income of individuals during their life (intragenerational changes).

Although there is still no consensus on the formal definition of these forward-looking concepts, recent empirical evidence has shown some robustness in the results obtained using different definitions and methods. This suggests that, despite the conceptual and methodological challenges, these measures are already capable of delivering policy recommendations to move towards more inclusive development (D'Ambrosio, 2018, p. 10).

Economic insecurity and vulnerability to poverty are the two measures I develop and implement for the case of LAC in this thesis. Below, I briefly describe these two new welfare measures that have a longitudinal perspective and have made a contribution to the 'beyond GDP' agenda in the last decade. A detailed empirical and theoretical review of these measures can be found in Stiglitz et al. (2018) and (D'Ambrosio, 2018). These reviews also address other social and economic welfare measures that are not included in this introduction, such as inequality of opportunity, social exclusion, social polarisation, horizontal inequalities and subjective well-being, among others.

Economic insecurity

Anxiety is a feeling of worry or fear caused by future events or situations that are challenging or threatening. When this state of mental unease is caused by financial uncertainty, economic insecurity is discussed. An example of economic insecurity is the anxiety and stress that households experience when they feel/think they will not be able to make ends meet if they lose their job or have an unexpected family medical expense. Thus, the relationship between economic insecurity and well-being is easy to intuit; the problem relies on its complex measurement (Stiglitz et al., 2009).

Measuring the impact of economic insecurity on a person's well-being depends on several factors. The first is the level of risk of occurrence of an adverse event and the negative economic consequence (and stigma) if the event takes place. In addition, it depends on the protections that potentially compensate or prevent the loss and especially on the preferences of the people themselves (e.g. loss aversion). Finally, measurement requires the availability of longitudinal data that adequately measure these factors (Hacker, 2018; Rohde & Tang, 2018; Stiglitz et al., 2009).

Several studies have shown an association between economic insecurity and different dimensions of well-being. Workers with safer jobs are happier than those in more vulnerable positions (Scheve & Slaughter, 2004). People with a higher risk of experiencing adverse economic events show behavioural changes that result in higher levels of obesity, a higher level of smoking and alcohol abuse (Barnes & Smith, 2009; Smith, Stoddard, & Barnes, 2009). Also, economic insecurity generates psychological distress in the family environment and makes it difficult for families to invest in education and housing (Hill, Morris, Gennetian, Wolf, & Tubbs, 2013; Jansson, 2017).

At an institutional level, economic security has been recognised as a social right from a human rights perspective and as a welfare concept from a human development perspective. In 1948, Article 25 of the United Nations' Universal Declaration of Human Rights stated that every member of society has the "right to security in the event of unemployment, sickness, disability, widowhood, old age or other losses of livelihood in circumstances that are beyond the control of each individual". The Human Development Report (HDR) of 1994 that economic security "requires an assured basic income for individuals, usually from productive and remunerative work or, as a last resort, from a publicly financed safety net" (HDR, p. 25). Although both statements refer to a broad concept of economic insecurity, they represent strong evidence of the value that societies and their governments attribute to it.

The following definition of economic insecurity first appeared in Osberg's work (1998, p. 7): "the anxiety produced by a lack of economic safety – that is, by an inability to obtain protection against subjectively significant potential economic losses". This definition underlies the idea that to avoid the anxiety of an uncertain financial future, people can acquire insurance (public or private), make less risky economic decisions, or build formal or informal social support networks (Osberg & Sharpe, 2002). However, formal private insurance or public social security options are not always available especially in Global South countries and, if they exist, they tend to be ineffective at the time they are needed (Morduch, 1999).

Economic insecurity is not just a problem of the Global South. In the aftermath of the financial crisis of the late 2000s, hundreds of millions of people in OECD countries faced economic losses associated with unemployment, the volatility of their income and sharp declines in wealth obtained from housing and other assets. Opinion polls in these countries show that citizens affected by the economic crisis are increasingly concerned about their degree of vulnerability to an unexpected economic loss (Hacker, 2018). This subjective barometer of fear and concern about economic uncertainty correlates with more objective measures. For example, 36 per cent of the population in OECD countries have insufficient financial assets to cover their expenses for more than three months without falling into poverty (Balestra & Tonkin, 2018). Similarly, Hacker (2018), using data panels from developed countries, estimates that about 12 per cent of adults experience a loss of income of 25 per cent in a year.

In this context, the report on well-being measures by Stiglitz et al. (2009, p. 202) represents a milestone in the field. The report highlighted the relevance of the measurement of economic insecurity to understand the economic well-being of people, while also acknowledging that it is a complex task due to the multiple dimensions contained in the concept. Since then, several definitions, measures and methods for studying economic insecurity have been proposed in and for the countries of the Global North (Bossert & D'Ambrosio, 2013; Bucks, 2011; Hacker et al., 2014; Osberg & Sharpe, 2014; Rohde, Tang, & Rao, 2014; Romaguera de la Cruz, 2017). These proposals are based on objective and subjective measures of economic insecurity that deepen in the economic losses and the role that buffers play in reducing those losses. These measures can focus on only one dimension of the phenomenon or summarise on synthetic indexes based on (weighted) multiple measures. A detailed review of the state of the art of these measures can be found in Chapter Four of this thesis and the reviews by Hacker (2018), Osberg (2018) and Rhode and Tang (2018).

Vulnerability to poverty

Although the economic literature has linked economic uncertainty to both economic insecurity and vulnerability to poverty, there is an important difference between the two concepts. While the entire population, independent of their position in the income distribution of a country, may feel economically insecure, only a part of the population, those who are vulnerable, are likely to experience poverty in the future.[11] Therefore, vulnerability to poverty is the risk of an individual having an economic loss in the future that would cause him to fall into poverty. In this way, reducing vulnerability not only improves the well-being of people ex-post but is also crucial to the design of anti-poverty policies (World Bank, 2001, p. 7).

For those who work in poverty eradication, it is apparent that alleviating poverty ex-post is not enough. Poverty alleviation should go hand-in-hand with the implementation of strategies that prevent poverty ex-ante (Chaudhuri, Jalan, & Suryahadi, 2002). The design of these types of policies requires identifying the non-poor people who are likely to fall into poverty (Zhang & Wan, 2009). However, since it is not possible to know the future distributions of results, it is necessary to study uncertainty as a determining part of poverty itself (Ceriani, 2018).

The first work linking the study of poverty with the economy of uncertainty appeared more than two decades ago (Morduch, 1994). However, it is since the economic crisis (2007–2008), and with the growing recognition that poverty is a dynamic phenomenon (Jenkins, 2011), that a series of contributions have been developed to measure vulnerability to poverty. Like the other ex-ante welfare measures (economic insecurity), a consensus has not yet been reached on how to define and measure it.

The definition of vulnerability to poverty has direct implications for its measurement. The main approaches found in the economic literature can be grouped into three definitions. The first definition, which is better known and commonly used, is of vulnerability as the ex-ante risk of an individual being poor in the future. In contrast to the definition of poverty, which is an ex-post measure of households' welfare, vulnerability is a prospective measure. Therefore, as stated

[11] Other similarities and differences between the two concepts are presented in more detail in Chapter Four of this thesis.

by Chaudhuri et al. (2002), while the 'poor' state is observable, the' vulnerable' state can only be estimated or inferred.

Within this definition, there are nuances. Some authors focus only on the probability of falling into poverty in the future (Chaudhuri et al., 2002; Dang & Lanjouw, 2017; López-Calva & Ortiz-Juarez, 2014; Pritchett, Suryahadi, & Sumarto, 2000; Suryahadi & Sumarto, 2003), while others consider both the probability of being poor and the extent (depth) of future poverty (Calvo & Dercon, 2013; Christiaensen & Subbarao, 2005).

The second definition of vulnerability follows a utilitarian approach has been used by authors such as Ligon & Schechter (2004) and Günther & Maier (2014). According to this approach, vulnerability corresponds to a consumption deficit threat for an average level of real consumption. In this definition, vulnerability depends not only on the variation in consumption (which can be broken down into two types of risk: aggregate and idiosyncratic) but also on average household consumption.

The third definition has been posited by a group of authors who define vulnerability as the risk of being poor due to the inability to smooth consumption (Banerjee, 2004; Glewwe & Hall, 1998; Kurosaki, 2006; Skoufias & Quisumbing, 2005). In this approach, someone is vulnerable if their current consumption is below the poverty line, although their permanent income is above it. Informal insurance mechanisms such as loans, assets and individuals' own savings, as well as formal insurance, allow individuals to smooth consumption over time. Hence, this type of vulnerability can also be understood as the inability to cope with economic shocks due to a lack of insurance (Ceriani, 2018).

These three definitions follow the same two steps in their measurement. First, quantify vulnerability. This step requires deciding on the welfare indicator to be used in the analysis. Given that a large number of these studies have been carried out in Global South countries, consumption is the indicator that has been most commonly used.[12] The second step in measuring vulnerability to poverty is to estimate the future distribution of the indicator chosen

[12] See Ceriani (2018) to a review of studies that using other welfare measures such as earnings and income.

for each household (or individual) in order to determine its vulnerability status. The different methods vary according to the types of data available (e.g. panel data or cross-sectional data).[13]

Finally, the first definition requires a third step to estimate the vulnerability threshold. Once estimated, all of those whose probability of falling into poverty is above that threshold are classified as vulnerable. A probability of 0.5 is used in most studies. (e.g. Pritchett et al., (2000); Suryahadi and Sumarto, (2003); Christiaensen and Subbarao,(2005); Chiwaula et al., (2011)). Therefore, those who have a probability of falling into poverty of above 50 per cent are considered vulnerable.

Recent works have linked the vulnerability threshold (risk) to a specific household income (Dang & Lanjouw, 2017; López-Calva & Ortiz-Juarez, 2014; Schotte, Zizzamia, & Leibbrandt, 2018). This income cut-off is known as the vulnerability line. In this way, individuals who have an income below the vulnerability line are considered vulnerable.

Summarising

In this section, I have presented the evolution of the measures of social progress and individual well-being that have arisen since the first apprehensions about using GDP for that purpose appeared. I focused primarily on showing those new measurements that offer a longitudinal perspective on the study of the economic well-being of households and individuals. Although these measures are related to each other since they use income changes over time as the primary indicator, seminal works did not use similar measures and analysis (e.g. Morduch (1994) for vulnerability to poverty and Osberg (1998) for economic insecurity).

Since the financial crisis (2007–08), a series of investigations have continued to develop these types of measures. Household panel surveys have made an essential contribution to the measures of economic insecurity as well as the measures that relate inequality to income mobility in developed countries. Additionally, some proposals to measure vulnerability to poverty in developing countries that lack longitudinal data have also contributed to this approach, though still insufficient. My thesis advances this line of knowledge, proposing better and more adequate methodologies to measure income position persistence, vulnerability to poverty, and economic

[13] For a detailed review of these methods, see Ceriani (2018), Calvo (2018) and Gallardo (2018).

insecurity in countries in the Global South that are moving towards inclusive and sustainable development.

1.3 The Chilean case

Chile, as a case study, illustrates particularly well the gap between traditional measures of progress and the social and economic reality at the household and individual level previously reviewed. Conventional social and economic welfare measures did not account for the profound and massive social discontent that led to strong protests and social uprising in October 2019 (Ferreira & Schoch, 2020). In Chile, GDP per capita grew from $ 14,000 in 1997 to $ 23,000 in 2017 (in PPP terms). In 2013, Chile entered in the select group of countries with the highest income according to the World Bank, and four years later, in 2017, was classified as a developed country by the Development Assistance Committee of the OECD (Tezanos, 2018). At the same time, poverty in Chile decreased significantly, reaching one of the lowest absolute poverty rates in Latin America (ECLAC, 2018).

Undoubtedly, the alarming level of inequality in its different dimensions has been one of the main explanations when analysing social unrest in Chile after the protests. However, the levels of income inequality have remained at the same high level during all periods of government since the return to democracy, showing even a slight decrease in recent years. Another measure of well-being, such as the Human Development index does not help to understand this crisis either. The UNDP classifies Chile as a country that has a very high human development index (UNDP, 2019).

In this way, recent events in Chile show the limitations of measures such as GDP, absolute poverty levels, income inequality measures and the Human Development Index in order to evaluate the progress and development of countries that are leaving behind underdevelopment.

Below, I provide a more detailed description of the evolution of social policies in Chile and its institutional background.

Income growth and poverty reduction with persistent inequality

Significant economic growth has been one of the most important hallmarks of the Chilean economy since the country's return to democracy in 1990. The economy has grown on average by over 5 per cent per year over the last 25 years, making the Chilean per capita income one of the highest in Latin America (OECD et al., 2019). As a consequence of this economic progress and its highly focused social policies, Chile has experienced a remarkable decline in poverty over the last decades (Larrañaga & Rodríguez, 2015). According to the official poverty measure used by the Chilean government during this period, the share of people living below the national absolute poverty line decreased from 38.6 per cent in 1990 to 8.6 per cent in 2017 (MDS, 2018).

However, the picture is different when the income distribution is analysed as a whole. Several measures of inequality indicate that the progress of the Chilean society towards a higher social inclusion has been limited. Based on post-transfer and post-tax household income per capita, official data from Chile shows that the Gini coefficient decreased only two points between 1990 and 2017, from 0.521 to 0.502 (MDS, 2018). These figures are among the highest for OECD countries (OECD, 2018c). The high level of inequality reflects a large gap between the top and mean incomes (Chauvel, 2018). As a result of this gap, the income distribution is narrower in the lowest decile groups with a high turnover of many households around the absolute poverty line (Larrañaga, 2009). This characteristic of the Chilean income distribution suggests that many households are extremely vulnerable to falling into poverty (Maldonado & Prieto, 2015; Neilson, Contreras, Cooper, & Hermann, 2008).[14]

Evolution of social policy in Chile

Some of the Chilean welfare state features can also help to understand the patterns observed in both poverty dynamic and labour market in Chile. In the context of Latin America, Chile belongs to the groups of pioneer welfare states, presenting middle level of welfare generosity in

[14] The trends in poverty and inequality in Chile are similar to those observed in the rest of Latin America. Poverty fell from 47 per cent to 26.4 per cent between 2002 and 2015, and the Gini coefficient declined from 0.550 to 0.467 during the same period (ECLAC, 2017). It is worth mentioning the remarkable change in income distribution unfolded in Brazil, which represents one-third of the region's population. During the 2000s and early 2010, Brazilian inequality fell by a fifth, and the share of the population living in poverty dropped by two-thirds. This change coincided with an expansion of the social safety net, steady progress in education, favourable demographics, and a long upturn in the business cycle (Sotomayor, 2019). However, between 2014 and 2017, poverty increased from 18 to 21 per cent of the population, revealing the high vulnerability in the lower end of the Brazilian income distribution (Vegh et al., 2019).

the region (Huber & Stephens, 2012). To explain the level of welfare generosity of Chile, scholars distinguish between periods of retrenchment and post-retrenchment reforms (Ewig & Kay, 2011). Although corporatist since 1920s (Haggard, Haggard, & Kaufman, 2008), Chile experienced radical neoliberal changes during the seventeen years of the dictatorship of Augusto Pinochet (1973–1989). The most commonly cited example of the liberalisation of the Chilean welfare state is the reform of the social insurance, the domain par excellence of the corporatist welfare state (Castiglioni, 2005). In the 1980s, policy reforms ended the pay-as-you-go social insurance system that had been in existence since the 1920s and established a system based upon individual contributions and compulsory private insurance administrated by private pension funds (Mesa-Lago & Bertranou, 2016). The reform of social insurance was accompanied by the privatisation of the health and education services (Cominetti & Raczynski, 1994). Most importantly to understand poverty dynamics is the fact that the Chilean retrenchment promoted a strong means-testing social policy that was meant to help only the extreme poor. The impact of this policy on poverty was limited because benefits were set at a low monetary level (Huber & Stephens, 2012).

In the 1990s, democracy was re-established in Chile, and a centre-left coalition (*Concertación*) came into office in successive periods until 2010. Based on a social citizenship conception of social policy, the centre-left governments undertook a set of initiatives towards universalising the coverage of healthcare as well as income support against risks. Another turn towards a more active role of government was the introduction of unemployment insurance in 2002. Its impact on low-income workers, however, has been quite limited, because the coverage is restricted to the formal sector and benefit levels are modest (Sehnbruch, Carranza, & Prieto, 2019b). The tax system also has had a modest redistributive effect because the government tax take is very low. Indeed, the Chilean system has the lowest tax burden in Latin America (Huber & Stephens, 2012).

Although governments in the 1990s introduced several benefits for the poor, an institutionalised anti-poverty policy appeared only in the 2000s. This policy began with the *Chile Solidario* program during the government of Ricardo Lagos (2000–2006). This program sought to establish an integrated system of social protection that included non-contributory income security and access to a variety of social services for those who were extremely poor. In 2010, when the right-wing coalition took office, this program was replaced by a new program called *Ingreso Ético Familiar* (Ethical Family Income). The new program combines unconditional and conditional transfers for people living in extreme poverty. It also provides psycho-social support for the participants, as well as labour activation programs. Assessments have shown that these programs have increased the coverage of the benefits, but there is no clear evidence that *Chile Solidario* helped to improve household income (Larrañaga, Contreras, & Cabezas, 2015).

In spite of the great changes experienced in Chile since 1990s when democracy was re-established, the success of these changes have remained circumscribed to poverty reduction and the provision of support to formal workers. Social policies have been somehow blind to informality, which helps to understand why although poverty reduction has been significant, vulnerability to poverty is still very high and informal labour rates have remained constant along the two past decades.

Welfare State in Chile: Small Subsidiary Government

The characteristics of the Chilean welfare state can also help to understand this relationship between sustained economic growth accompanied by a significant reduction in poverty but without relevant changes in income inequality. The Chilean government characterises for being relatively small and based on the principle of subsidiarity.

Table 1.2: Revenues and expenditures of the Chilean Central Government (Percentage of GDP)

	1990	2000	2003	2007	2011	2013	2014	2015	2016
Total revenues	23.6	22.2	20.2	25.5	22.6	20.9	20.6	21.2	21.1
Total expenditures	19.0	19.5	20.7	17.7	21.3	21.5	22.2	23.3	23.8
Social spending	12.5	14.7	na	na	11.6	12.3	12.6	13.3	13.9
Social spending as a % of the total expenditures	65.8	75.4	na	na	54.5	57.2	56.8	57.1	58.4

Source: Government Budget Division Data appear on page 82 in Repetto (2016) and on page 15 in OECD (2018c).

Note: For the years 1990 and 2000, central government expenditures include social protection, education, health and housing. For the other years, social spending does not include housing, only social protection, education and health.

Table 1.2 presents the size of the Chilean government, defined based on its revenues and expenses as a percentage of GDP. Total tax revenue remained relatively constant over the period observed, despite the rise in tax collection during the 1990s and the 2014 tax reform. On average, OECD member countries collect about 15 per cent more of their GDP in taxes

(OECD, 2015a). Although government expenditure has increased slightly and social spending shows a growing weight within the budget, Chile still has a small government that executes reduced social spending.

The difference between the level of public spending in Chile compared to other countries is partly due to the privatisation of social services. For example, while the public sector finances almost 85 per cent of education spending in OECD member countries on average, in Chile, only 60 per cent is funded with fiscal revenues (OECD, 2015a). Similar differences are observed in health financing and pensions.

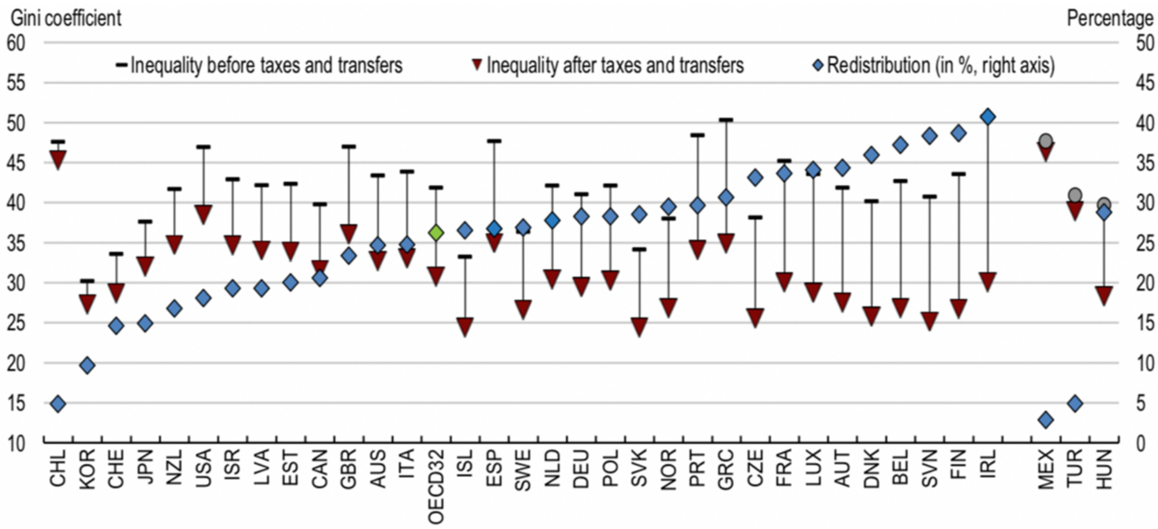
Public spending in Chile is highly progressive. The logic of targeting (generally in the first decile groups and even lower) has been central to Chile's success in reducing poverty. The redistributive income strategy consists of low-money monetary transfers where the family allowance becomes only in a minor proportion of a household's income. Also, a subsidy was introduced for low-income families that are not eligible for this transfer, as well as a welfare pension for those excluded from social security (PNUD, 2017). However, the budget constraint that this relatively small state entails does not allow households to benefit in the decile groups around the median. Chile's income distribution shows that those who are not poor do not differ much in terms of the material resources available from those who are (Maldonado et al., 2019).

In the context of Latin America, Chile belonged to the group of pioneer welfare states in the 1990s, presenting the highest levels of welfare generosity – education, health and social protection – in the region, alongside Brazil, Uruguay and Costa Rica (Martín-Mayoral & Sastre, 2017). However, although total public social expenditure as a percentage of the GDP in Chile reached its highest value in 2016 (13.9 per cent), it was still lower than the average level of social spending in the OECD (OECD, 2018c). This reality is directly associated with a low collection and slightly regressive tax system, in which the primary source of fiscal resources is value-added tax (VAT), which taxes almost all goods and services at a single rate. In 2017, the Chilean system ranked 35th out of 36 OECD countries in terms of the tax-to-GDP ratio (OECD, 2018c).[15]
The public policy that the majority of OECD members countries have implemented to change the income redistribution is a progressive combination of public spending and income tax. In

[15] In 2017, Chile had a tax-to-GDP ratio of 20.2 per cent compared with the OECD average of 34.2 per cent (OECD, 2018c).

these countries, the inequality-reducing effect of taxes and transfers is slightly more than 25 per cent (Causa, Browne, & Vindics, 2018). However, as Figure 1.6 shows, Chile is the country that shows the lowest income redistribution level. The Gini coefficient in Chile – pre-monetary subsidies and pre-income taxes – is 47.2 for the working-age population. After these taxes and transfers, the Gini falls only five per cent (or 2.4 Gini points).

Figure 1.6: Effect of taxes and transfers in Gini coefficient across OECD countries



Source: OECD Income Distribution Database. Figure appears on page 10 in Causa et al. (2018).

Note: The Gini index measures the extent to which the distribution of incomes among households deviates from perfect equal distribution. A value of zero represents perfect equality and a value of 100 extreme inequality. Redistribution is measured by the difference between the Gini coefficient before personal income taxes and transfers (market incomes) and the Gini coefficient after taxes and transfers (disposable incomes) in per cent of the Gini coefficient before taxes and transfers. For Hungary, Mexico and Turkey household incomes are only available net of personal income taxes, implying that inequality can only be measured after taxes and before transfers. The three countries are not included in the OECD average. Working-age populations include all individuals aged 18-65. Data refer to 2012 for Japan; 2015 for Chile, Finland, Israel, Korea, the Netherlands, the United Kingdom and the Unite Sates; and 2014 for the rest.

The highly focused social expenditure, limited solidarity role and slightly regressive tax system, explains why Chile, although successful in fighting poverty, has failed to achieve greater equality in its income distribution (Repetto, 2016). During the last decades, social spending has materialised through monetary transfers in low-income households and in subsidising the offer of services in education, health and housing, with substantial participation of the private sector in the provision.

In practice, this has resulted, on the one hand, in a social policy that segments their services socio-economically. Low-income households receive low-quality free services, middle-income ones can acquire intermediate quality services through the co-financing of benefits, and those with higher incomes have access to quality services that they acquire in private markets. On the other hand, the tax system in Chile is designed to promote business savings and investment and not to reduce income inequality. The system treats with preference those who generate income in the form of business income and individuals who belong to the highest income groups of the population.

The role of gender in welfare policies in Chile

In order to have a complete understanding of the Chilean case, the role of gender in welfare policies in Chile is of particular importance. Chile has one of the lowest employment rates of women among the OECD countries. Chilean female labour participation rate in 2014 was 51.7 per cent, only six percentage points above the average rate of classical familialistic regimes of Southern Europe such as Spain, Italy, Greece and Portugal (OECD, 2015b). Just like these regimes, one explanation for the low labour activation of women in Chile is the gender-biased regime characterised by a strong male breadwinner model. Following Pribble's (2006) classic breadwinner model, the household is the unit and recipient of family benefits in the Chilean regime. More specifically, the level of family allowances in this welfare system is lower for working women than for working-men, and the coverage of this benefit is limited because the entitlement is assigned to formal workers with open-ended contracts.

Childcare policies offer a similar picture. Childcare coverage also focuses on the formal segment of workers, but additionally, it is restricted to those who have a proven need for which a means-test is applied. It follows that the childcare system excludes several groups, such as women whose income exceeds the benefit threshold, inactive women, and women working in the informal sector. As a result of these exclusions, the traditional male breadwinner model may produce high levels of in-work poverty in Chile. Moreover, the risk of living in this type of deprivation should be characterised by a significant gender gap at the level of individuals.

1.4 Data sources

In this section, I include a description of the databases I have used in the research in my thesis. The three empirical chapters or papers use data from two Chilean surveys: the Panel CASEN 2006–2007–2008–2009, and the Financial Survey 2007–2011–2014–2017. Both surveys of households contain detailed information about the employment and income of each individual surveyed, among other socioeconomic and social security variables. Here I present a brief description of their main features.

P-CASEN 2006–2007–2008–2009

The Socioeconomic Household Panel Survey (P-CASEN) was carried out by the MIDEPLAN (former Ministry of Social Development) in 2006, 2007, 2008 and 2009.[16] The P-CASEN had the objective of gathering information to describe the socioeconomic conditions of Chileans over time and evaluate social policies. It is a household-based panel study that collected information related to income, education, employment, health, household composition, housing and so on. The interviews were conducted annually with all members of each household (adults and children).

The P-CASEN is representative nationwide for urban and rural areas and was specifically designed to collect longitudinal data. It used a sub-sample of 8,079 households composed of 30,104 individuals from the nationwide CASEN cross-sectional survey of 2006. Each person in the original sample was followed and re-interviewed consecutively at a time interval of about one year. 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.[17] The balanced database has 18,065 individuals (adults and children) present in each of the four waves. The potential attrition bias will be discussed in more detail late in both chapter 2 and chapter 3.

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

[17] Respondents from wave 1 did not know they were going to participate in a panel survey. This situation explains the high non-response in the second wave. For the following waves, respondents agreed to participate in the longitudinal study, and response rates were reached that were similar to those reported by international household panels.

The initial selection process was systematic and proportional, in order to obtain homogeneous probabilities of selection (EPSEM – equal probability selection method – design for each household). The stratification of the sample was done considering geographic, socioeconomic and demographic variables. This design ensured the representativeness of important groups of the population, like poor households, and again improved the accuracy of the estimates (Lynn, Zubizarreta, & Castillo, 2007).

The P-CASEN is the only household survey in Latin America that collected data each year over a period of four years. Unfortunately, the new government administration that took office in 2010 took the decision to discontinue funding for the following waves, prioritising the idea of increasing the frequency of the cross-sectional CASEN survey from three years to one year.

FHS 2007–2011–2014–2017

The Financial Household Survey (FHS) has been implemented by the Central Bank of Chile since 2007 and aims to generate detailed information on household income and expenses, as well as to provide a follow-up of their financial situation over time. Four surveys with urban national representativeness have so far been carried out, in 2007, 2011, 2014 and 2017.[18] The size of the sample in 2007 was 3,827 households. The 2011 sample comprised 4,057 households and the samples in 2014 and 2017 comprised 4,502 and 4,449 households respectively.

The FHS used a stratified, multi-stage probability sample selected from the population Census (2002 and 2012) sampling frame and included an oversample of well-off households using taxpayer information from the Chilean Internal Revenue Service (SII for its acronym in Spanish). The FHS design is similar to that of the U.S.A. Survey of Consumer Finances (Kennickell & Woodburn, 1999), and the Household Finance and Consumption Survey coordinated by the European Central Bank (HFCN, 2016).[19]

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[18] For more information on the SHF, see: https://www.bcentral.cl/financiera-de-hogares

[19] These characteristics have made it possible to include the Chilean FHS in the OECD Wealth Distribution Database, which has been used for comparative studies on households' wealth inequality (Balestra & Tonkin, 2018; Murtin & d'Ercole, 2015; OECD, 2013b).

1.5 Thesis outline

The rest of the thesis is built around three empirical chapters (or papers). Each paper addresses a different type of question. The second chapter assesses income mobility at the bottom and the top of the income distribution. I answer the question of why, in Chile, people who have been in the low-income or high-income groups are more likely to persist in the same position in the income distribution again in the future. The third chapter estimates degrees of vulnerability to poverty. This enables the measurement of the proportion of both those who are highly vulnerable to falling into poverty and those who belong to the income-secure middle class. The fourth chapter develops a multidimensional approach to measuring economic insecurity at the household level.

The second chapter contributes to the economic literature that relates income mobility to income inequality. I examine the mechanisms that explain why those that are in the lower end of the income distribution have a low probability of moving up (sticky floor) and, why those that are in the higher end of the income distribution have a low chance of moving down (glass floor). I measure persistence at the bottom and the top of the income distribution, breaking-down the persistence observed at both ends of the income distribution into the components that can be attributed to state dependence and to non-observed heterogeneity as well as to the effects of the observed characteristics of individuals and households.

The contributions of this chapter are three. First, I use econometric strategies that allow for the first time the estimation of state dependence for different income persistence groups along the income distribution. Second, until now, to the best of my knowledge, no studies have analysed the causes of persistence at both the bottom and the top of the income distribution in any Latin American country. Third, I perform robustness checks to validate the results concerning attrition bias.

I find that income mobility at the bottom and the top of the income distribution in Chile is much higher than the expected, showing signs of high economic insecurity. That is, all groups within the income distribution are likely to move upwards in the income ladder, but this does not ensure the sustainability of those changes over time. Second, the observable individual characteristics have a much stronger impact than the true state dependence to explain the current income position of individuals.

In the third chapter, I propose an approach to identify different degrees of vulnerability to poverty using two vulnerability lines that measure the risk of falling into poverty in the next period. This enables the identification of three types of households: those with high vulnerability, moderate vulnerability and low vulnerability to poverty. The last of these is the income-secure middle class. My approach makes three contributions. Firstly, it extends the model proposed by López-Calva & Ortiz-Juarez (2014) by distinguishing different degrees of vulnerability to poverty (rather than simply vulnerable versus non-vulnerable). Second, it uses a more sophisticated model of income dynamics than previous works as part of the vulnerability estimation procedures. Third, having two vulnerability lines allows for improving the efficiency and efficacy of risk-management and anti-poverty policies by enabling the design of supporting strategies tailored to the specific needs of the three vulnerable populations identified.

The vulnerability cut-offs obtained (using the poverty line for upper-middle-income countries) are for the low vulnerability line $20.0 dollars per person per day (pppd) and for the high vulnerability line $9.9 dollars pppd (both in 2011 purchasing power parity (PPP)). The vulnerability lines I derive differ significantly from those estimated in earlier research on vulnerability and the middle-class in Latin America. I argue that the previous research has underestimated the size of the population that is vulnerable to falling into poverty and has overestimated the growth of the middle-class. Misclassifying the vulnerable as middle-class limits their chances of accessing to anti-poverty protection policies.

In the fourth chapter , I propose a measure of economic insecurity at the household level that can be applied in contexts where: i) inequalities in household wealth are high, ii) the social safety net is limited, iii) indebted households are increasing due to strong credit growth, and iv) the reduction of absolute income poverty rather than relative poverty is the primary concern for policy. I build an index that combines four indicators of economic insecurity (each of which represents a specific vulnerability) that cause stress and anxiety: unexpected economic shocks, unprotected employment, over-indebtedness and asset poverty. In this way, the index offers a measure that directly relates households' economic uncertainty to stress due to the lack of protection and buffers to face an unexpected economic shock.

This chapter makes two contributions. First, I use the two components of the economic insecurity definition as the dimensions of my measure: i) an unexpected economic event and, ii) the household buffer to protect from this potential economic loss. This distinction allows understanding the Multidimensional Economic Insecurity Index (MEII) results comprehensively. In previous research, the focus in terms of the selection of indicators has either been on choosing between subjective and objective indicators or on just one source of economic insecurity. Second, this is the first time that economic insecurity has been measured in a Latin-American country, delivering a measure of well-being that contemplates the risk of adverse economic event in the future, which complements the forward-looking measures of vulnerability to poverty used in the region.

My estimates for Chile between 2007/2017 show high levels of economic insecurity regarding both the risk of an unexpected economic event and the lack of a household buffer to offset a potential loss. More than a third of households were exposed to unexpected economic shocks during this period. The indicators providing information about households' lack of protection reveal that 62.8 per cent were asset poor, 30 per cent had workers without social protection or non-workers, and 15.4 per cent faced over-indebtedness. When I combine the measures in the MEII, I find two main results. First, about half of the Chilean households experienced, on average, two or more economic vulnerabilities during the last decade with an intensity of 2.3 vulnerabilities. And second, economic insecurity affects households on the entire income distribution, even in the highest income deciles groups.

The final thesis chapter summarises the findings of the three empirical chapters. Additionally, it discusses the main implications and contributions of these findings, both concerning policy and methodology, in particular how my proposals improve these approaches to measuring economic and social well-being.

Chapter 2

Poverty traps and affluence shields: Modelling the persistence of income position

Abstract

I propose analysing the dynamics of income positions using dynamic panel ordered probit models. I disentangle, simultaneously, the roles of state dependence and heterogeneity (observed and non-observed) in explaining income position persistence, such as poverty persistence and affluence persistence. I apply my approach to Chile exploiting longitudinal data from the P-CASEN 2006–2009. First, I find that income position mobility at the bottom and the top of the income distribution is much higher than expected, showing signs that income mobility in the case of Chile, might be connected to economic insecurity. Second, the observable individual characteristics have a much stronger impact than true state dependence to explain individuals' current income position in the income distribution extremes.

2.1 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, 2015a). 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 chapter, 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). This is addressed in Chapter 4.

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 chapter 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 chapter 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.

2.2 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.[20] 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

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[20] 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).[21] 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.

[21] 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, 2012a; 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.

2.3 Data and definitions

The dataset I use is the Chilean Socioeconomic Household Panel Survey (P-CASEN) for the years 2006, 2007, 2008 and 2009.[22] The P-CASEN provides longitudinal data on the socioeconomic conditions of the Chilean population at a household and individual level (Observatorio Social, 2011c). For more details of the P-CASEN see data section in Chapter 1.

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,

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

imputed rent, private transfers and public transfers.[23] 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 relative and absolute cut-offs in parallel in order to identify groups in the income distribution. Conceptually, this strategy constitutes a midpoint between two different views. On the one hand, are those who advocate for a fixed real income cut-off

[23] 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.

because poverty should decrease as real income goes up (Ferreira et al., 2013). On the other hand, those who 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 2.5 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.[24] 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

[24] As will be seen in chapter 3, those who are between the poverty line and the affluence line can be divided into groups according to degrees of vulnerability. Based on this approach, the middle class is the group of households with a low risk of falling into poverty.

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 et al., 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.

2.4 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 2.1 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.[25] 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 2.1 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 poverty persistence and affluence persistence in absolute terms.

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

Table 2.1: 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 2.2 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 2.2: 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

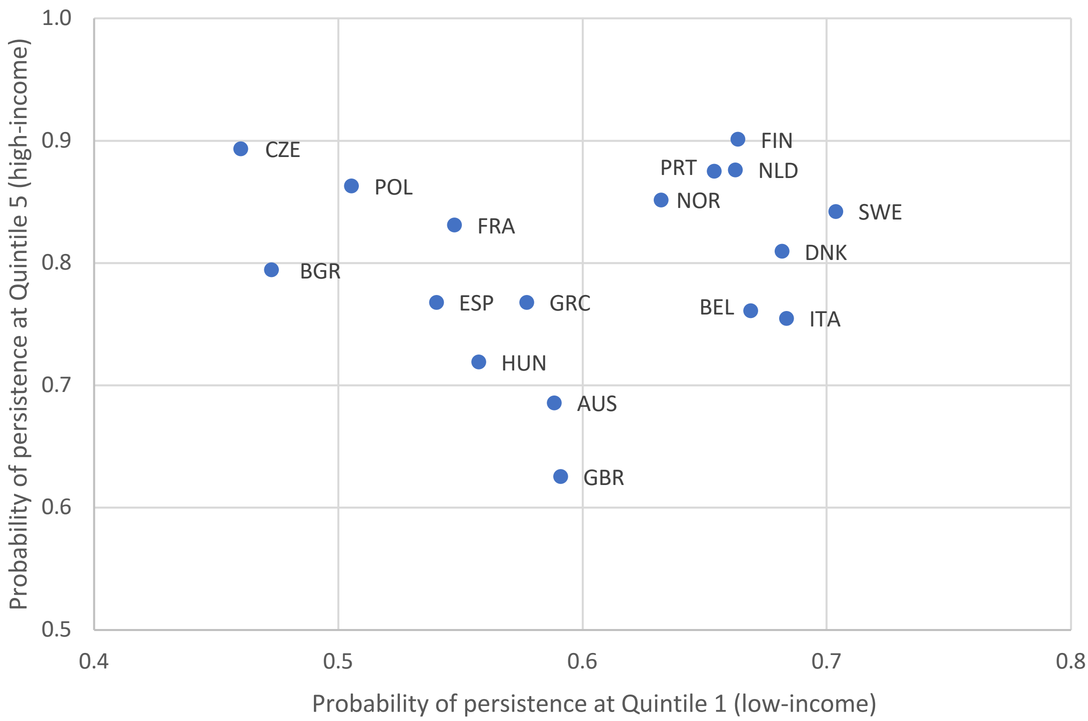
Welfare year *t* -1	Welfare, year *t* (row %)		
	Poor	Middle Class	Affluent
Poor	36.1	62.9	1.0
Middle class	7.4	88.2	4.4
Affluent	1.8	37.3	60.8
Total	9.8	81.0	9.2

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

In this way, the elements of Table 2.2 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.2.2 (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 2.1: 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.[26] Since changes in annual income are smoother than

[26] 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 2.1 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 2.1 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 2.1), 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 2.1). 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 2.2 with Figure 2.1, 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). An approach to measure economic insecurity in Chile is presented in the fourth chapter of the thesis.

2.5 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 traps.[27] 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 persistence to low income and persistence to high income is explained by the true or genuine state dependence (known as own-state traps) 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:

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

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

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.[28] 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,

[28] 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:

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

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:

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

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).

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

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.[29] 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 $t = 2, \dots, T$ 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:

[29] 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.

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

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}).[30] Thus, equation (4) is rewritten as follows:

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

[30] 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.

2.6 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 for both low-income and high-income probabilities are reported in Tables 2.3. 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 2.3. 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 2.3: Random effect dynamic ordered probit models for low-income/high-income probabilities

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 2.3 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.[31]

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 2.3). The latent

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[31] It is worth mentioning that I imputed the head of household partner variables' mean value to run the econometric models for those without a household head's partner. Models' estimates do not show significant changes when the head's partner variables are excluded.

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 2.3 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 2.4.

The γ' coefficients are presented in the first two rows of Table 2.3. 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 of moving to 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 of staying in the same income position. There is, therefore, a genuine state dependence in both 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 2.4: 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 2.4 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 2.3 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 2.4 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 2.4, 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 2.5 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.[32] 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.

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

Table 2.5: 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.[33] 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.2.1 (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.2.1 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.[34]

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

[33] 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.

[34] 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 2.6: 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 2.6 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).[35]

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:

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

[35] 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 2.7: 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 2.7 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.

2.7 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.

2.8 Appendices

Table A.2.1: 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.2.2: 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.

Chapter 3

Degrees of vulnerability to poverty: A low-income dynamics approach for Chile

Abstract

I propose an empirical framework to identify different degrees of vulnerability to poverty using two vulnerability lines that classify currently non-poor people into risk groups: low, moderate and high risk of falling into poverty in the next period. My approach features two contributions. First, it extends earlier work on vulnerability to poverty by looking at degrees of vulnerability rather than a simple dichotomy of vulnerable versus non-vulnerable. Second, it uses two models to predict both poverty entry probability and household income as part of the estimation procedures. The former controls for initial conditions effects and attrition bias and the latter addresses the retransformation problem. I apply my approach to Chile using longitudinal data from the P-CASEN 2006–2009. My vulnerability lines differ significantly from those estimated in earlier research in Latin America, suggesting that the size of the vulnerable might be underestimated and the growth of the middle-class overestimated.

3.1 Introduction

In the last decade, international agencies together with some governments in developing countries, have adopted a new forward-looking perspective in the design of social policies to identify those who, in spite of having exited poverty, are likely to fall back into it (see Birdsall et al. (2014) for Latin America, Klasen & Waibel (2015) for South-East Asia, and Dang & Dabalen (2018) for Africa). Knowing ex-ante which households are vulnerable to poverty makes it possible to develop effective anti-poverty protection strategies and improve risk-management policies such as risk insurance programs and incentives for self-protecting savings (Dercon, 2005). However, although the vulnerability to poverty concept dates back to the seminal work of Morduch (1994), there is still no consensus concerning the operationalisation and measurement of vulnerability to poverty due to the difficulty of analysing unknown future distributions of poverty (Ceriani, 2018; Gallardo, 2018).

My primary aim in this study is to derive income thresholds (vulnerability lines) to measure vulnerability to poverty. I define vulnerability to poverty as the risk for non-poor people in the current year of falling into poverty next year based on the approach that considers vulnerability as expected poverty (e.g. Chaudhuri (2003) and Christiaensen & Subbarao (2005)). I achieve this by using a new vulnerability measure based on a first-order Markov model that allows me to move away from the vulnerable versus non-vulnerable dichotomic analysis identifying instead, different levels of vulnerability within the non-poor population. I apply my approach to Chile between 2006 and 2009.

Until now, the vulnerability line most frequently used in comparative studies has classified non-poor households other than the affluent group into two groups, the vulnerable and the middle class or non-vulnerable (López-Calva & Ortiz-Juarez, 2014). This approach fails to acknowledge that, within the vulnerable group, households face different degrees of vulnerability; the vulnerability of a household close to the poverty line differs significantly from that of a household that is just below the income secure middle-class line. I address this issue by estimating two vulnerability lines to identify social groups with different degrees of vulnerability to poverty: the non-poor with a low, moderate and high probability of falling into poverty.

Using two vulnerability lines makes it possible to design policy strategies tailored to each of the groups identified. This is particularly relevant in countries that have managed to reduce absolute poverty yet show high income mobility explained by a precarious and unstable labour market and weak social safety net systems that fail to help households to cope with idiosyncratic shocks (OECD, 2018a; Torche, 2005).

My research has three objectives. Overall, I aim to measure the degree of vulnerability to poverty for the currently non-poor population. To do this, I developed a model of falling below a poverty line for each non-poor household in a base year. My approach derives vulnerability lines to identify vulnerable sub-groups inside non-poor sub-populations that are associated with their predicted poverty entry rates. My second objective is to propose two specific vulnerability lines. A high vulnerability line that focuses on households that are located in the central part of the income distribution and a low vulnerability line that focuses on the upper part of the income distribution. The former identifies those with a high risk and those with a moderate risk of falling into poverty in the next period. The latter serves the dual purpose of identifying the lower income cut-off for the income-secure middle-class as well as the higher income cut-off for the moderately vulnerable. The third objective is to analyse the determinants of vulnerability to poverty in Chile.

My approach builds upon three pieces of work that have made significant contributions to the study of vulnerability to poverty: López-Calva & Ortiz-Juarez (2014) who estimate a vulnerability line based on household characteristics in three countries in Latin America[36]; Dang & Lanjouw (2017) who derive the income cut-off (vulnerability line) for India, USA and Vietnam applying a non-parametric approach; and Schotte et al. (2018) who use a poverty dynamic approach to identify the (non-poor) vulnerable group in South Africa. My approach addresses some of the weaknesses of these previous research (for reasons explained later) and generates new measures of vulnerability.

My approach follows a three-step strategy. First, I estimate the probability of a currently non-poor household being poor in the next period. Unlike López-Calva & Ortiz-Juarez (2014), who assume a logistic model to quantify the predicted household risk of poverty, I use the endogenous switching first-order Markov model developed by Cappellari & Jenkins (2004) to

[36] In April 2018, the World Bank updated the vulnerability line for upper-middle-income countries from $10.0 dollars pppd in 2005 PPP (this cut-off updates López-Calva & Ortiz-Juarez (2014) work) to $13.0 dollars pppd 2011 PPP. More information can be found in the following link http://www.worldbank.org/en/topic/poverty/lac-equity-lab1/poverty/head-count

estimate poverty entries for non-poor people. This model, also used by Schotte et al. (2018), allows one to simultaneously control for the potential endogeneity of unobserved heterogeneity, attrition and initial conditions. Second, I use a log-linear model between household income and household characteristics to predict households' income. Unlike many applications that incorrectly does not address the retransformation problem (transforming the dependent variable by taking the natural logarithm complicates prediction (Santos Silva & Tenreyro, 2006)), I avoid bias in the retransformation scale of the household income by following the method proposed by Duan (1983). Third, I define the vulnerability line as the average predicted income among households whose probability of falling into poverty is within ± 1 percentage-point of the poverty entry rate estimated for a non-poor population. The range that I propose is not a function of the sample size (or sample design), which is a desirable property, by comparison with to Schotte et al. (2018) who use a range equal to an estimated confidence interval (which is sample contingent).

My approach, similar to Dang & Lanjouw (2017), calculates a vulnerability line and in doing so identifies vulnerable subpopulations. However, while their approach allows calculation of only one vulnerability line to identify a vulnerable subset of the population, my approach can be extended to derive more than one vulnerability line, and hence to also identify subgroups with different degrees of vulnerability.

Using my approach, I derive two vulnerability lines for Chile using four waves of panel data from the CASEN survey covering the period between 2006 and 2009.[37] The Panel CASEN is a national survey of households that is unique in Latin America since, despite being a short panel (four waves), it provides annual information on household income as well as on education, health, labour market, housing, and social benefits.

The income threshold I estimate to identify an income-secure middle-class differs significantly from the threshold suggested by the World Bank to measure the middle-class in upper-middle income countries set at $13 dollars pppd (2011 PPP). I estimate a $20.0 dollars pppd (2011 PPP) threshold for the low vulnerability line (middle-class) and $9.9 dollars pppd (2011 PPP) for the

[37] This Panel CASEN replaced the 'old' Panel CASEN 2001-2006 used by López-Calva & Ortiz-Juarez (2014), which collected longitudinal data over a five year interval of a sample representative of 4 out of the 15 regions in the country. The 'new' Panel CASEN 2006-2009 was designed and implemented by the Ministry of Planning of Chile and the Social Observatory of the Alberto Hurtado University (for more details see OSUAH (2011a)).

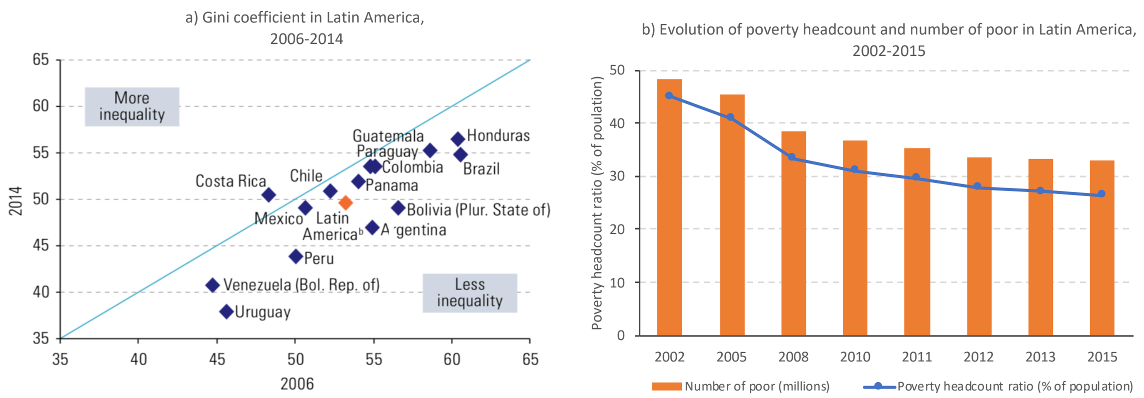
high vulnerability line. Using my two vulnerability lines in countries similar to Chile allows to open the discussion on the design and target of anti-poverty protection policies focus on the current distinction of vulnerable versus non vulnerable.

This chapter is organised as follows. In section 2, I discuss the importance of vulnerability lines for understanding the implications of the systematic reduction in absolute poverty rates in Latin America. In Section 3, I review the literature on vulnerability to poverty and middle-class identification and discuss the main approaches to calculating vulnerability lines. In section 4, I explain how I identify degrees of vulnerability to poverty. In Section 5, I describe data and definitions. Also, I present the descriptive statistics of poverty dynamics. In section 6, I apply my approach to the case of Chile. In Section 7, I present the conclusions.

3.2 Poverty reduction in Latin America: the emergence of the middle-class or the rising of the vulnerable?

In Latin America, cross-sectional surveys show that between 2002 and 2015 more than 75 million people exited poverty (see Panel B in Figure 3.1). This is explained by a reduction in the wage differential between skilled and unskilled workers, as well as the increase in cash transfers to the most deprived groups (Lustig, López-Calva, Ortiz-Juarez, & Monga, 2016). Also, although Latin America is one of the regions with the highest income inequality in the world, since the 2000s, the level of inequality has decreased slightly. The Gini coefficient declined from an average of 0.550 in 2002-2003 to 0.467 in 2015-16, due to a faster increase in the income of the lower quintile groups compared to the rest of the population (ECLAC, 2017).

Figure 3.1: Poverty and income inequality in Latin America over time



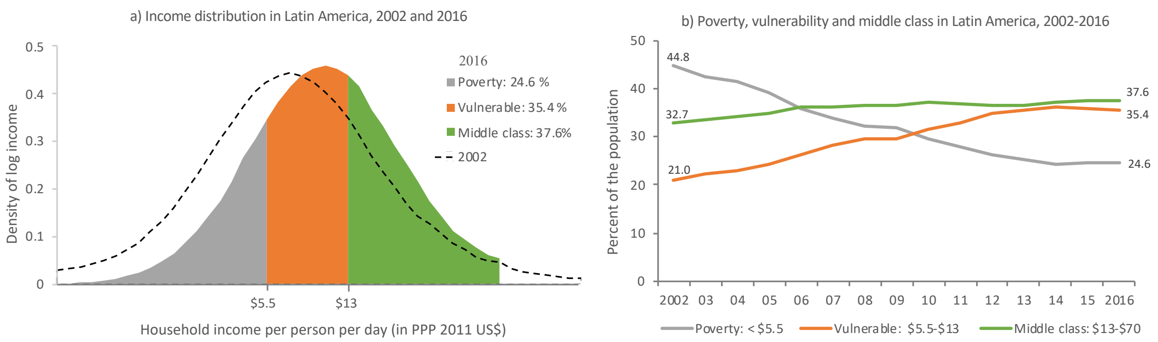
Sources: Figure of panel A appears on page 17 in Social Panorama of Latin America, 2016. Santiago, Chile: ECLAC, UN. In panel B, data from database: Poverty and Equity, World Bank, Development Research Group.
Note: In panel B, I used the cut-off of 5.50 dollars a day (2011 PPP) to define poverty. This poverty line is suggested for upper-middle-income countries (World Bank, 2018a).

This new reality led to a new wave of studies on the implications of the systematic reduction in absolute poverty rates in Latin America (Birdsall et al., 2014; Ferreira et al., 2013; Stampini, Robles, Sáenz, Ibarrarán, & Medellín, 2016a). These studies all use both the World Bank poverty line and López-Calva & Ortiz-Juarez (2014) vulnerability line to distinguish the vulnerable group from the poor and the middle class. Those vulnerable to poverty are individuals living in a household with a daily income per capita that falls between the lines of poverty and vulnerability ($4 and $10, respectively, at 2005 constant purchasing power parity (PPP) dollars). The rationale behind this classification is that people with incomes between the poverty line and the vulnerability line have high chances of falling into poverty, i.e. are vulnerable, whereas those who are above the vulnerability line have achieved a level of economic stability that reduces their poverty risk, i.e. are middle-class (Birdsall, 2015; Torche & López-Calva, 2013).

Ferreira et al. (2013) analysed household surveys from 19 countries in Latin America. These authors identify the year 2009 as the turning point in the region, since it marked the first time that a third of the population fell into the middle-class. According to the authors, the emerging middle-class group shared five features: i) they are more educated than those who remain in poverty; ii) live in urban areas; iii) work in the formal sector of the economy; iv) women participate more in the labour force; and v) have fewer children than those in poor or vulnerable households. Ferreira et al. (2013) stated that Latin America is a middle-income region that is on its way to becoming a middle-class society.

However, these trends reflecting improved living standards of those at the bottom of the income distribution need to be reassessed. Data from 2011 show that almost 40 per cent of the non-poor population in the region was vulnerable to poverty (Panel A in Figure 3.2) and, since 2012, despite a reduction in absolute poverty, the rate of growth of the middle-class has slowed down (Panel B in Figure 3.2).

Figure 3.2: Evolution of poverty, vulnerability and middle class in Latin America, 2002-2016



Source: In both panel A and panel B, author's calculation from Socio-Economic database for LAC (CEDLAS and LAC Equity Lab, the World Bank).
Note: The income thresholds I use to classify the poor, vulnerable and middle class taken from López-Calva & Ortiz-Juárez (2014).

Birdsall et al. (2014), using López-Calva & Ortiz-Juarez (2014) approach, identify the vulnerable group in 16 countries in Latin America portraying it as the 'strugglers' for the continuous effort made by this type of household to keep up their level of income and to not enter poverty again. This group characterises for (i) not being covered by social security programmes, since most work in the informal sector; (ii) paying high consumption taxes; and (iii) despite having improved their income, manifest a general discontent with their living conditions.

Stampini et al. (2016a), using synthetic panels constructed from cross-sectional household surveys, show that the middle-class in Latin America is also substantially affected by the risk of falling into poverty. These authors found for 12 Latin American countries that 65 per cent of those with a pppd income between $4 and $10 dollars in 2005 PPP terms, and 14 per cent of those in the middle-class had experienced poverty at least once over a 10-year period. These results suggest that the vulnerability line that they use to identify the middle-class does not reflect the idea that middle-class households enjoy economic security. A more demanding vulnerability line that adequately measures the middle class would make the size of the vulnerable group in Latin-America larger than official figures from the World Bank show (Birdsall et al., 2014; Ferreira et al., 2013).

The findings of this literature change the initially optimistic reading of poverty reduction seen as an expansion of the middle class in developing countries (Banerjee & Duflo, 2008; Ravallion, 2010). This new approach to measure vulnerability shows that being non-poor does not necessarily entail becoming non-vulnerable and therefore part of the middle-class (Birdsall et al., 2014). Based on this approach, poverty reduction can be related to an increase in either the middle class or those who are vulnerable to poverty (Wietzke & Sumner, 2018). In the case of Latin America, the evidence collected suggests that the emerging group in the region rather than being the middle-class is the vulnerable.

This new reality marked by poverty reduction across regions in the last two decades turned the attention towards the new low middle-class, opening a debate about the most appropriate way to measure the middle-class (Atkinson & Brandolini, 2013; Reeves, Guyot, & Krause, 2018), as well as the economic, social and political implications of an increase in the size of the vulnerable in these countries and regions (Dayton-Johnson, 2015; Wiemann, 2015).

3.3 Vulnerability-to-poverty and middle-income class identification: from divergent to convergent approaches

Until very recently, the economic research focused on the middle-class (e.g. Atkinson & Brandolini (2013)) advanced in parallel to research on the vulnerable group (e.g. Chaudhuri et al., (2002)), showing no relevant connection or dialogue although the research studies two sides of the same coin.

Measures to identify middle class: income as the main indicator

The research that focuses on defining the middle-class uses economic resources as the primary indicator, especially, household income (Gornick & Jäntti, 2014). Indeed, the middle-class is commonly analysed as the middle group within the income distribution, for which several strategies to define income thresholds, either relative or absolute, have been implemented.

Relative measures define the middle-class using household income to find a threshold that is anchored to the information provided by the income distribution of each country. See Estache & Leipziger (2009) and Atkinson & Brandolini (2013).[38] However, these measures fail to adequately compare the middle-class between countries with different income distributions. In developing countries, the income of middle-class individuals is significantly modest compared to the middle-class income of developed countries. Only a minority of the population of low- and middle-income economies qualify as middle-class if the economic welfare of developed countries is used as a reference (Milanovic & Yitzhaki, 2002; Ravallion, 2010).

By contrast to the relative measures, absolute measures of the middle-class use thresholds based on a particular level of income or expenditure. Early research suggested that the lower cut-off of the middle-class was $2 dollars pppd and the upper limit was $10 dollars or $13 dollars pppd

[38] Among these measures, there are three main definitions: i) distance from the median income, e.g. those whose income falls between 75 and 125 per cent of the median income are considered middle-class (Birdsall, Graham, & Pettinato, 2000; Davis & Huston, 1992); ii) a range in the distribution of income, e.g. those whose income falls within the 3rd and 4th quintile groups are considered middle-class (Alesina & Perotti, 1996; Barro, 2000; Easterly, 2001); and iii) a specific distance from the poverty line, e.g. those whose income is above 130 per cent of the country's official poverty line are considered middle-class (World Bank, 2012).

(Banerjee & Duflo, 2008; Ravallion, 2010).[39] The income cut-off used by these authors to define middle-class has been highly contested since the vulnerable group above the $2 dollars income cut-off lack the core characteristics of the middle-class, namely, income stability, access to social security benefits and being contributors to the social security system through tax payments (Birdsall, 2015). In recent years, the absolute purchasing power approach has been highlighted as a strategy to compare the middle-class between different countries at a global level (e.g. $11 to $110 dollars pppd in 2011 purchasing power parity (PPP) terms (Kharas, 2017)).

Vulnerability-to-poverty approach: measuring downward mobility

The economic work that focuses on the vulnerable group has developed a conceptual framework known as vulnerability-to-poverty (Hoddinott & Quisumbing, 2010). This literature can be sorted into three groups: i) papers that emphasise the element of expected poverty, that is, that consider as vulnerability the probability of a household falling into poverty in a future period (e.g. Pritchett et al., (2000); Chaudhuri et al., (2002)); ii) papers that stress the element of exposure to risk, for example, to indicate, retrospectively, whether an observed economic shock produced a loss of well-being in a household (e.g. Skoufias & Quisumbing (2005)); and iii) papers that define vulnerability as the difference between a household's utility derived from certainty equivalent consumption and its expected utility derived from actual consumption (e.g. Ligon & Schechter (2003)).

The most commonly used is the vulnerability as expected poverty (VEP). It has the advantage of being not only a relatively simple to implement with data that is widely available or can easily be collected, but also a forward-looking concept easier to comprehend and interpret by policymakers than the other two definitions (Hohberg, Landau, Kneib, Klasen, & Zucchini, 2018).

To develop measures based on these definitions, the same steps are followed. First, quantify vulnerability. This step requires a decision about the welfare indicator to be used in the analysis. Because a large number of these studies have been carried out in Global South countries (where household surveys track consumption expenditure instead of income), consumption is the

[39] The lower limit is equivalent to the World Bank's poverty line for developing countries and the $13 dollars upper threshold proposed by Ravallion (2010) is equivalent to the poverty line in the United States.

indicator most commonly used (Ligon & Schechter, 2003; Pritchett et al., 2000; Skoufias & Quisumbing, 2005). However, studies have also been conducted using earnings (Bourguignon, Goh, & Kim, 2004) and income when these measures of welfare are available.

The second step in measuring vulnerability to poverty is to estimate the future distribution of the chosen indicator (e.g. household income) in order to determine vulnerability status. The different parametric methods used to estimate both expected income and the variance of income for each household vary according to the types of data available. The best scenario is to have panel data, as is the case in this study, to estimate the income variance and also to incorporate more information in the model such as prior-period income (Hohberg et al., 2018; Skoufias & Quisumbing, 2005; Suryahadi & Sumarto, 2003). The shortage of longitudinal data in countries in the Global South has made it necessary to develop methodologies for estimating household's income variance from cross-section datasets (Chaudhuri et al., 2002; Günther & Harttgen, 2009) as well as for repeated cross-sections and synthetic panels (Bourguignon et al., 2004). For a detailed review of these methods, see Ceriani (2018), Calvo (2018) and Gallardo (2018).

The first definition of VEP needs a third step to estimate the vulnerability threshold. Once the threshold is estimated, all the currently households (poor and non-poor) whose probability of being poor in the next period is above the threshold are classified as vulnerable. A probability of 0.5 is used in most studies (e.g. Pritchett et al. (2000); Suryahadi & Sumarto (2003); Christiaensen & Subbarao (2005); Chiwaula et al. (2011)).[40] Pritchett et al. (2000) argue that this cut-point has two appealing features. First, it is the point where the expected consumption (or income) coincides with the poverty line. Second, it accords with common sense to say that a household is vulnerable if faces at least 50 per cent probability of being poor in the future.

The simplest approach to define VEP supposes that the outcome is determined by the following stochastic process:

$$ln\, y_i = \beta X_i + \varepsilon_i \quad (1)$$

[40] A recent study determines the vulnerability cut-off endogenously (Hohberg, Landau, Kneib, Klasen, & Zucchini, 2018). These authors find that their cut-off substantially increases predictive performance when compare both cut-offs.

where $ln\, y_i$ is the logarithm of household income i (or household consumption), X_i is a vector of household characteristics, β is a vector of parameters, and ε_i and is a disturbance term with mean zero. Then, both the expected log outcome and the outcome variance are calculated as follows:

$$E[ln\, y_i | X_i] = X_i\hat{\beta} \tag{2}$$

$$Var[ln\ y_i | X_i] = \hat{\sigma}^2_{\varepsilon_i} \tag{3}$$

Then the probability of a household with characteristics X_i being poor is:

$$\hat{v}_i = \widehat{Pr}(ln\ y_i <\ ln\ \mathrm{Z}\,|\,X_i) = \Phi\left(\frac{ln\ \mathrm{Z} - X_i\hat{\beta}}{\hat{\sigma}}\right) \tag{4}$$

Assuming that $y_{i,t}$ is log-normally distributed, the probability that a given a household's income (y_i) is lower than the poverty line (Z) conditional on household characteristics (X_i) is denoted vulnerability to poverty (v_i). Finally, a household is considered vulnerable if its $\hat{v}_i$ is above an established threshold probability value (e.g. $\hat{v}_i \geq 0.5$).

The VEP approach has two drawbacks. First, although vulnerability measures have a good performance as predictors of poverty at aggregate levels, face significant problems of precision in the identification at micro-level (Celidoni, 2013). For example, Bérgolo et al. (2012) assess the predictive power of vulnerability measures using panel data from Argentina and Chile. They find a relatively high level of misclassification at the household level, although these errors are substantially lower among households in the bottom of the income distribution. Second, VEP methods that use panel data do not take into account important methodological issues widely studied in the poverty dynamics literature about developing countries contexts such as bias estimates caused by non-random sample drop-out (e.g. Alderman, Behrman, Watkins, Kohler, & Maluccio, 2001; Falaris, 2003; Maitra & Vahid, 2006; Rosenzweig, 2003).

Using vulnerability line to identify both the vulnerable and middle-class

While the economic literature has used income cuts-off to identify the middle-class, most of the VEP studies define vulnerability thresholds in terms of a specific probability of falling into poverty. However, three new methods based on the VEP approach have linked the vulnerability threshold (risk) to household income levels namely those developed by López-Calva & Ortiz-Juarez (2014); Dang & Lanjouw (2017); and Schotte et al. (2018). This income threshold, known as the vulnerability line, allows identification of the vulnerable and non-vulnerable in the same way the economic research on middle-class does, as discussed above. Households are considered vulnerable to poverty if their income is below the vulnerability line, and middle-class if their income is just above the vulnerability line.

These methods (including my approach explained later) assume that there is a monotonic relationship between the predicted poverty entry probability and the household income. Although this assumption is plausible, it does not guarantee that higher base period income (among the non-poor) implies a lower probability of falling into poverty. The implication of this assumption in the identification of both the vulnerable and middle-class households will be discussed later.

The vulnerability line is defined as the income (V_t) such that having an income (y_t) below V_t at t (but above the poverty line (Z) at t) means that the risk of being poor at t+1 ($\Pr(y_{t+1} < Z)$) is greater than or equal to some critical probability level know as risk threshold. The vulnerability line V_t distinguishes households that are still vulnerable to poverty from those groups that are economically more secure. This definition is closely related to the Weberian notion that households should enjoy a certain minimum of economic security to be considered middle-class (Goldthorpe & McKnight, 2006; López-Calva & Ortiz-Juarez, 2014). This vulnerability line has served the purpose of closing the gap between the research on the income-secure middle class and the vulnerable group (Schotte et al., 2018).

López-Calva & Ortiz-Juarez (2014) derive a vulnerability line related to households' characteristics. Using longitudinal household surveys from Chile, Mexico and Peru, these authors fitted to a sample of non-poor two models i) a logistic model to estimate the probability of being poor at $t+s$ ($p_{i,t+s}$) given household characteristics at t ($X_{i,t}$); and ii) a log-linear regression model estimating household per capita income at t to the same explanatory variables measured at t ($X_{i,t}$). The equations are as follows:

$$p_{i,t+s} = Pr(y_{i,t+s} < Z_{t+s} = 1 \mid X_{i,t}) = \frac{1}{1 + e^{-(\beta_0 + \beta X_{i,t})}} \tag{5}$$

$$ln\, y_{i,t} = \gamma X_{i,t} + \varepsilon_{i,t} \tag{6}$$

where $y_{i,t+s}$ is the household per capita income in year $\mathrm{t+s}$, and β and γ are the parameters for each model.[41]

Then they calculate "the average of the independent variables for an array of estimated probabilities of falling into poverty. The resulting coefficients from Eq. [6] are thus used to produce the predicted income associated to each probability. […] As the middle class, ideally, should consist of those households facing a low risk of falling into poverty over time we use a 10 % probability of falling into poverty as a dividing line between economic security and vulnerability, and define the predicted income associated to that probability as the lower-threshold that depicts the lower bound of the middle class" (López-Calva & Ortiz-Juarez, 2014, p. 33).

Another way to explain López-Calva & Ortiz-Juarez's (2014) procedure is in terms of a transformation of Eq. 5 to obtain a linear model given by:

$$\log\frac{p_{i,t+s}}{1-p_{i,t+s}} = \beta_0 + \beta X_{i,t}\ , \tag{7}$$

with the objective of obtaining $X_{i,t}$ as a function of the probability of falling into poverty ($p_{i,t+s}$):

$$X_{i,t} = \frac{\log\frac{p_{i,t+s}}{1-p_{i,t+s}} - \beta_0}{\beta} \tag{8}$$

For simplicity, I assume that $X_{i,t}$ refers to one variable. The next step López-Calva & Ortiz-Juarez (2014) follow is to calculate the mean of the observable variable ($\overline{X_{k,t}}$) of all non-poor households (k) at time t whose probability of falling into poverty ($p_{k,t+s}$) lies in the range between 9 and 11 per cent. They used this level of poverty risk based on the annual poverty entry rate of 10 per cent estimated by Cruces et al. (2011) from synthetic panels for Chile, Nicaragua and Peru.

[41] The gap s, varies by country: for Chile it is 5 years, for Mexico 3 years, and for Peru 4 years.

Finally, López-Calva & Ortiz-Juarez (2014) assume that the re-transformation of the income variable is:

$$E(y_{i,t}|X_{i,t}) = \exp\{E(ln\, y_{i,t}|X_{i,t})\}\ , \tag{9}$$

and they calculate the vulnerability line using γ (parameters estimated in Eq. 2) and $\overline{X_{k,t}}$ as follow:

$$\widehat{V_{k,t}} = E(y_{i,t}|\overline{X_{k,t}}) = \exp(\hat{\gamma}\overline{X_{k,t}}) \tag{10}$$

One of the main advantages of the López-Calva & Ortiz-Juarez (2014) approach is that it provides a vulnerability line that can be used to compare upper-middle-income countries since it is based in the World Bank poverty line for these countries. This explains its extensive use to identify and measure those who are vulnerable to poverty and also those who qualify as middle-class in contexts of absolute poverty reduction (e.g. Birdsall et al., 2014; Ferreira et al., 2013; Stampini et al., 2016; Wietzke & Sumner, 2018).

However, the López-Calva & Ortiz-Juarez (2014) approach does not address important issues that may bias their results. First, their model assumes a logit relationship between the poverty entry probability for the non-poor and observable variables without taking into consideration panel attrition, which is significant for the data they used. In the case of Chile, the panel data at $t + s$ analysed by López-Calva & Ortiz-Juarez (2014) is non-randomly selected (Bendezú, Denis, & Zubizarreta, 2007), and it biases estimates of some measures such as income mobility (Paredes, Prieto, & Zubizarreta, 2006).

Second, the López-Calva & Ortiz-Juarez (2014) model for predicting household income (Eq. 6) neglects the retransformation problem (Duan, 1983). They obtain the vulnerability line ($E(y_{i,t}|X_{i,t})$) in Equation (9) assuming a straightforward retransforming of the income scale. However, they predict $E(ln\, y_{i,t}|X_{i,t})$ and take the exponent as result, which is incorrect because the expected value of the logarithm of the variable of interest is different from the logarithm of its expected value ($E(y_{i,t}|X_{i,t}) \neq \exp\{E(ln\, y_{i,t}|X_{i,t})\}$) (Santos Silva & Tenreyro, 2006). Thus, it biases estimates of household income.

Schotte et al. (2018) use the observed average rate of poverty entry for the non-poor population as a probability cut-off to separate the vulnerable from the middle class in South Africa. They calculate the vulnerability line as "the average monthly per capita household expenditure of those respondents whose predicted poverty transition probability falls within the 95 percent confidence interval around [this] probability threshold" (Schotte et al., 2018, p. 95). Importantly, they use the Cappellari and Jenkins (2004) poverty dynamics model to estimate the poverty entry probability for non-poor people. Unlike the López-Calva & Ortiz-Juarez (2014) poverty risk model, the Schotte et al. (2018) model estimates poverty transitions probabilities while simultaneously controlling for attrition and for initial conditions effects (whether a household is poor or non-poor in the base year is a non-random event).

Schotte et al. (2018) use the probability cut-off and a vulnerability line to distinguish between people who are non-poor but vulnerable and people who are middle class. They show there is a high level of misclassification error: i) 40 per cent of those classified as vulnerable by their observed income position would be classified as middle class using their risk of falling into poverty; and ii) 20 per cent of those who would be classified as middle class based on their observed income position would be identified as vulnerable given their poverty risk. "We show that class divisions based on monetary thresholds inadequately capture a household's chances […] of downward mobility and would lead to non-negligible misclassification errors" (Schotte et al., 2018, p. 102).[42]

Schotte et al.'s (2018) approach has three weakness: i) the use of the confidence interval to estimate the vulnerability line is undesirable because the poverty risk range is a function of sample size and design; ii) how to obtain a vulnerability line if no sample observation falls in the confidence interval estimated is unclear; and iii) the use of observed household expenditure to estimate the vulnerability line could make it more volatile than other alternatives such as the predicted household expenditure.

Finally, Dang & Lanjouw's (2017) approach differs from those of López-Calva & Ortiz-Juarez (2014) and Schotte et al. (2018) because they use a non-parametric estimation method to estimate vulnerability lines as a function household consumption or income. Thus, information about households' characteristics is not used in their approach. Dang & Lanjouw (2017) derive income cut-offs (vulnerability lines) that enable them to differentiate between the population that is not currently poor but that is vulnerable to poverty. They define V_0 "as the vulnerability

[42] Yet, the authors do not mention that their results show that the poverty dynamic model used for estimating the entry probabilities is not a guarantee of a monotonic relationship between income and the predicted entry probability.

line such that a specified proportion of the population with a consumption level above this line in time 0 will fall below the poverty line Z_1 in time 1" (Dang & Lanjouw, 2017, p. 637). They refer to this proportion as the "insecurity" index P^1, where V_0 satisfies the following expression:

$$P^1 = P(y_1 \leq Z_1 \mid y_o > V_0) \tag{11}$$

They also propose a second definition "that focuses on those with a consumption level higher than the poverty line but still below the vulnerability line in period 0" (Dang & Lanjouw, 2017, p. 639). The proportion of this population of falling into poverty in period 1 is designated as the "vulnerability" index P^2, where V_0 satisfies the following equality:

$$P^2 = P(y_1 \leq Z_1 \mid Z_0 < y_0 < V_0) \tag{12}$$

In other words, to get a three by three transition matrix (poor, vulnerable and middle class) requires a poverty line (Z) and vulnerability line (V_0), where the vulnerability threshold is such that a specified proportion of the population (P^2) above Z and below V_0 will be poor in the future. For example, Dang & Lanjouw (2017) employ a vulnerability index (P^2) of 10 per cent for their analysis of Vietnam and USA, and a vulnerability index of 15 per cent for India. They solve the equality (12) for the vulnerability line (V_0) in each country iterating from the poverty line upward until they reach a value for V_0 that provides P^2.

The main advantages of the Dang & Lanjouw (2017) approach are: i) unlike studies that fix the vulnerability index at 50 per cent (e.g. Chiwaula et al. (2011)), their vulnerability index is flexible; it can change or adapt based on practical complexities related to the design of social programs such as budgetary planning or targeting issues; and ii) the implementation of this approach is simple, and of intuitive understanding for policymakers.

Dang & Lanjouw (2017) approach has a crucial supposition. It relies on a key monotonicity assumption to derive V_0 in equalities (11) and (12). "…, since P^1 (P^2) is a decreasing function of V_0, we can iterate from the poverty line upward until we reach a value for V_0 that provides the specified insecurity (vulnerability) index" (Dang & Lanjouw, 2017, p. 604). This assumption implies that households are lined up in the same order in both period 0 and period 1. However, longitudinal studies in developed countries show the importance of addressing the re-ranking of households across years (Jenkins & Van Kerm, 2016).[43]

3.4 A low-income dynamics approach to identify degrees of vulnerability to poverty

In this section I discuss the three steps I follow to identify degrees of vulnerability to poverty. First, I explain the econometric approach to modelling poverty transitions probabilities (same model used by Schotte et al. (2018)). Second, I describe my proposal to derive a vulnerability line from poverty entry rates for non-poor in the base year, and third, I show how to extend my approach to have two vulnerability lines, not only one.

First step: A first-order Markov approach to modelling poverty entries

In the initial step, I employ the endogenous switching model proposed by Cappellari & Jenkins (2004) to identify the relationship between household characteristics at t and poverty transitions probabilities, and specifically the probability of falling into poverty between t and $t+1$ for non-poor people. This model is a Markovian transition model approach and provides estimates that address two important sources of bias.[44]

First, there is the bias that arises from ignoring the problem of initial conditions. This refers to the fact that the group who are poor in the base period may be a non-random sample of the population. Ignoring this may bias poverty transition estimates because it is difficult to assume that being poor in the base year is exogenous and uncorrelated with unobserved characteristics (Jenkins, 2011). For example, unobservables can make individuals more likely to be at the lowest extreme of income distribution in a given year. Second, there is potential bias resulting from non-random survey attrition. If the attrition process is not random and is correlated with the probability of poverty entry, estimates of the relation between poverty entries and covariables may be biased as a result of endogenous selection. For example, individuals that are more likely to be observed successively in the panel can be less likely to fall into poverty compared to those that attrit.

[43] Since the mean consumption in period 1 does not necessarily imply there was a far and wide increase in consumption in period 0, new research using panel data is needed to understand the implications of assuming no re-ranking of households between periods to derive V_0.

[44] See Jenkins (2011) for a detailed review of the standard approaches used to model poverty transitions such as hazard regression models, covariance structure models and variance component models.

In order to address the initial conditions problem and non-random panel attrition, I employ the Cappellari & Jenkins (2004) model. The model accounts for the endogeneity of both processes to poverty transitions probabilities by freely estimating the correlations between unobservables affecting. Thus, the model consists of three equations: i) the main equation of interest for conditional poverty status in year $t+1$ for all of the pooled annual transitions; ii) an equation for the poverty status in the base year t (in order to account for the initial conditions problem); and iii) an equation for sample retention from one wave to the next (to account for non-random attrition bias).

The latent propensities for these equations are represented by $P^*_{i,t+1}$ (conditional poverty status in period $t+1$), $P^*_{i,t}$ (poverty status in the base period t), and $R^*_{i,t+1}$ (retention in the sample between t and $t+1$), and modelled using the following linear specifications:

$$P^*_{i,t+1} = \left[(P_{i,t})\gamma_1' + \left(1 - P_{i,t}\right)\gamma_2'\right]\mathrm{X}_{i,t} + u_{i,t+1} \qquad \text{with} \quad u_{i,t+1} = \mu_i + \delta_{i,t+1} \sim N(0,1) \tag{13}$$

$$P^*_{i,t} = \beta'\mathrm{Z}_{i,t} + v_{i,t} \qquad \text{with} \quad v_{i,t} = o_i + \pi_{i,t} \sim N(0,1) \tag{14}$$

$$R^*_{i,t+1} = \psi'\mathrm{Z}_{i,t} + \varepsilon_{i,t+1} \qquad \text{with} \quad \varepsilon_{i,t+1} = \eta_i + \xi_{i,t+1} \sim N(0,1) \tag{15}$$

where $\mathrm{X}_{i,t}$ is a vector of covariates that has an impact on the conditional poverty status in the next period ($t+1$). The vector of covariates for the initial poverty equation $\mathrm{Z}_{i,t}$ is the same as $\mathrm{X}_{i,t}$ with additional exclusion restrictions, and similarly, $\mathrm{W}_{i,t}$ is vector of the variables that determine retention, including those in $\mathrm{X}_{i,t}$, plus a number of exclusion restrictions. The inclusion of a retention equation allows for using an unbalanced panel and therefore for drawing on all the information available in the panel.

The error term in each equation ($u_{i,t+1}, v_{i,t}, \varepsilon_{i,t+1}$) is defined as the sum of a normal individual-specific effect (μ_i, o_i, η_i) plus a normal orthogonal white noise error ($\delta_{i,t+1}, \pi_{i,t}, \xi_{i,t+1}$) where the latter follows a standard normal distribution. I estimate the model assuming that the joint distribution of these error terms is trivariate standard normal. The unobserved heterogeneity, that is, the individual-specific component of the error term, can be summarised by the following three correlation coefficients:

$$\rho_1 \equiv \mathrm{corr}\left(u_{i,t+1}, v_{i,t}\right) = \mathrm{cov}(\mu_i, o_i) \tag{16}$$

$$\rho_2 \equiv \text{corr}(v_{i,t}, \varepsilon_{i,t+1}) = \text{cov}(o_i, \eta_i) \tag{17}$$

$$\rho_3 \equiv \text{corr}(u_{i,t+1}, \varepsilon_{i,t+1}) = \text{cov}(\mu_i, \eta_i) \tag{18}$$

The identification of the correlation coefficients requires exclusion restrictions. Therefore, in order to allow the identification of equations (13), (14) and (15), Cappellari and Jenkins (2004) suggest using instrumental variables for both endogenous selection mechanisms that are correlated with the initial poverty status and with the attrition of the sample in the base year (t) but that are not correlated with the poverty status in time $t+1$.

Following other studies (e.g. Cappellari and Jenkins (2004), Ayllon (2013), and Schotte et al. (2018)) I use two types of exclusion restrictions. First, as an instrumental variable for the retention of the sample I use a dichotomous variable that identifies, among all the survey respondents, those individuals who were original members of the sample (interviewed in the first round), distinguishing them from those temporarily integrated into the panel sample because they were part of a household with an original member. The rationale behind this variable is that the original sample members have a higher probability of continuing in the sample than the temporary members regardless of the income level of their households.

Second, I use retrospective recall data as instrumental variables for the initial condition of poverty: i) the levels of education of the mother and father of each respondent; as well as ii) the type of work of both parents. The assumption behind these variables is that both the level of education of the parents and the work they did in the past affects the initial condition of poverty in the base year for the individual that belongs to the panel sample but does not directly affect transitions of poverty of the individual from one year to another.

Using the estimated parameter values of my model, I derive the poverty entry probabilities for every non-poor household in the base year (t). This probability is the proportion of households who are non-poor in period t that become poor in $t+1$. Specifically, the poverty entry probability ($e_{i,t+1}$) as a function of households' characteristics ($\mathrm{X}_{i,t}$) can be written:

$$e_{i,t+1} = \Pr(P_{i,t+1} = 1 | P_{i,t} = 0) = \frac{\Phi_2(\gamma_2' \mathrm{X}_{i,t}; -\beta' \mathrm{Z}_{i,t}; -\rho_1)}{\Phi(-\beta' \mathrm{Z}_{i,t})} \tag{19}$$

where $\Phi_2(\cdot)$ and $\Phi(\cdot)$ denote respectively the cumulative density functions of the trivariate and bivariate standard normal distribution (for details refer to section 2 in Cappellari & Jenkins, 2004).

Finally, I estimate the poverty entry rate between t and $t+1$ ($\bar{e}_{i,t+1}$) as the average probability ($\mathrm{N}^{-1}\sum_{i=1}^{N}\widehat{e_{i,t+1}}$) of falling into poverty for a non-poor household.

Cappellari and Jenkins's model (2004) has two additional advantages related to the use of panel data. It can be applied to relatively short panels because it only requires two waves of data, and the model can accommodate left-censored poverty spells because of its first-order Markov assumption. Individuals who remain in the same state at each wave (i.e. are always poor or never poor) are included in the estimation sample.[45]

However, I do not control for duration dependence in poverty status. As Jenkins (2011, p. 332) explains: "Markovian models assume that the accumulated impact of a person's history of poverty (and non-poverty) is expressed entirely by last year's poverty status". Arranz & Canto (2012b) show that poverty transitions vary not only with individual or household characteristics but also with spell accumulation and the duration of current and past spells. Though, there is evidence that the duration of spells might be showing a spurious effect rather than a duration dependence effect when models control by unobserved characteristics (Devicienti, 2011; Kiefer, 1988), which is what the endogenous switching model does.

Second step: Strategy to associate predicted poverty entry rates with a household's per capita income level

The predicted poverty entry rate ($\bar{e}_{i,t+1}$) is a probability threshold that allows me to distinguish between those who face an above average risk of being poor next year and those who face a below average risk of falling into poverty (the more secure). However, as I explain below, my objective is to derive a vulnerability threshold expressed in terms of income. Therefore, I derive the vulnerability line by calculating the incomes associates with the relevant poverty entry risks.

My approach, like that of López-Calva & Ortiz-Juárez (2014), Dang & Lanjouw (2017) and

[45] Other poverty transition models without a first-order Markov assumption such as hazard models can control for duration dependence. But the price paid is they cannot accommodate left-censored poverty spells. This may bias estimates because a large number of observations is dropped, thereby making the sample less representative (Kanabar, 2017).

Schotte et al. (2018), has an implicit monotonicity assumption: the higher the income -above the poverty line- the lower the poverty entry probability.

There are two reasons to propose a vulnerability threshold in terms of household income even though a monotonic relationship assumption may not always apply. First, using vulnerability line instead of the probability threshold estimated in the first step facilitates its interpretation for social protection and poverty reduction policies because it has a natural compatibility with the poverty line used in its calculation (Dang & Lanjouw, 2017). Second, as it happens with poverty measures, where theory supports the selection of the poverty line cut-off criterion (e.g. basic needs approach), the vulnerability line measures connect with the well-defined notion of vulnerability to poverty approach (López-Calva & Ortiz-Juarez, 2014), which sets a criterion to estimate the lower-threshold of the middle class. By doing so, my measures deal with the economic literature that uses income thresholds to define the middle class (e.g. Banerjee & Duflo (2008); Birdsall (2010)).

Furthermore, following López-Calva & Ortiz-Juarez's (2014) argument, I believe it is important to use predicted income rather than observed average income because the outcome of a parameterised model is less volatile than the observed values. Therefore, I can assume that a predicted household income better reflects the household income generation capacity because it is related to its composition, the types of assets owned by the household, and its environment (location of the house).

I calculate a vulnerability line for a non-poor sample as follows:

I use a log-linear regression model to estimate a cross-sectional household income equation for the base year at the household level. I use the same time-fixed predictor variables as in the endogenous switching model in the following expression:

$$ln\, y_{i,t} = \beta X_{i,t} + \varepsilon_{i,t} \tag{20}$$

where $\ln y_{i,t}$ is the log of household per capita income for year t. I predict household per capita income for year t, for each non-poor household i, based on the coefficient estimates from equation (20).

As seen above, some authors predict $\ln y_{i,t}$ and take the exponent as outcome $(\exp\{\beta X_{i,t}\})$. However, that procedure is incorrect because the expected value of the logarithm of a random variable is different from the logarithm of its expected value. See Santos Silva & Tenreyro (2006) for more details about the retransformation problem of $\ln y_{i,t}$.

I take into consideration the fact that $E(y_{i,t}|X_{i,t}) \neq \exp\{E(\ln\ y_{i,t})\}$. I address the problem by applying Duan's (1983) solution. I fit the log-linear regression using Poison regressions methods as a way of obtaining estimates of $y_{i,t}$, namely:

$$y_{i,t} = \exp\left(\beta X_{i,t} + \varepsilon_{i,t}\right) \tag{21}$$

That is, instead of taking the expectation of $\ln\ y_{i,t}$, I estimate the expected value of $y_{i,t}$.

$$E(y_{i,t}) = \exp\left(\beta X_{i,t}\right) E\{\exp(\varepsilon_{i,t})\} \tag{22}$$

Assuming that $\varepsilon_{i,t}$ is independent and identically distributed, I estimate $E\{\exp\left(\varepsilon_{i,t}\right)\}$ by the sample average $N^{-1}\sum_{i=1}^{N}\exp\left(\widehat{\varepsilon_{i,t}}\right)$.[46]

At the final, third step, I calculate the vulnerability line (V_t) as the mean predicted per capita income at t for non-poor households (k) with a predicted households' probability to enter into poverty in t that falls $\pm$ 1 percentage points probability around the poverty entry rate $(\bar{e}_{t+1} \pm 0.01)$. That is:

$$V_t = E(y_{k,t}|x_{k,t}) = \exp\left(\beta x_{k,t}\right) E\{\exp(\varepsilon_{k,t})\} \tag{23}$$

for all $e_{k,t+1}|x_{k,t}$ (as defined in equation (19)) such that:

$$\bar{e}_{t+1} - 0.01 \leq e_{k,t+1}|x_{k,t} \leq \bar{e}_{t+1} + 0.01\ .$$

The vulnerability line (V_t) obtained using a range around the poverty entry rate allows me to

[46] When comparing the average of the observed income of the household using the base year t of the survey Panel CASEN with a simple prediction, we obtain a difference of 15.2 per cent between the two values (CL $158,215, and CL $134,126, respectively). When using Duan's (1983) method to address the retransformation problem, the prediction of the average is CL $159,300. This value differs by less than 0.01 per cent from the sample mean value, thus showing that ignoring the retransformation bias leads to a poor prediction of household income.

reduce the volatility of the risk cut-off point and to provide enough observations to get a robust estimate of $E(Y_{k,t}|x_{k,t})$ in Eq. 23. This strategy is both independent of the size and design of the panel sample and it provides similar vulnerability thresholds when I use narrower or wider percentage points probability bands. It is worth mentioning that vulnerability lines are sensitive to the household income used in their calculation (observed income, predicted income, and predicted income addressing the retransformation bias). See Table 3.8 in section 3.6 for both sensitive analyses.

Extension: Using more than one vulnerability line to classify social groups according to their degrees of vulnerability to poverty

López-Calva & Ortiz-Juárez (2014), Dang & Lanjouw (2017) and Schotte et al. (2018) apply their approach to countries sharing two characteristics. They have reduced income poverty rates in the last two decades and the median income is not far from the poverty line. This means that a considerable proportion of the non-poor population in these countries is vulnerable to falling into poverty. In these contexts, classifying non-poor households as vulnerable versus non-vulnerable (or middle class) using one vulnerability line has three disadvantages depending on the chosen poverty risk criterion. First, if the vulnerability line is associated with a single average risk of falling into poverty, the likelihood of misclassification increases. For instance, those with a moderate risk of falling into poverty (i.e. with household income close to the vulnerability line) might be classified either as vulnerable or middle class.

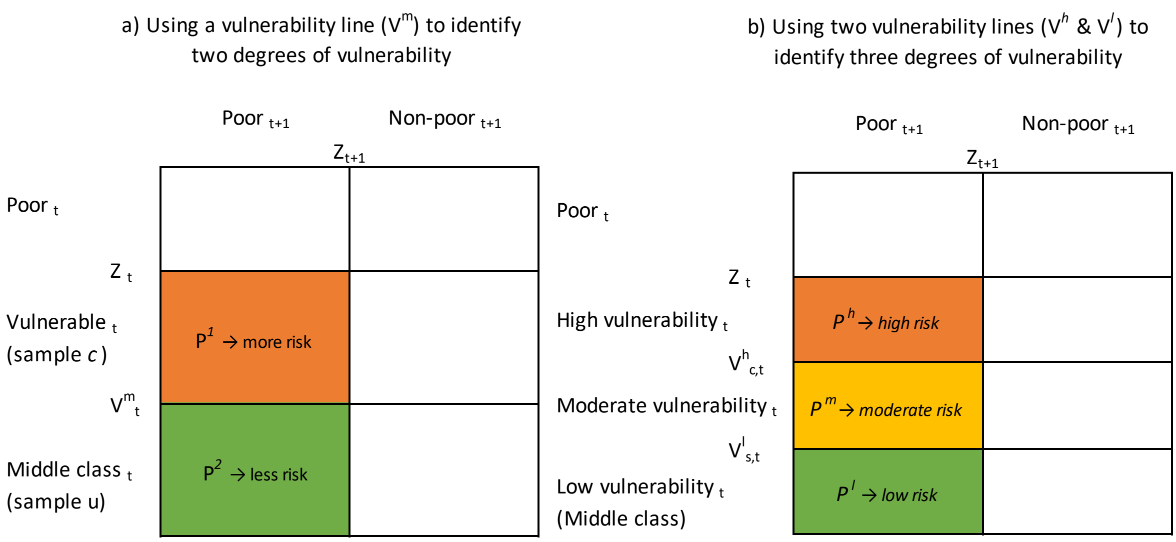
Second, if the vulnerability line is associated with a low risk of falling into poverty while it enables a better identification of the middle class based on economic security, it makes it challenging to implement social policies that efficiently use public resources. For instance, a cash transfer program targeting all vulnerable households that fall under this cut-off, may inefficiently allocate public resources since several households would continue to be non-poor vulnerable regardless of whether or not they received monetary transfers from the social program.

Third, if the vulnerability line is associated with a high risk of falling into poverty the line would identify a smaller vulnerable group (number) for whom a cash transfer would likely have a greater impact since it would be targeting households that show high vulnerability to poverty. However, those who are just above this vulnerability line might not find themselves in a situation of economic stability either. These households would likely require a set of social protection policies tailored to their degree of vulnerability to poverty. Yet, using a high vulnerability line would classify this group as middle class, misguidedly assuming they have reached a reasonable degree of economic security.

To address these shortcomings, I propose to classify non-poor households according to degrees of vulnerability using more than one vulnerability line simultaneously. This strategy has two advantages. On the one hand, it allows for the design of more efficient social protection programs using different vulnerability lines for targeting non-poor sub-populations (e.g. income decile groups). On the other hand, improves the identification of the middle class since it uses a vulnerability line derived from a low risk of falling into poverty instead of the average risk of being poor in the future.

Although my approach allows for calculating several vulnerabilities lines, I derive only two since this is the minimum number of cut-offs that enables me to address all the disadvantages of using one vulnerability line while keeping the number of income groups identified handy for policy purposes. The two vulnerability lines allow me to distinguish within the non-poor population groups with three levels of risk of falling into poverty: high, moderate and low.

Figure 3.3: Mobility matrices to illustrate how to identify degrees of vulnerability to poverty



One vulnerability line focuses on households that are located in the central part of the income distribution (sample *c*), and the other line focuses on the upper part of the income distribution (sample *u*). The mobility matrix in Figure 3.3. describes how I identify three degrees of vulnerability to poverty using two vulnerability lines.

First, I calculate a moderate (m) vulnerability line ($V_{n,t}^{m}$) for all non-poor households in the base year (sample n, which does not include the rich) using Eq. 23. This moderate vulnerability line is associated with the poverty entry rate ($\bar{e}_{n,t+1}$) and it allows me to split sample n in two sub-samples in time t: i) sample c with households with their income between the poverty line (Z_t) and $V_{n,t}^{m}$; and ii) sample u with households with their income above $V_{n,t}^{m}$. Assuming that increase in income can lower the probability of poverty entry, the probability of falling into poverty for all households in sample C is higher than $\bar{e}_{n,t+1}$, and for all households in sample u is lower than $\bar{e}_{n,t+1}$.

Including the moderate vulnerability line allows me to estimate two vulnerability indexes or transition proportions shown in the mobility matrix of Panel A in Figure 3.3. One is the vulnerable index (P^1) and the other is the insecurity index (P^2). P^1 and P^2 correspond to the expected proportions of those falling into poverty at more and less risk than the average, orange cell and green cell, respectively.

$$P^1 = P(y_{t+1} \leq Z_{t+1} | Z_t < y_t \leq V_{n,t}^{m}) \tag{24}$$

$$P^2 = P(y_{t+1} \leq Z_{t+1} | V_{n,t}^{m} < y_t) \tag{25}$$

P^1 and P^2 are transition proportions in a mobility matrix similar to Dang & Lanjouw's (2017) vulnerability indexes.[47] However, unlike their approach in which the proportions in the matrix are given, and the vulnerability line is derived, I estimate both vulnerability indexes from my moderate vulnerability line ($V_{n,t}^{m}$).

Second, since my approach (step 1 and 2) makes it possible to obtain vulnerability lines for different non-poor populations in the base year, I can simultaneously obtain a high vulnerability line ($V_{c,t}^{h}$) associated with the poverty entry rate ($\bar{e}_{c,t+1}$) for households in the central part of the

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[47] Dang & Lanjouw (2017) provide two measures of vulnerability to poverty: the "insecurity index" and "vulnerability index", "but the insecurity index focuses on households in the top part of the consumption distribution while the vulnerability index focuses instead on those located in the middle" (Dang & Lanjouw, 2017, p. 639). These authors approach offers greater flexibility in defining vulnerability to poverty, yet, in practice, they use a single income threshold.

income distribution (sample c), and a low vulnerability line ($V_{u,t}^{l}$) associated with the poverty entry rate ($\bar{e}_{u,t+1}$) for those in the upper part of the income distribution (sample u).

The mobility matrix of Panel B in Figure 3.3 shows how the high vulnerability line and low vulnerability line allow me to estimate three vulnerability indexes: the high vulnerability index P^{h} (orange cell); the moderate vulnerability index P^{m} (yellow cell); and the low vulnerability index P^{l} (green cell).

P^{h} corresponds to the expected proportion of falling into poverty in $t+1$ of those at high risk ($\bar{e}_{c,t+1} \leq e_{i,t+1}$, assuming a monotonic relationship between poverty risk predicted and income).

$$P^{h} = P(y_{t+1} \leq Z_{t+1} | Z_t < y_t \leq V_{c,t}^{h}) \tag{26}$$

P^{m} is the transition probability for non-poor people with a moderate risk of falling into poverty ($\bar{e}_{u,t+1} \leq e_{i,t+1} < \bar{e}_{c,t+1}$, ditto).

$$P^{m} = P(y_{t+1} \leq Z_{t+1} \; | V_{c,t}^{h} < y_t \leq V_{u,t}^{l}) \tag{27}$$

Finally, P^{l} corresponds to the expected probability of being poor in $t+1$ for those with a low risk ($e_{i,t+1} < \bar{e}_{u,t+1}$, ditto).

$$P^{l} = P(y_{t+1} \leq Z_{t+1} \; | V_{u,t}^{l} < y_t) \tag{28}$$

My approach can be easily adapted to derive more than two vulnerability lines (e.g. for income quintile or decile groups). This feature might suggest that if, in the limit, I end up using the poverty risk (or corresponding income) information as a continuous, my approach would not be different from a VEP approach. However, this is not the case. In the VEP approach (see Eq. 4 in the simplest approach to defining VEP) the probability of a household being poor refers to all current poor and non-poor households in its estimation. In my approach, the relevant population is the currently non-poor households.

3.5 The case of Chile: data, definitions and poverty dynamics

I apply the framework described above to Chile. This country shows some specific characteristics that makes it a compelling case to derive the vulnerability lines. First, in 2013 Chile was classified by the World Bank as a high-income country, reaching a Gross National Income per capita of around US$13,000 adjusted by international inflation (Tezanos & Sumner, 2016). As a consequence of this economic progress and its highly focused social policies, Chile has experienced a remarkable decline in poverty over the last decades (Cingano, 2014; Larrañaga & Rodríguez, 2015).[48] However, several studies reported that the improvement of this measure of economic well-being was accompanied by a generalised social discontent with the economic and political model (e.g. PNUD (2017)). This was evidenced by the massive protests that started in October 2019 when an increase in the public transport fare was announced (Pons, Mullins, Masko, Lobb, & Tella, 2020).

Second, the progress of the Chilean society towards higher levels of social inclusion has been limited. Based on post-transfer and post-tax household income per capita, official data from Chile show that the Gini coefficient decreased only two points between 1990 and 2017, from 0.521 to 0.502 (MDS, 2018). These figures are among the highest among OECD countries (OECD, 2018c). The high level of inequality reflects a large gap between the top and mean incomes (Chauvel, 2018). As a result of this gap, the income distribution is narrower in the lowest decile groups with a high turnover of many households around the absolute poverty line (Denis, Prieto, & Zubizarreta, 2007; Larrañaga, 2009). This characteristic of the Chilean income distribution suggests that many households are extremely vulnerable to falling into poverty (Maldonado, Prieto, & Lay, 2016; Neilson et al., 2008).

Third, Chile conducted a household panel survey between 2006-2009. It is the only household survey in Latin America that collected data each year over a period of four years, providing a great opportunity to study the dynamics of poverty in Chile in order to propose vulnerability lines to study both the vulnerable group and the middle class.

[48] According to the official poverty measure used by the Chilean government during this period, the share of people living below the national absolute poverty line decreased from 38.6 per cent in 1990 to 8.6 per cent in 2017 (MDS, 2018).

Data and definition of income poverty

For the analysis presented in this chapter, I exploit the rich data set of the Chilean Socioeconomic Household Panel Survey (P-CASEN) for the years 2006, 2007, 2008 and 2009.[49] The P-CASEN is a household-based panel study that collected information related to income, education, employment, health, household composition, and housing (Observatorio Social, 2011c). The interviews were conducted annually with all members of each household (adults and children). The target population consisted of all private households throughout the national territory. For the selection of cases, the National Socioeconomic Characterization Survey (CASEN) 2006 was used as the sampling frame. The first round of the P-CASEN in 2006 consisted of 8,079 households, comprising a total of 30,104 individuals (Lynn et al., 2007). The main advantage of this dataset is that it follows individuals and households over time. For more details of the P-CASEN see data section in Chapter 1.

Although the household is the unit of measurement for income, I study the dynamics of poverty at the individual level. The reasons for this decision are threefold. First, it offers the methodological advantage of giving greater weight to households with more members. Second, it allows for following the level of well-being of the individual when changes in the structure of the family occur due to divorce, marriage, children no longer living with their parents, or the birth or death of a family member. See OECD (2001) for both arguments. Third, the variables I use to control the endogeneity of both poverty status in the initial period and non-random attrition are at the individual level and not at the household level.

A relevant methodological decision is whether or not to work with a sample restricted to the adult population. In most studies of the dynamics of poverty, the analysis is limited to the population aged between 25 and 64 years (Ayllón, 2013; Buddelmeyer & Verick, 2008; Cappellari & Jenkins, 2004). The justification for this is that children and young people under 26 do not have an impact on decisions related to the income of the household. Also, by not including individuals over 64 years of age, researchers aim to avoid the impact of retirement on poverty dynamics transitions, particularly the impacts of pensions on income levels. Yet, the studies that propose vulnerability lines generally do not limit the age of adults for their analysis

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

(Dang & Lanjouw, 2017, 2017; López-Calva & Ortiz-Juarez, 2014; Zizzamia, Schotte, Leibbrandt, & Vimal Ranchhod, 2016). Therefore, given that one of the objectives of this research is to compare the results obtained with these types of works, I consider all of the adult population.

In this research, the welfare of individuals is named in terms of monthly income. Specifically, the income corresponds to the sum of the income of the household (mainly salaries, wages and earnings from independent work), cash transfers received from social programmes, and the imputation of the rent when the house is inhabited by its owners. November was the reference month for questions about net income (after taxes). Questions without answers and values lost in the components that form the income have been solved by using imputation procedures (Observatorio Social, 2011b).

To identify the low-income population, I use two absolute poverty lines. This procedure implies identifying the poor using the same income cut-off for each round. The first absolute cut-off is the official line of urban poverty in Chile in 2009, which in Chilean pesos (CL$) corresponds to a monthly income of CL$ 64,134 ($6.41 dollars per person per day (pppd) in 2011 purchasing power parity (PPP)). This poverty line was defined according to the minimum monthly income established per person to satisfy basic needs, which was calculated by ECLAC (Mideplan, 2010).

The second income cut-off corresponds to the international poverty line recommended by the World Bank to compare levels of poverty in countries in Latin America that are considered upper-middle income. Even though Chile is a high-income country according to the World Bank, I do not use the poverty line for this group of countries because it is too high to be applied to Chile. Instead, I use the poverty line for upper-middle-income countries, which better fits the Chilean context. This value is $5.5 dollars pppd in 2011 PPP terms. This threshold is based on the work of Jolliffe & Prydz (2016), who linked the poverty lines of 115 countries that are close to the 2011 PPP reference period with the income levels of each country, proposing four international poverty lines for four country categories: low income, lower-middle income, upper-middle income, and high income.

As mentioned before, in the Latin American context, cross-sectional data show that Chile has been particularly successful in reducing poverty. However, behind these gross changes between one period and another, the net changes remain hidden. Table 3.1 shows the transition rates of poverty entry and exit in Chile from one year to the next for two measures during the period analysed. The first part of the table shows the results of the balanced panel, which considers the cases that were interviewed in the four rounds, and the second part of the table corresponds to the unbalanced panel, which includes all of the cases interviewed for all of the rounds.

Table 3.1: Annual rates of entry and exit into poverty in Chile for the balanced and unbalanced panels

Poverty status, year *t*	Poverty status, year *t+1*				
	Balanced sample		Unbalanced sample		
	Non-poor	Poor	Non-poor	Poor	Missing
Upper middle-income countries poverty line					
($5.5 per person per day in 2011 PPPP)					
Non-poor	88.6	11.4	73.1	9.5	17.4
Poor	53.5	46.5	46.7	40.6	12.6
All	81.7	18.3	68.3	15.2	16.6
Chilean official poverty line					
($6.41 per person per day in 2011 PPPP)					
Non-poor	85.8	14.2	70.4	11.7	17.9
Poor	46.6	53.5	40.7	46.8	12.5
All	75.5	24.5	63.1	20.3	16.6

Source: Author's calculations based on the P-CASEN 2006-2009 (pooled data).

Table 3.1 shows that using the balanced panel, the probability of being poor depends on whether or not the individual was poor in the previous year. Using the official Chilean poverty line, only 14.2 per cent of people living in non-poor households entered poverty in the following period. In contrast, the probability of staying poor is 53.5 per cent.

The unbalanced panel gives us information about the transition patterns of the missing cases. Table 3.1 shows that 17.9 per cent of the individuals who were non-poor exited the sample in the next period. Among those observed to be poor, the percentage is 12.5. At first glance it would seem that the sample that remains during the four measurements is endogenous to the poverty condition of the previous period. In other words, the results suggest that the process of attrition is non-random and possibly correlated with the probability of being poor. This potential non-random selection of the sample, which could bias the estimates, is addressed in the econometric methodology that I use in this study, as will be explained in the next section.

Table 3.2: Poverty transition rates in Chile over period 2006-2009

Initial year		Income poverty for different poverty lines			
		Upper middle-income countries poverty lines		Chilean official poverty line	
		($5.5 per person per day in 2011 PPPP)		($6.41 per person per day in 2011 PPPP)	
		Non-poor	Poor	Non-poor	Poor
	Final year: 2007				
2006	Non-poor	89.9	10.1	88.0	12.0
	Poor	49.8	50.2	44.0	56.0
	All	83.2	16.8	77.9	22.1
	Final year: 2008				
2007	Non-poor	88.5	11.5	86.1	13.9
	Poor	49.7	50.3	43.6	56.4
	All	82.0	18.0	76.5	23.5
	Final year: 2009				
2008	Non-poor	89.5	10.5	86.9	13.1
	Poor	56.0	44.0	48.5	51.5
	All	83.4	16.6	77.8	22.3
	Final year: 2009				
2006	Non-poor	92.0	8.0	89.6	10.4
	Poor	61.5	38.5	53.2	46.8
	All	86.0	14.0	80.4	19.6

Source: Author's calculations based on the P-CASEN 2006-2009.
Notes: Based on balance data using all individuals and survey longitudinal weights.

Table 3.2 provides information on the different probabilities of transition from one year to the next for two different poverty lines. It also includes the rates of transitions between 2006 and 2009 (without considering the years 2007 and 2008). For the official poverty cut-off, it is observed that the annual entry rate fluctuates between 12.0 and 13.1 per cent while the annual exit rate ranges between 44.0 and 48.5 per cent. Using the poverty line of $5.5 dollars pppd in 2011 PPP, the poverty entry rate between 2006 and 2009 is 8.0 per cent. If the $5.5 dollars pppd in 2011 PPP were transformed into the $4 dollars pppd in 2005 PPP, this would be 6.5 per cent. This percentage is similar to the poverty entry rate of 6.4 per cent estimated by López-Calva & Ortiz-Juárez (2014) for the period between 2001 and 2006. This suggests that the probability of falling into poverty for those who were poor in the year 2001 was higher than that found by these authors, since they had only two measurements of income four years apart.

Table 3.3 confirms there is a high dynamism in households' income around the poverty line during a given period. The balanced sample with its longitudinal weights shows that 18 per cent were poor for at least one year, using the new World Bank income cut-off for upper-middle-income countries; 9.7 and 6.0 per cent were poor for two and three years, respectively, while 2.7 per cent remained in poverty from 2006 to 2009. Most important is the fact that a third of the Chilean population experienced at least one episode of poverty during the four years analysed (poverty prevalence rate). This percentage rises to 44.3 per cent when using the official poverty line in Chile.

Table 3.3: Percentage of poor in Chile by years in poverty over period 2006-2009

Number of years in poverty	Income poverty for different poverty lines	
	Upper middle-income countries poverty line	Chilean official poverty line
	($5.5 per person per day in 2011 PPP)	($6.41 per person per day in 2011 PPP)
0 of 4 years	63.6	55.7
1 of 4 years	18.0	18.8
2 of 4 years	9.7	12.0
3 of 4 years	6.0	8.3
4 of 4 years	2.7	5.2
Poverty prevalence rate	36.4	44.3

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

Notes: Based on balanced data using all individuals and survey longitudinal weights. The poverty prevalence rate is the proportion of individuals that experienced poverty at least once over the period analysed.

These descriptive results demonstrate the importance of understanding the nature of the dynamics of poverty in the process of distinguishing the poor from the non-poor who are vulnerable versus the non-poor who are middle-class. Given that the main contribution of this study is to propose a definition of vulnerability to poverty lines to identify these two groups that are non-poor, it is crucial to understand what factors drive the poverty dynamics, particularly the entry into poverty of those who, in the previous period, were non-poor.

Table 3.4: Descriptive statistics by poverty status (average values 2006-2009)

Variables	All population		At least once poor		Never poor	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Household head characteristics						
Female	0.39	(0.006)	0.38	(0.010)	0.39	(0.008)
Age	46.3	(0.201)	44.4	(0.295)	47.2	(0.260)
Education: Primary school	0.30	(0.005)	0.39	(0.009)	0.25	(0.006)
Education: Secondary school	0.5	(0.006)	0.51	(0.009)	0.52	(0.008)
Education: University degree	0.12	(0.005)	0.03	(0.004)	0.16	(0.007)
Labour status: Formal employed	0.70	(0.005)	0.61	(0.009)	0.74	(0.006)
Labour status: Informal employed	0.12	(0.004)	0.17	(0.006)	0.10	(0.004)
Labour status: Unemployed	0.02	(0.001)	0.04	(0.003)	0.01	(0.001)
Labour status: Inactive	0.16	(0.004)	0.19	(0.007)	0.15	(0.005)
HH head's partner characteristics						
Age	44.7	(0.214)	41.7	(0.306)	46.3	(0.282)
Education: Primary school	0.31	(0.007)	0.42	(0.012)	0.25	(0.008)
Education: Secondary school	0.53	(0.008)	0.50	(0.013)	0.54	(0.011)
Education: University degree	0.10	(0.007)	0.02	(0.004)	0.13	(0.009)
Labour status: Formal employed	0.37	(0.008)	0.19	(0.009)	0.46	(0.011)
Labour status: Informal employed	0.09	(0.004)	0.10	(0.006)	0.08	(0.005)
Labour status: Unemployed	0.05	(0.003)	0.07	(0.006)	0.04	(0.004)
Labour status: Inactive	0.50	(0.008)	0.65	(0.011)	0.42	(0.010)
Household characteristics						
Household type: Couple without children	0.27	(0.005)	0.17	(0.007)	0.31	(0.007)
Household type: Single without children	0.15	(0.005)	0.10	(0.006)	0.18	(0.006)
Household type: Couple with children	0.37	(0.006)	0.49	(0.010)	0.31	(0.007)
Household type: Single with children	0.14	(0.004)	0.20	(0.008)	0.11	(0.005)
Household type: Lone person	0.08	(0.004)	0.05	(0.005)	0.09	(0.005)
Number of persons	3.8	(0.022)	4.2	(0.038)	3.6	(0.026)
Number of children < 15	0.8	(0.012)	1.2	(0.023)	0.6	(0.013)
Number of workers	1.4	(0.011)	1.0	(0.014)	1.5	(0.014)
Housing: Own housing (no mortgage)	0.57	(0.006)	0.50	(0.009)	0.59	(0.008)
Housing: Own housing, mortgage	0.12	(0.004)	0.06	(0.005)	0.15	(0.005)
Housing: Rent	0.16	(0.006)	0.16	(0.008)	0.15	(0.008)
Housing: Subsidized or rent free	0.15	(0.004)	0.25	(0.007)	0.10	(0.004)
Rural	0.11	(0.003)	0.17	(0.007)	0.09	(0.004)
Regions: 1st, 2nd, 3rd and 4th	0.11	(0.004)	0.12	(0.006)	0.10	(0.004)
Regions: 5th, 6th, 7th, 8th, 9th and 10th	0.47	(0.006)	0.56	(0.010)	0.43	(0.008)
Regions: 11th and 12th	0.02	(0.001)	0.01	(0.001)	0.02	(0.002)
Regions: 13th	0.41	(0.007)	0.31	(0.010)	0.45	(0.008)
Nº household year-observations	26,463		9,052		17,411	

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

Notes: Balanced sample with longitudinal weights are used. All results are rates (%) unless stated otherwise. For the three samples the average variables are shown.

Table 3.4 compares those households that experienced poverty at least once with those households that were never poor. The first sample corresponds to all of the households interviewed in the four waves of the panel survey. The second sample considers those households that were poor for at least one year. The third sample corresponds to households that never experienced poverty during the four years.

A systematic difference is observed between the variables that describe the characteristics of the head of the household, his/her partner and the household in general.[50] As expected, the head of the household in non-poor households tends to be older, and show higher educational attainment, as well as a higher proportion of formal work compared to the heads of households that were poor during the period studied. For household head's partner in non-poor household, the average age is 46.3 years old while in households at least once poor the age is 41.7. Similar differences are observed in educational achievement and employment status. In non-poor households, 13 per cent have a university education and 46 per cent had a formal job, while in households that fell into poverty at least once, only 2 per cent have a university education, and 19 per cent had a formal job.

Regarding the characteristics of households, the presence of children increases the likelihood of experiencing poverty, regardless of the type of household (single-parent or head of a household with a partner). In non-poor households, the average number of children is 0.6 children while in poor households the average is 1.2 children. The size of the household together with the number of people working also shows important differences. In households that experienced poverty, on average only one member worked, and the average household size was 4.2 people. In contrast, in non-poor households, on average 1.5 members worked, and the average household size was 3.6 people. As for housing tenure and its location, those who owned their house and lived in an urban area, particularly in the city of Santiago (Region 13), were more likely not to be poor compared to households in subsidised or rent-free housing located in rural areas.

[50] I define the head of the household as the member of the household who contributes the highest earnings to the household income. In the case of a workless household, the self-reported household head is considered.

3.6 Predicting vulnerability lines using the low-income dynamic model estimates

In this section, I present the results of the poverty dynamic approach to identifying the degrees of vulnerability to poverty in the distribution of income in Chile. The discussion of these results is presented in the following four sub-sections. In the first sub-section, I test the specifications of the model that will allow me to estimate the probability of falling into poverty for non-poor households. For that, I compare the estimates of the model with the data, estimate the correlation between unobservables, and perform several tests to determine the ignorability of both initial conditions and attrition. In the following sub-section, I present the results of the estimates for the conditional poverty equation using the poverty line recommended by the World Bank for upper middle-income countries. In the third sub-section, I show the vulnerability lines associated with the risk of falling into poverty for each sample of households specified in the three stages of my proposal. Finally, I use the low and high vulnerability lines to classify currently non-poor people into three risk groups: low, moderate and high risk of falling into poverty in the next period.

Testing model specification

First, I present an assessment of the degree of fit of the model to the CASEN data panel. Panel 1 in Table 3.5 presents the predictions that the model calculates from equation (13) for the official poverty line in Chile. The overall average of individuals that enter poverty in period $t + 1$ (since they were not poor in period t) is 0.146, which is close to the 0.142 from the matrix of annual poverty transitions in Table 3.1. For the proportion of individuals that remain in the panel sample, the value of the predicted probability and the raw value are both 0.834. The same is true for the initial poverty ratio (0.257). These predictions show that the specified model replicates the sample averages closely.

One of the advantages of using a first-order Markov approach is that it takes into account the initial conditions and non-random survey attrition. In order to evaluate the possible ignorability of these two selection mechanisms in the model, I test for the separate and joint significance of the correlation coefficients associated with the selections in equations (14) and (15). The term ignorability here means that the different equations of the model can be estimated separately without worrying that the estimates are biased.

Table 3.5: Predicted probabilities, estimates of the model correlations and statistics tests

1. Predicted probabilities	Estimate		Std. Dev.
Poverty entry	0.146		(0.106)
Initially poor	0.257		(0.206)
Survey retention	0.834		(0.183)
2. Correlations between unobservable components			
ρ_1: Initial and conditional poverty	0.043		(0.044)
ρ_2: Survey retention and initial poverty	0.025	**	(0.012)
ρ_3: Survey retention and conditional poverty	0.032	**	(0.013)
3. Wald test of correlations (null hypotheses for tests)	Test statistic		p-value
$\rho_1 = \rho_2 = 0$: No evidence of initial conditions	6.48	**	0.0391
$\rho_1 = \rho_3 = 0$: No evidence of non-random attrition	10.12	***	0.0064
$\rho_1 = \rho_2 = \rho_3 = 0$: Joint exogeneity	10.71	**	0.0134

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

Notes: Robust standard errors clustered at the individual level. Simulated pseudo maximum likelihood estimation with 250 random draws. *** significance at 1 percent; ** significance at 5 percent; * significance at 10 percent.

As illustrated in Panel 2 in Table 3.5, there is no significant evidence of an unobserved correlation ρ_1 between initial and conditional poverty in the P-CASEN data. However, there is strong statistical evidence that the unobservable factors of non-random attrition are positively correlated with both the initial poverty in the base year ρ_2 and with the conditional poverty status ρ_3.

These results should not be surprising because they confirm what is described in Table 3.1; that is, a greater retention in the panel sample of those who were poor initially compared with those who were non-poor and also those who were poor in the next period compared to those who were above the poverty line. This result implies that the sample panel contains a non-random attrition problem. The exogeneity tests of the two selection processes considered could be rejected by the Wald tests conducted. Thus, both initial condition of poverty status and survey retention could be regarded as endogenous to the model (see panel 3 in Table 3.5).

In summary, the tests in the correlations of the unobservable factors indicate that the initial condition and the attrition of the sample are endogenous. Therefore, it is necessary to use the three equations (13, 14 and 15) of the endogenous switching framework to estimate the entry rates into poverty.

The drivers of poverty entry

Table 3.6 shows the coefficients for the probability of entering poverty from equation (19) using the poverty line of $5.5 dollars pppd in 2011 PPP terms, which corresponds to the cut-off suggested by the World Bank to compare upper-middle income countries.[51]

In terms of the characteristics of the household head, those who are less likely to fall into poverty are older males with a university education. Work wise, for heads of households in both informal jobs and for the unemployed the conditional probability of poverty entry is higher.

The characteristics of the partner of the household head that affect poverty entry differ in some respects from the characteristics of the heads of households. In this regard, when the partner has a university degree has a greater impact on reducing the risk of the household of entering into poverty than when the head of household has a university degree. When the partner is inactive it has a significant impact on increasing the household's likelihood of entering poverty. On the contrary, although working in an informal job and unemployment are both statistically significant, they have a lower weight in explaining falls in poverty than in the case of the head of the household. These results confirm the findings found in other studies on poverty dynamics carried out in Chile (e.g. Denis et al., 2007; Maldonado et al., 2016).

Finally, regarding the characteristics of the household, singles with children have a higher risk of falling into poverty. The same counts for larger families with more children. The attributes that reduce the risk of falling into poverty are: (i) the number of working household members, (ii) owning the house where they live (or paying a mortgage) and, in terms of location, (iii) living in urban areas and regions 11 and 12. Similar results are found in the works of Neilson et al. (2008) and Maldonado & Prieto (2015).

As I have already explained, the model controls for the endogeneity of poverty status in the

[51] In the Appendix Table A1 shows the coefficients using the official line of urban poverty in Chile.

initial period (equation 14) and non-random attrition (equation 15). When looking at column of poverty entry in Table 3.5, it can be seen that most of the covariates that are statistically significant in the association with initial poverty in time (t) are also significant in the case of conditional poverty status. It should be mentioned that covariates, such as having a university degree or the number of individuals working in the household, have a larger impact on the increase and decrease in the risk of being poor in the base year, than in the case of the equation to estimate the chances of falling into poverty.

As to the exclusion restrictions used in this equation, it stands out that when the mother of the individual surveyed works as a salaried employee this increases the probability of being poor in the base year, whereas when the father also works as a salaried employee the likelihood of entering poverty decreases. In the case of the education levels of the parents of the interviewee, both parents have a negative impact on the initial condition of being poor when the parents have only finished secondary education.

Column of survey retention of Table 3.6 shows the factors that explain the attrition of the P-CASEN sample. The two characteristics of the heads of households that make them less likely to be retained in the sample in the following period are (i) being male and (ii) having a university degree. The occupational categories do not seem to have a significant impact on attrition. In the case of the characteristics of the partner of the head of the household that increase the probability of remaining in the sample, these are (i) having completed only primary education, and (ii) being unemployed or inactive.

In the case of the characteristics of the household, being a household that is single with children has a positive impact on retention. Conversely, for single-person households, the impact is negative. Lastly, the variable that indicates whether the individual is an original member of the sample has a positive and the highest coefficient, which indicates that an individual who interviewed in the first round has a high probability of not leaving the sample in the next period.

Table 3.6: Model estimates of poverty entry rates, initial poverty status and survey retention, Chile (2006-2009)

Variables (measured at *t*)	Poverty entry: Poor at t+1| Non-poor at t			Poverty status at t			Survey retention		
	Coefficient		Std. Dev.	Coefficient		Std. Dev.	Coefficient		Std. Dev.
Household head characteristics									
Female	0.039	*	(0.020)	0.171	***	(0.020)	-0.046	**	(0.021)
Age	-0.006	***	(0.001)	-0.014	***	(0.001)	0.001		(0.001)
Education: Ref. Secondary school									
Primary school	0.140	***	(0.020)	0.362	***	(0.018)	0.133	***	(0.020)
University degree	-0.331	***	(0.037)	-0.679	***	(0.047)	-0.163	***	(0.029)
Labour status: Ref. Formal employed									
Informal employed	0.416	***	(0.025)	0.555	***	(0.022)	0.011		(0.025)
Unemployed	0.425	***	(0.093)	0.993	***	(0.055)	-0.004		(0.076)
Inactive	-0.048		(0.041)	0.146	***	(0.033)	-0.006		(0.037)
HH head's partner characteristics									
Age	-0.008	***	(0.001)	-0.005	***	(0.001)	-0.001		(0.001)
Education: Ref. Secondary school									
Primary school	0.240	***	(0.023)	0.329	***	(0.023)	0.045	*	(0.024)
University degree	-0.400	***	(0.063)	-0.742	***	(0.121)	-0.056		(0.042)
Labour status: Ref. Formal employed									
Informal employed	0.255	***	(0.033)	0.376	***	(0.039)	-0.004		(0.035)
Unemployed	0.168	***	(0.052)	0.350	***	(0.043)	0.227	***	(0.057)
Inactive	0.100	***	(0.022)	0.184	***	(0.022)	0.046	**	(0.022)
Household characteristics									
Household type: Ref. Couple without children									
Single without children	0.153	***	(0.034)	0.121	***	(0.038)	-0.033		(0.033)
Couple with children	0.136	***	(0.029)	0.255	***	(0.030)	0.030		(0.027)
Single with children	0.329	***	(0.035)	0.546	***	(0.036)	0.155	***	(0.035)
Lone person	0.021		(0.062)	-0.083		(0.065)	-0.198	***	(0.056)
Number of persons	0.054	***	(0.008)	0.274	***	(0.007)	-0.028	***	(0.007)
Number of children < 15	0.140	***	(0.013)	0.085	***	(0.012)	0.065	***	(0.012)
Number of workers	-0.201	***	(0.017)	-0.930	***	(0.015)	0.009		(0.010)
Housing: Ref. Own housing (mortgage)									
Own housing, mortgage	-0.366	***	(0.030)	-0.415	***	(0.034)	-0.149	***	(0.025)
Rent	0.217	***	(0.026)	0.380	***	(0.026)	-0.364	***	(0.024)
Subsidized or rent free	0.204	***	(0.025)	0.661	***	(0.019)	-0.075	***	(0.023)
Rural	0.133	***	(0.023)	0.154	***	(0.022)	0.094	***	(0.026)
Regions: Ref. 13th									
1st, 2nd, 3rd and 4th	0.094	***	(0.026)	0.083	***	(0.026)	0.034		(0.025)
5th, 6th, 7th, 8th, 9th and 10th	0.152	***	(0.018)	0.275	***	(0.019)	0.147	***	(0.018)
11th and 12th	-0.215	***	(0.050)	-0.287	***	(0.052)	0.271	***	(0.055)
Time (*t*): Ref. 2007									
2008	0.105	***	(0.018)	-0.173	***	(0.016)			
2009	-0.154	***	(0.019)	-0.007		(0.016)			
Individual characteristics (Exclusion restrictions)									
Mother education: Ref. No schooling									
Primary school				-0.050		(0.033)			
Secondary school				-0.156	***	(0.047)			
University degree				-0.155		(0.103)			
Type of work done by mother: Ref. Self-employed									

Employership	0.005		(0.123)			
Paid employment	0.116	***	(0.033)			
Non-employment	0.018		(0.028)			
Father education: Ref. No schooling						
Primary school	0.016		(0.034)			
Secondary school	-0.107	**	(0.045)			
University degree	0.028		(0.098)			
Type of work done by father: Ref. Self-employed						
Employership	-0.115		(0.073)			
Paid employment	-0.069	***	(0.026)			
Non-employment	0.014		(0.108)			
Original sample member				0.509	***	(0.056)
Constant	-1.181	***	(0.063)	0.602	***	(0.081)
Log-pseudolikelihood	-61,078.240					
Wald chi-square (d.f. = 131)	316,449.326 (p<0.000)					
Number of observations (person-waves)	65,205					

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

Notes: Robust standard errors clustered at the individual level. Simulated pseudo maximum likelihood estimation with 250 random draws.

*** significance at 1 percent; ** significance at 5 percent; * significance at 1 percent.

Vulnerability lines by poverty entry rates

In this sub-section, I present the results of predicted household income by poverty entry rates for different non-poor samples. Table 3.7 shows vulnerability lines in the base year for three subsamples of non-poor associated with the average probability of falling into poverty next year. When using the World Bank poverty line ($5.5 dollars pppd in 2011 PPP), the moderate vulnerability line is $12.8 dollars pppd with a poverty entry rate of 11.2 per cent for the all non-poor. The value obtained do not differ much from the $13.0 pppd delivered by the World Bank (2018) after its most recent update of the vulnerability line. However, the interpretation offered by the World Bank differs significantly from the one obtained from my result. While the vulnerability line of the World Bank is associated with a risk of falling into poverty of 10 percent in a time horizon of between 3 and 5 years (López-Calva & Ortiz-Juarez, 2014), I obtain a vulnerability line related to the average risk that households have of falling into poverty from one year to the next.

The low vulnerability line enables to identify the income-secure middle class. The second line in Table 3.7 shows that the income threshold for the lower bound for this group is $20.0 dollars pppd with an average probability of falling into poverty of 4.6 per cent.[52] This value is a third higher than the vulnerability line used by the World Bank for the same purpose, namely, to be the lower limit to identify those who are the income-secure middle class due to having a low risk of falling into poverty.

Furthermore, the low vulnerability line that I propose is close to the $21.19 dollars pppd in 2011 PPP terms of the poverty line used to compare high-income countries (Jolliffe & Prydz, 2016). In this way, the cut-off line to define the income-secure class in upper-middle-income countries would provide a direct association with the absolute poverty line of high-income countries that could be used in future research to study and compare changes in the income distribution among high-income countries with upper-middle-income countries.

The high vulnerability line is 9.9 dollars pppd and the poverty entry rate for the non-poor sub-sample is 17.1 per cent.[53] The fact that the value of the high vulnerability line is a 30 per cent lower than the vulnerability line for the non-poor should not be a surprise. As discussed below, this is due to the high proportion of the non-poor population that is very close to the poverty line.

Table 3.7: Vulnerability lines for subsamples of non-poor in the base year (t) using different poverty lines

Vulnerability lines for different poverty lines	Sub-samples of non-poor in the base year (t)	Poverty entry rate next year (t+1)				Vulnerability line in base year (t)			
		Mean	Std. Dev.	[95% Conf. Interval]		Mean	Std. Dev.	[95% Conf. Interval]	
Z_t: $5.5 pppd in 2011 PPP									
1. Moderate vulnerability line (V_t^m)	$Z_t < y_t$	0.112	0.001	0.109	0.115	12.77	0.11	12.54	12.99
2. Low vulnerability line	$V_t^m < y_t$	0.046	0.001	0.043	0.049	20.03	0.17	19.71	20.36
3. High vulnerability line	$Z_t < y_t < V_t^m$	0.171	0.002	0.167	0.176	9.86	0.06	9.75	9.97
Z_t: $6.41 pppd in 2011 PPP									
1. Moderate vulnerability line (V_t^m)	$Z_t < y_t$	0.138	0.002	0.135	0.141	11.79	0.05	11.69	11.90
2. Low vulnerability line	$V_t^m < y_t$	0.067	0.002	0.064	0.070	17.40	0.07	17.26	17.55
3. High vulnerability line	$Z_t < y_t < V_t^m$	0.233	0.003	0.223	0.239	8.57	0.06	8.45	8.69

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

Note: To describe the sub-samples I used the following notation: Z_t (poverty line in year *t*) y_t (household income in year *t*), V_t^m (moderate vulnerability line in year *t*).

[52] The low vulnerability line comes from the non-poor subsample where all households have income in the base year over the moderate vulnerability line ($V_t^m < y_t$).

[53] The high vulnerability comes from the non-poor subsample where all households have income in the base year between the poverty line and the moderate vulnerability line ($Z_t < y_t < V_t^m$).

For the Chilean official poverty line ($6.41 dollars pppd in 2011 PPP) the moderate vulnerability line is $11.8 dollars pppd, the low vulnerability line is $17.4 dollars pppd, and the high vulnerability line is $8.6 dollars pppd. As expected, these income cut-offs are lower than the vulnerability line based on World Bank poverty line used in upper-middle-income countries.

Sensitivity analysis of the vulnerability line approach to associate poverty entry rates with household income

I assess the sensitivity of the calculated vulnerability lines to some of the choices I made in deriving them. First, I evaluate the sensitivity to the selection of using the ± 1 per cent interval to calculate the average monetary threshold associated with a poverty entry rate. Panel A in Table 3.8 shows that a choice of a narrower probability interval of ± 0.5 per cent would have led to similar income cut-offs for both high vulnerability line and low vulnerability line. For a wider interval around the poverty entry rate such as ± 2 per cent the high vulnerability line and low vulnerability line change less than 3 per cent compared with the vulnerability lines for the ± 1 per cent interval.

Table 3.8: Sensitive analysis for the association of vulnerability lines with predicted poverty entry rates

Sensitive analysis for vulnerability lines	High vulnerability line associated with a poverty entry rate of 4.6 per cent				Low vulnerability line associated with a poverty entry rate of 13.4 per cent			
	Mean	Std. Dev.	[95% Conf. Interval]		Mean	Std. Dev.	[95% Conf. Interval]	
a) Percentage points probability around the poverty entry rate								
± 0.5	9.88	0.07	9.74	10.03	20.15	0.12	19.91	20.40
± 1	9.86	0.06	9.75	9.97	20.28	0.09	20.10	20.46
± 2	9.92	0.04	9.84	9.99	20.85	0.07	20.71	20.98
b) Household income								
Observed income	8.30	0.05	8.21	8.40	23.17	0.17	22.84	23.49
Predicted income without addressing the retransformation bias	8.38	0.05	8.29	8.47	17.23	0.08	17.08	17.39
Predicted income addressing the retransformation bias	9.86	0.06	9.75	9.97	20.28	0.09	20.10	20.46

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

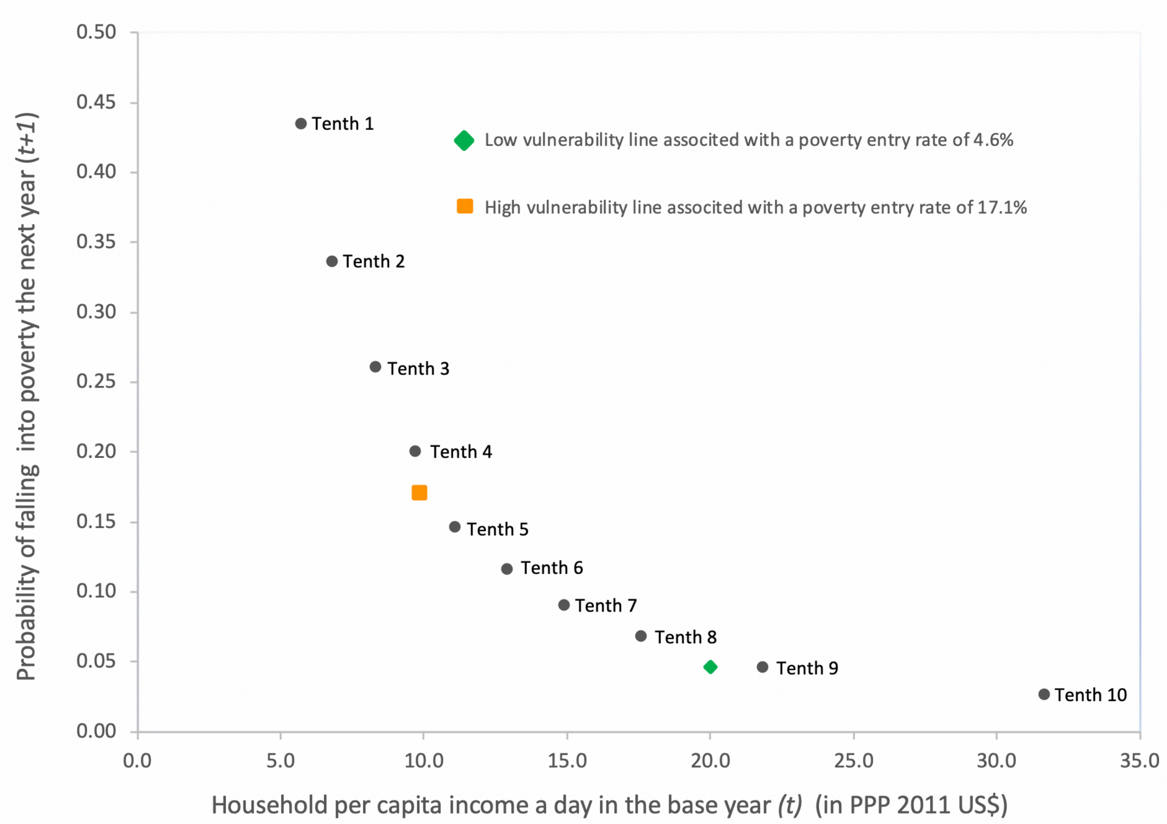
Notes: Vulnerability lines derived from the World Bank poverty line ($5.5 dollars pppd in 2011 PPP). In Panel B, all household income used the ± 1 per cent interval around the poverty entry rate.

Second, I assess the difference between vulnerability lines depending on the household income used (see panel B, Table 3.8). My high vulnerability line is around 17 per cent higher than the high vulnerability lines that are calculated using the observed income and the predicted income (without addressing the retransformation bias). When I compare the low vulnerability lines, the differences are even more significant. My low vulnerability line is 34 per cent higher than the low vulnerability line based on the predicted income without addressing the retransformation bias and 18 lower than the one calculated with observed income.

Using both high and low vulnerability lines to measure high, moderate and low vulnerable

Based on the results of Table 3.7 and using the World Bank poverty line, Figure 3.4 shows the poverty entry rate associated with both the low and high vulnerability lines. It also shows the association between the average risk of falling into poverty from one year to the next and the level of household income for each of the tenths of the income distribution. Although the deciles correspond to the entire income distribution, the subsample of decile 1 considers only those that were non-poor in the period t, and decile 10 considers only those households that had an income inferior to $70 pppd.

Figure 3.4: Vulnerability lines by poverty entry rates for non-poor subsamples



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

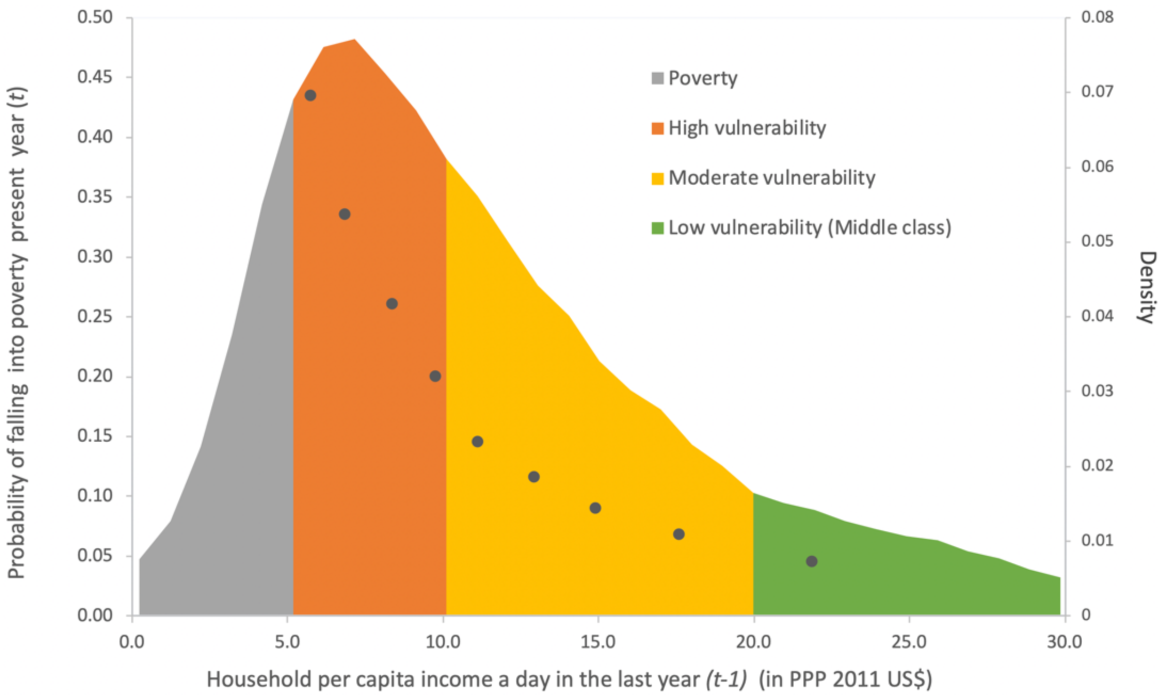
Note: I used the World Bank upper middle-income countries poverty line ($5.5 dollars pppd in 2011 PPP).

The green diamond in Figure 3.4 shows the low vulnerability line ($20.0 dollars pppd) associated with its probability of entering into poverty (4.6 per cent). The absolute cut-off for the low vulnerability line is in between the average risk of falling into poverty of decile groups 8 and 9 of the income distribution. This indicates that less than 20 percent of the population in Chile can be considered part of an income-secure middle class.

The orange square indicates the high vulnerability line ($9.9 dollars pppd) associated with its probability of entering into poverty (17.1 per cent). Vulnerability lines associated with the average risk of falling into poverty of income decile groups 1, 2, 3 and 4 are below the proposed high vulnerability line.

Figure 3.5 shows the income distribution and the two vulnerability line cut-offs that create and classify three groups within the distribution according to their degree of vulnerability, that is: high, moderate and low. The figure shows the size of each group within the income distribution, providing clear guidance to prioritise social policies tailored to each group. This is, policies aimed to prevent that those facing high vulnerability fall into poverty again, and support those experiencing moderate vulnerability so they can enter the income secure middle-class instead of moving backwards to face either high vulnerability or poverty.

Figure 3.5: Income distribution by degrees of vulnerability to poverty in Chile



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

Notes: The dark dots indicate the association between the probability of falling into poverty in the next year and the income level for the deciles of the income distribution.

Furthermore, Figure 3.5 shows the average risk of falling into poverty for the decile groups of the income distribution, which is associated with the average household income in each decile group. This information is also relevant for the design of social policies that aim to focus resources and obtain a greater impact within these three groups with different levels of vulnerability to poverty. For example, Figure 3.5 shows that almost one-third of the population face a high vulnerability, where decile groups 2 and 3 have a probability of falling into poverty of more than a 25 per cent, while decile group 4 has a probability of entering poverty of 20 per cent. Knowing this gradient enables the design of differentiated policies for each of the groups.

Other advantage of the strategy that I have designed is that it shows the relationship between the household per capita income and the probability of falling into poverty for each of the three groups separately. This allows for using the point estimates of the poverty transition equations to examine how the predicted probabilities of poverty entry vary for individuals and households in each group with different combinations of characteristics.

In order to ascertain whether the three groups identified according to their level of vulnerability to poverty differ from each other, I estimate a three-group mean comparison to test if there is a significant difference between the characteristics of: i) the poor and those who are highly vulnerable, ii) those who are highly vulnerable and those who are moderately vulnerable, and iii) households that are moderately vulnerable and those who show low vulnerability.

Table 3.9 shows that the differences between the four groups are broad and statistically significant for most of the variables, particularly those related to the type and structure of the household. However, when comparing the moderately vulnerable with those less vulnerable to poverty, the variables related to the labour status of the head of household and the number of workers in the household are not statistically significant, whereas the variable that reports on whether the head of household has a university degree presents the greatest average difference between the two groups. This suggests that for a household to transit to a low risk of falling into poverty (i.e. to become income-secure middle class) the number of household members that are working is less relevant than the head of household or the partner having a university degree.

Table 3.9: Characteristics of the household in the last year (t-1) by degrees of vulnerability to poverty in Chile (*Percentage of household and three-group mean-comparison t-test*)

Variables	Vulnerability to poverty classification				Level of significance of differences between two groups (ref. 95 %)		
	Poverty	High vulnerability	Moderate vulnerability	Low vulnerability	Poverty & High vul.	Hig vul. & Mod. vul.	Mod. vul. & Low. vul.
Household head characteristics							
Female	0.28	0.25	0.28	0.33	0.047	0.012	0.004
Age	44.7	47.0	49.2	49.5	0.000	0.000	0.527
Education: Primary school	0.50	0.42	0.33	0.19	0.000	0.000	0.000
Education: Secondary school	0.43	0.51	0.57	0.53	0.000	0.001	0.063
Education: University degree	0.01	0.02	0.08	0.27	0.199	0.000	0.000
Labour status: Formal employed	0.53	0.67	0.75	0.77	0.000	0.000	0.142
Labour status: Informal employed	0.22	0.15	0.09	0.09	0.000	0.000	0.770
Labour status: Unemployed	0.04	0.02	0.00	0.01	0.002	0.000	0.384
Labour status: Inactive	0.18	0.15	0.13	0.12	0.034	0.085	0.368
HH head's partner characteristics							
Age	41.7	43.6	45.6	46.1	0.000	0.000	0.151
Education: Primary school	0.31	0.27	0.21	0.10	0.04	0.000	0.000
Education: Secondary school	0.24	0.31	0.35	0.35	0.000	0.004	0.801
Education: University degree	0.00	0.01	0.02	0.12	0.018	0.000	0.000
Labour status: Formal employed	0.04	0.11	0.20	0.28	0.000	0.000	0.000
Labour status: Informal employed	0.04	0.07	0.07	0.06	0.002	0.890	0.283
Labour status: Unemployed	0.04	0.03	0.02	0.01	0.100	0.028	0.024
Labour status: Inactive	0.44	0.39	0.31	0.22	0.026	0.000	0.000
Household characteristics							
Household type: Couple without children	0.11	0.21	0.30	0.36	0.000	0.000	0.000
Household type: Single without children	0.05	0.08	0.13	0.18	0.032	0.000	0.000
Household type: Couple with children	0.60	0.52	0.39	0.28	0.000	0.000	0.000
Household type: Single with children	0.22	0.16	0.10	0.05	0.001	0.000	0.000
Household type: Lone person	0.02	0.03	0.07	0.13	0.073	0.000	0.000
Number of persons	4.7	4.3	3.8	3.2	0.000	0.000	0.000
Number of children < 15	1.7	1.2	0.7	0.5	0.000	0.000	0.000
Number of workers	1.0	1.4	1.7	1.7	0.000	0.000	0.871
Housing: Own housing (no mortgage)	0.50	0.59	0.62	0.59	0.000	0.071	0.033
Housing: Own housing, mortgage	0.04	0.09	0.15	0.21	0.000	0.000	0.000
Housing: Rent	0.11	0.12	0.11	0.13	0.485	0.191	0.032
Housing: Subsidized or rent free	0.35	0.20	0.12	0.07	0.000	0.000	0.000
Rural	0.24	0.18	0.10	0.06	0.000	0.000	0.000

Regions: 1st, 2nd, 3rd and 4th	0.13	0.12	0.13	0.13	0.322	0.395	0.781
Regions: 5th, 6th, 7th, 8th, 9th and 10th	0.63	0.57	0.47	0.42	0.006	0.000	0.002
Regions: 11th and 12th	0.00	0.01	0.01	0.02	0.002	0.091	0.371
Regions: 13th	0.24	0.30	0.38	0.43	0.001	0.000	0.006
Nº household	922	1,667	2,267	1,391			

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

Notes: Reference year is 2006. Cross-sectional weights are used.

3.7 Implications of using vulnerability lines based on a low-income dynamics approach

Using income thresholds based on a poverty dynamics approach to identifying degrees of vulnerability to poverty allows me: i) to study the predicted probabilities of poverty entry for different combinations of household types; and ii) to have a better understanding of cases that do not meet the monotonicity assumption between both predicted income and predicted probability poverty entry. Below I explain both of them.

Predicted probabilities of poverty entry for different household characteristics

In order to demonstrate the scope of the analysis enabled by this approach I have estimated for twelve family types the household income and their probability of falling into poverty along with their non-poverty spell duration.[54] To carry out this exercise I used the estimated points of the parameters of the model that controls for the selection biases associated with initial condition and attrition (Table 3.6).

Table 3.10 shows the results of the stylised families associated with the household welfare classification obtained from the low and high vulnerability lines. The households are listed according to their position in the income distribution. The reference household type (Case 1) is at the upper end of the income distribution with an estimated income of $81.1 dollars pppd in 2011 PPP, and a risk of falling into poverty close to zero; it is classified in the category "affluent professional".

[54] Based on the assumption that the relevant processes occur under a steady state equilibrium, it is possible to estimate the length of time spent as non-poor. I use the median non-poverty duration defined as log(0.5)/log(1-e_{it}) (Boskin & Nold, 1975; Cappellari & Jenkins, 2004).

Table 3.10: Estimates of predicted probability of falling into poverty and durations for stylised households

Household Characteristics (types)	Household per capita income a day (in 2011 PPP)	Household welfare classification	Upper middle-income countries poverty line ($5.5 pppd in 2011 PPPP)	
			Poverty entry rate (e_{it})	Non-poverty spell duration in years (median)
Case 1: Couple with one child aged over 15 years. The head of the household is a 50-year-old male. His partner is 45 years old. Both have completed university education and, are employed in formal work. They reside in their own housing (paying a mortgage) in an urban area in the Capital city.	81.1	Affluent professionals	0.001	692.8
Case 2: Case 1 except child is under 15 years old. The head of the household is 45 years old and his partner is 40 years old.	64.3	At the edge of income-secure middle class	0.003	230.7
Case 3: Case 2 except head of household's partner has only completed secondary school.	46.4	Income-secure middle class	0.010	69.0
Case 4: Case 3 except they rent their house.	35.4	Income-secure middle class	0.042	16.2
Case 5: Case 4 except head of household's partner is inactive.	25.1	Income-secure middle class	0.075	8.9
Case 6: Case 5 except head of household has only completed secondary school and his partner is employed in formal work.	19.9	At the edge of moderate vulnerability	0.080	8.3
Case 7: Case 6 except they have one additional child aged over 15 years old in the household.	16.9	Moderate vulnerability	0.088	7.5
Case 8: Case 7 except head of household's partner is employed in informal work.	15.3	Moderate vulnerability	0.137	4.7
Case 9: Case 8 except head of household's partner is inactive.	12.0	At the edge of high vulnerability	0.148	4.3
Case 10: Case 9 except household is employed in informal work.	9.9	High vulnerability	0.264	2.3
Case 11: Case 10 except head of household's partner has only completed primary school.	7.9	High vulnerability	0.312	1.9
Case 12: Case 11 except the head of household is female and her partner is unemployed.	6.1	At the edge of poverty	0.348	1.6

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

Note: Estimates are based on expressions 19 and 23, point estimates from Table 3.6.

In column 1 of Table 3.10, the characteristics of households that change from one case to another are detailed. These changes are related to an increase in the probability of falling into poverty. In this way, the table offers a depiction of the household types that fit into the different classifications. It also provides information on the households whose income is close to the vulnerability lines used to distinguish one group from another.

For example, a household that is classified as 'income-secure middle class' has an income of \$25.1 dollars pppd in 2011 PPP and a risk of entering into poverty of 7.5 per cent. This case, which corresponds to Case 5 in Table 3.10, is a household formed by a couple with one child aged over 15 years. The head of the household is a 45-year-old male, who has completed university education and is formally employed. His partner is 40 years old, has completed secondary school, and is inactive. They rent their house in an urban area in the capital city.

Of particular interest is Case 8 in Table 3.10. This household differs from Case 5 because it has two children, the head of the household has only secondary education, and his partner works in the informal sector of the economy. The estimated household income is \$15.3 dollars pppd in 2011 PPP and the probability of entering into poverty in the next year is 13.7 per cent. Following the current criterion of the World Bank (2018) this household would be considered middle-class despite having a risk of falling into poverty of over 10 per cent. Under the criteria I propose, using two lines of vulnerability, this household would be classified as moderately vulnerable.

Plausible inconsistencies between predicted income household and predicted probability poverty entry

As I have mentioned, my approach has an implicit assumption of monotonicity between the base period household income (among non-poor) and the probability of poverty entry, that is, higher income implies a lower probability of falling into poverty. However, when applying vulnerability lines to distinguish the degree of vulnerability to poverty, I risk making misclassification errors because there are cases where that assumption is not met. I argue that these cases can be seen as 'plausible inconsistencies'. Looking at the variables of the models that predict both the probability to falling into poverty and household income, 'plausible inconsistencies' are found to explain, for example, cases of households that share the same income but face different poverty entry probability, and inversely, households that share the same poverty entry risk but have different incomes.

Table 3.11 illustrates some examples of 'plausible inconsistencies'. I take two households that would be classified as middle-class using the World Bank's vulnerability line, with an income per capita close to \$15.0 dollars pppd in 2011 PPP, and compare them (Case A and Case B are shown in the first panel of Table 11). Household A differs in terms of two characteristics from household B: instead of two children they have only one, and the head of the household works in an informal job.

Table 3.11: Comparison between different households with the same predicted daily income and with the same probability of falling into poverty in the next year

Household Characteristics	Household per capita income a day (in 2011 PPP)	Upper middle-income countries poverty line $5.5 pppd in 2011 PPPP)	
		Poverty entry probability (e_{it})	Non-poverty spell duration in years (median)
Base Case: Household compound by a couple. They rent their house and reside in an urban area in the Chilean capital city of Santiago.			
1. Two types of household with similar predicted daily income			
Family A: Couple with one child. The head of the household is a 40-year-old male. His partner is 35 years old. Both have completed secondary education. The head of the household is employed in the informal sector of the economy. His partner is also employed in informal work.	15.0	0.232	2.6
Family B: Couple with two children. The head of the household is a 45-year-old male. His partner is 40 years old. Both have completed secondary education. The head of the household is employed in the formal sector of the economy. His partner is employed in informal work.	15.3	0.137	4.7
2. Two types households with a similar probability of falling into poverty in the next year			
Family C: Couple with two children. The head of the household is a 40-year-old male. His partner is 35 years old. Both have completed secondary education and are employed in the formal sector of the economy.	16.2	0.101	6.5
Family D: Couple without children. The head of the household is a 60-year-old male. His partner is 50 years old. Both have completed secondary education. The head of the household is unemployed. His partner is employed in formal work.	11.2	0.101	6.5

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

Note: Estimates are based on equations 19 and 23, point estimates from Table 3.6.

The probability of falling into poverty for Case B (a household of four people) is 13.7 per cent, whereas Case A, though a smaller household, has two members working in the informal sector and shows a probability of falling into poverty that is around double that of Case B. This result should not be surprising because it reflects the economic insecurity of a household with two informal workers, despite the fact that it has fewer members than the other.

Likewise, there are households with the same risk of entering poverty and different income levels. In panel B of Table 3.11, an example of this is shown. Case C and Case D describe households with different characteristics, namely, number of children, age of the couple, size of the household and number of people working. However, despite their level of per capita income being different, they have the same risk of entering poverty.

The existence of 'plausible inconsistencies' in the classification of the households according to degrees of vulnerability to poverty connects with the discussion posed by Schotte et al. (2018), who strongly question the use of income cut-offs, proposing instead the use of the poverty entry probability thresholds to classify groups within the income distribution. My results show that non-compliance with the monotonicity assumption between income and risk of falling into poverty may not necessarily be seen as a classification problem. Both outcomes are plausible to be used to classify groups with different risks of falling into poverty. However, it could be argued that the use of vulnerability lines could have a greater problem of 'accuracy' that using poverty risk thresholds (Celidoni, 2013; Hohberg et al., 2018).

Table 3.12: Comparison of predictive performance between degrees of vulnerability to poverty and vulnerability to poverty for different vulnerability cut-offs

a) Degrees of vulnerability to poverty					
Two vulnerability lines			Two probability cut-offs		
	2008			2008	
2007	Poor	Non-poor	2007	Poor	Non-poor
Highly vulnerable	24.8	75.2	Highly vulnerable	21.3	78.74
Moderately vulnerable	7.8	92.2	Moderately vulnerable	7.7	92.3
Lowly vulnerable (Middle-class)	3.7	96.3	Lowly vulnerable (Middle-class)	1.7	98.4
b) Vulnerability to poverty					
One vulnerability line			One probability cut-off		
	2008			2008	
2007	Poor	Non-poor	2007	Poor	Non-poor
Vulnerable	20.0	80.0	Vulnerable	17.9	82.13
Non-vulnerable (Middle-class)	4.3	95.7	Non-vulnerable (Middle-class)	4.4	95.6

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

Notes: Estimates are based on balance data between 2007-2008 using survey longitudinal weights. Vulnerability lines derived from the World Bank poverty line ($5.5 dollars pppd in 2011 PPP).

Table 3.12 shows the results of the comparison of predictive performance for both vulnerability cut-offs. It also compares the use of degrees of vulnerability to poverty versus a simple dichotomy of vulnerable versus non-vulnerable. I chose the years 2007 and 2008 to show the households 'situation just before the economic crisis and one year after.[55]

Panel A of Table 3.12 shows those who were classified with degrees of vulnerability using two vulnerability cut-offs. Using vulnerability lines in the classification, one of four highly vulnerable households fell into poverty. Using probability cut-offs this percentage is lower: 21.3 per cent of highly vulnerable households were poor in 2008. For those who are moderately vulnerable to both types of cut-offs, the percentage was close to 8 per cent. The percentage of households with a low vulnerability that fall into poverty was 3.7 per cent for the income threshold and less than 2 per cent for the poverty risk cut-offs. Using the official poverty line for Chile, the proportion of households that enter into poverty is similar, except among the moderately vulnerable where the percentage that falls into poverty in 2008 is around 10 per cent. See Table A.2 in the Appendices.

As in Panel A, Panel B of Table 3.12 shows that the vulnerability line performs better to predict who fell into poverty than the probability cut-off. From the comparison of Panel A with Panel B, it is possible to identify two advantages of classifying households according to their degree of vulnerability rather than a simple dichotomy of vulnerable versus non-vulnerable. First, using two vulnerability lines allows for a better prediction of those who fall into poverty. For instance, it enables to compare the highly vulnerable with those identified as vulnerable using one vulnerability line. Second, it identifies the moderately vulnerable group whose proportion of households that fall into poverty is significantly higher than the percentage among the economically secure (middle class) group.

In the short term, using more than one vulnerability line to identify different non-poor vulnerable groups provides better information to policymakers to design and implement social protection programs to face situations such as an economic crisis. In the long-term, it improves the anti-poverty targeting performance in countries with a weak welfare state and a distribution of income that is markedly displaced to the left around the poverty line.

[55] Although the collapse of the housing bubble in the United States began in 2006, the so-called subprime mortgage crisis began to spread to international markets from October 2007 onward, with 2008 being its worst year (IMF, 2009).

3.8 Conclusion

In this chapter, I have proposed an empirical framework to identifying different degrees of vulnerability to poverty within the income distribution using a poverty dynamics approach. Applying this approach to household data from Chile, I estimate low and high vulnerability lines. This enables the identification of three types of households: those with high vulnerability, moderate vulnerability and low vulnerability to poverty. The last of these is the income-secure middle class.

Making the distinction between the different types of vulnerability is crucial not only for the design of social policies targeted at families with a high risk of poverty, but also to understand the characteristics of those that show greater economic stability or security.

Assuming that the economic conditions that determine vulnerability remain unchanged in the future, the thresholds denominated in real income terms can be used to measure the size and evolution of vulnerable groups using cross-sectional household surveys. This is important because there are few household panel surveys in most upper-middle-income countries. Furthermore, these thresholds allow for comparing countries where the income distribution are similar (sharply shifted to the left), and there is a weak welfare system — a feature shared by most of the countries in Latin America at least.

In countries that use a poverty line of $5.5 dollars pppd (2011 PPP), household with high vulnerability are those with a per capita income of between $ 5.5 and $ 9.9 dollars (above the poverty line and below the high vulnerability line), household facing moderate vulnerability are those with a per capita income of between $ 9.9 and $ 20.0 dollars (between the high and low vulnerability lines, respectively), and household experiencing low vulnerability -the income-secure middle class- are those with a per capita income of between $ 20 and $ 70 dollars per day.

My approach proposes a more demanding definition of the middle class than the one suggested by the World Bank (between $13.0 and $70.0 dollars pppd (2011 PPP)). This is because it distinguishes two vulnerable groups rather than one: those at high versus moderate risk of experiencing poverty in the near future. It is worth mentioning that the World Bank's vulnerability line and the ones that I propose have different interpretations. The World Bank's vulnerability line is associated with the risk of all non-poor households falling into poverty estimated using panel data with long interval periods (3 to 5 years apart). Instead, I propose low and high vulnerability lines that are associated with the probability of falling into poverty from one year to the next for different groups within the income distribution. The use of a "one year to the next" criterion not only provides more precision in the identification of the vulnerable groups but can also better serve the implementation of risk-management and anti-poverty policies.

The implications of these results are significant. A high proportion of the population that would be classified as middle class using the World Bank's vulnerability line are households that, according to my approach, face considerable economic insecurity. I would classify them as moderately vulnerable. I argue on the basis of these findings that previous research has underestimated how many people in Chile are vulnerable to falling into poverty and that it has overestimated the growth of the middle-class. These sobering conclusions should be of great interest to Chilean policy makers and others in other middle-income countries, especially in Latin America.

Vulnerability to poverty lines offer to governments a concrete way to improve the targeting accuracy of programmes that seek to reduce absolute poverty. The extension of social protection coverage to these new social groups should be accompanied by the comprehensive design of social security programmes that consider vulnerability to poverty as part of economic welfare measures to assess social progress. In this way, the approach to vulnerability to poverty that I have proposed should fulfil a dual role: targeting and monitoring these new social groups.

Finally, my study is at the intersection of interest in multiple disciplines, particularly economics and sociology. It contributes to the economic literature, not only by bridging the gap between the vulnerability to poverty and poverty dynamics approaches but also by empirically determining the income cut-offs to identify degrees of vulnerability to poverty going beyond the distinction between vulnerable and non-vulnerable. It also contributes to the discussion around social stratification in sociology, since the approach I propose based on degrees of vulnerability to poverty better adjusts to the reality of middle-income countries and to the definitions proposed by this discipline to conceptualise and measure the middle class.

3.9 Appendices

Table A.1: Model estimates of poverty entry rates, initial poverty status and survey retention, Chile (2006-2009)

Variables (measured at *t*)	Poverty entry: Poor at t+1 | Non-poor at t			Poverty status at t			Survey retention		
	Coefficient		Std. Dev.	Coefficient		Std. Dev.	Coefficient		Std. Dev.
Household head characteristics									
Female	0.028		(0.021)	0.098	***	(0.021)	-0.046	**	(0.021)
Age	-0.006	***	(0.001)	-0.015	***	(0.001)	0.001		(0.001)
Education: Ref. Secondary school									
Primary school	0.129	***	(0.019)	0.3	***	(0.019)	0.133	***	(0.020)
University degree	-0.356	***	(0.041)	-0.717	***	(0.058)	-0.163	***	(0.029)
Labour status: Ref. Formal employed									
Informal employed	0.394	***	(0.025)	0.6	***	(0.024)	0.011		(0.025)
Unemployed	0.171	*	(0.102)	1.086	***	(0.055)	-0.004		(0.076)
Inactive	0.007		(0.042)	0.22	***	(0.036)	-0.006		(0.037)
HH head's partner characteristics									
Age	-0.009	***	(0.001)	-0.002	*	(0.001)	-0.001		(0.001)
Education: Ref. Secondary school									
Primary school	0.228	***	(0.023)	0.281	***	(0.025)	0.045	*	(0.024)
University degree	-0.433	***	(0.074)	-0.872	***	(0.176)	-0.056		(0.042)
Labour status: Ref. Formal employed									
Informal employed	0.283	***	(0.035)	0.306	***	(0.045)	-0.004		(0.035)
Unemployed	0.08		(0.054)	0.295	***	(0.050)	0.227	***	(0.057)
Inactive	0.124	***	(0.023)	0.094	***	(0.025)	0.046	**	(0.022)
Household characteristics									
Household type: Ref. Couple without children									
Single without children	0.154	***	(0.036)	0.145	***	(0.041)	-0.033		(0.033)
Couple with children	0.073	**	(0.029)	0.189	***	(0.033)	0.030		(0.027)
Single with children	0.303	***	(0.035)	0.493	***	(0.038)	0.155	***	(0.035)
Lone person	0.031		(0.067)	-0.052		(0.075)	-0.198	***	(0.056)
Number of persons	0.038	***	(0.008)	0.251	***	(0.008)	-0.028	***	(0.007)
Number of children < 15	0.133	***	(0.013)	0.114	***	(0.013)	0.065	***	(0.012)
Number of workers	-0.162	***	(0.014)	-0.959	***	(0.019)	0.009		(0.010)
Housing: Ref. Own housing (mortgage)									
Own housing, mortgage	-0.307	***	(0.032)	-0.315	***	(0.038)	-0.149	***	(0.025)
Rent	0.233	***	(0.026)	0.43	***	(0.028)	-0.364	***	(0.024)
Subsidized or rent free	0.212	***	(0.024)	0.716	***	(0.021)	-0.075	***	(0.023)
Rural	0.079	***	(0.023)	0.127	***	(0.024)	0.094	***	(0.026)
Regions: Ref. 13th									
1st, 2nd, 3rd and 4th	0.054	**	(0.026)	0.017		(0.029)	0.034		(0.025)
5th, 6th, 7th, 8th, 9th and 10th	0.13	***	(0.019)	0.214	***	(0.021)	0.147	***	(0.018)
11th and 12th	-0.133	***	(0.051)	-0.299	***	(0.059)	0.271	***	(0.055)
Time (*t*): Ref. 2007									
2008	0.145	***	(0.019)	-0.178	***	(0.018)			
2009	-0.101	***	(0.020)	0.012		(0.018)			
Individual characteristics (Exclusion restrictions)									
Mother education: Ref. No schooling									
Primary school				-0.064	*	(0.033)			

Secondary school	-0.142	***	(0.047)			
University degree	-0.227	**	(0.103)			
Type of work done by mother: Ref. Self-employed						
Employership	-0.054		(0.123)			
Paid employment	0.094	**	(0.033)			
Non-employment	0.011		(0.028)			
Father education: Ref. No schooling						
Primary school	0.009		(0.034)			
Secondary school	-0.099	**	(0.045)			
University degree	-0.015		(0.098)			
Type of work done by father: Ref. Self-employed						
Employership	-0.036		(0.073)			
Paid employment	-0.063	***	(0.026)			
Non-employment	-0.022		(0.108)			
Original sample member				0.509	***	(0.056)
Constant	-1.345	***	(0.063)	0.602	***	(0.081)
Log-pseudolikelihood	-52,691.112					
Wald chi-square (d.f. = 131)	487,629.326 (p<0.000)					
Number of observations (person-waves)	65,205					

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

Notes: Model used the Chilean official poverty line ($6.41 dollars pppd in 2011 PPP). Robust standard errors clustered at the individual level. Simulated pseudo maximum likelihood estimation with 250 random draws. *** significance at 1 percent; ** significance at 5 percent; * significance at 1 percent.

Table A.2: Comparison of predictive performance between degree vulnerability to poverty and vulnerability to poverty for different vulnerability cut-offs

a) Degree vulnerability to poverty					
Two vulnerability lines			Two probability cut-offs		
	2008			2008	
2007	Poor	Non-poor	2007	Poor	Non-poor
Highly vulnerable	25.4	74.6	Highly vulnerable	21.2	78.8
Moderately vulnerable	10.7	89.3	Moderately vulnerable	10.1	89.1
Lowly vulnerable (Middle-class)	3.3	96.7	Lowly vulnerable (Middle-class)	0.9	99.1
b) Vulnerability to poverty					
One vulnerability line			One probability cut-off		
	2008			2008	
2007	Poor	Non-poor	2007	Poor	Non-poor
Vulnerable	19.9	80.1	Vulnerable	17.6	82.4
Non-vulnerable (Middle-class)	4.6	95.4	Non-vulnerable (Middle-class)	5.2	94.8

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

Notes: Estimates are based on balance data between 2007-2008 using survey longitudinal weights. Vulnerability lines derived from the Chilean official poverty line ($6.41 dollars pppd in 2011 PPP).

Chapter 4

A multidimensional approach to measuring economic insecurity in the Global South

Abstract

I propose a strategy to measure economic insecurity in countries in the Global South. I build a 'Multidimensional Economic Insecurity Index' that combines four indicators of economic vulnerability that cause stress and anxiety: unexpected economic shocks, unprotected employment or non-workers in the household, over-indebtedness and asset poverty. In this way, the index offers a measure that directly relates economic uncertainty to stress and anxiety due to the lack of protection and buffers to face an unexpected economic shock. I apply my approach to Chile using Survey of Household Finances (SHF) cross-sectional data (2007, 2011, 2014 and 2017). The results show, first, that about half of the Chilean households experienced, on average, two or more economic vulnerabilities during the last decade with an intensity of 2.3 vulnerabilities. And second, economic insecurity affects households on the entire income distribution, even in the highest income deciles groups.

4.1 Introduction

Although the macroeconomic effects of the financial crisis of the late 2000s, such as the decline in economic activity and the rise in unemployment, affected–with different intensities–all high-income countries, it did not cause significant changes to income inequality or poverty (Jenkins, Brandolini, Micklewright, & Nolan, 2013). However, a high proportion of households experienced unemployment, descending income mobility, and sharp falls in their assets (wealth) all of which contributed to an increase in the perception of economic insecurity as well as a deterioration in the public's confidence in the capacity of political leaders and public policies to address these problems effectively (Hacker, 2019; Rohde & Tang, 2018).

Stiglitz, Sen, and Fitoussi (2009) highlighted the importance of measuring economic insecurity in order to understand how economic risks are related to individuals' well-being and offer social policies with a wider perspective that the one obtained through static measures of poverty and material deprivation. Since then, several authors have proposed measures of economic insecurity that address the stress and anxiety produced by exposure to adverse economic events and the incapacity to face them when they occur. For reviews see Osberg (2018) and Hacker (2018).

Although a unique definition of economic (in)security has not yet been established (Rohde & Tang, 2018), a comprehensive measure of economic security should account for three elements: i) the household risk of a having an adverse event, ii) the negative economic consequence of that event occurring, and iii) some set of protections such as self-insurance through wealth or unemployment insurance to compensate or prevent the losses (Hacker, 2018). The measures proposed up to now have made use of the available data, mainly from developed nations, that capture the economic insecurity dimensions (usually giving an emphasis to some of them), for instance, the estimation of the probability of economic shocks using data from longitudinal surveys (Hacker et al., 2014; Rehm, 2016a; Rohde et al., 2014), or the measurement of households and individual buffers using data from household financial surveys (Balestra & Tonkin, 2018; Bossert & D'Ambrosio, 2013; Haveman & Wolff, 2004).

In middle-income countries such as Chile, Brazil, Colombia and Mexico, there is a little theorical or empirical discussion on economic insecurity even though a large proportion of the population are exposed to economic shocks that not only generate income losses for the households but also lead them to experience poverty. In the case of the Latin-American region, the social group most exposed to economic shocks has been described as the 'strugglers' (Birdsall et al., 2014) due to the permanent effort made by this type of household to maintain their income levels. This social group faces high economic insecurity since they have neither sufficient assets to offset an economic shock, nor access to unemployment insurance or compensation in case of dismissal when working in the informal sector. The emergence of this group of households that are vulnerable to poverty in Latin America has been accompanied by a massive increase in access to credit for consumption and mortgages (Matos, 2017). However, the rapid credit growth in the region is explained as being a credit boom instead of a financial deepening (Hansen & Sulla, 2013). This economic situation increases the risk of over-indebtedness in low-income households (Guérin, Morvant-Roux, & Villarreal, 2013; Schicks, 2013). In addition, several countries in Latin America are highly vulnerable to natural disasters such as floods, droughts and earthquakes, which cause aggregate shocks to both the assets and income of households living in the affected areas.

In this paper, I propose a measure of economic insecurity at the household level that can be applied in contexts where: i) inequalities in household wealth are high, ii) the social safety net is limited, iii) indebted households are increasing due to strong credit growth, and iv) the reduction of absolute income poverty rather than relative poverty is the primary concern for policy. In particular, I study the adverse effect on households' well-being of the uncertainty of not being able to cope financially with an unexpected event that triggers an economic loss. I use the Chilean Survey of Household Finances (SHF) cross-sectional data (2007, 2011, 2014 and 2017) and build four objective indicators (unexpected economic shocks, unprotected employment or non-workers, over-indebtedness and asset poverty) for two dimensions of economic insecurity: i) household risk to an unexpected economic event, and ii) lack of household buffers to face an economic shock.

I combine these indicators using a multidimensional approach to build an adjusted multidimensional vulnerability rate for Chile called the 'Multidimensional Economic Insecurity Index' (MEII). This approach has two stages. First, I identify the economic vulnerabilities, and then, I apply an aggregation procedure to integrate the multidimensional information on economic insecurity into a single scalar measure (Alkire & Foster, 2011).

The MEII I propose has two advantages that make it an appropriate measure for policy analysis.

The first advantage is that it simultaneously measures the incidence (proportion of economically insecure households) and the intensity of the economic insecurity (number of vulnerabilities affecting it). The second advantage is that the MEII can be decomposed by population subgroups (e.g. income decile groups or geographic areas) and economic insecurity domains (e.g. employment, income, indebtedness, and wealth). Thus, it allows for monitoring each of the dimensions of insecurity that are targeted by multi-sectoral policy strategies such as unemployment insurance, investment in social and affordable housing, micro-finance interventions, cash transfers, and policies to stimulate saving, among others. My proposed measure is the first to apply the concept of economic insecurity to middle-income countries and complement other well-being measures, such as vulnerability to poverty and multidimensional poverty, which are more commonly used in these countries.

My estimates for Chile between 2007/2017 show high levels of economic insecurity in regard to both the risk of an unexpected economic event and the lack of a household buffer to offset a potential loss. More than a third of households were exposed to unexpected economic shocks during this period. The indicators providing information about households' lack of protection reveal that 62.8 per cent were asset poor, 30 per cent had only unprotected workers or non-workers, and 15.4 per cent faced over-indebtedness. When I combined the measures in the MEII, I found that, on average, about half of Chilean households experienced two or more economic vulnerabilities during the last decade, with an intensity of 2.3 vulnerabilities. The index tracks the GDP growth rate and labour informality rate, which shows its highest levels between 2007 and 2011, before registering a significant decrease between 2011 and 2014, followed by an increase between 2014 and 2017.

This chapter makes three contributions. First, from a conceptual point of view, I use two dimensions of economic insecurity related to an unexpected economic event and the household buffer to protect from this potential economic loss. Although both dimensions (and their respective indicators) are sources of insecurity, each of which may trigger stress and anxiety in individuals and households, the origin of these adverse psychological effects differs. In previous work, the focus in terms of the selection of indicators has either been on choosing between subjective and objective indicators (Rohde, Tang, Osberg, & Rao, 2015; Romaguera de la Cruz, 2017) or on just one source of economic insecurity (Azzopardi, Fareed, Lenain, & Sutherland, 2019; Balestra & Tonkin, 2018; Bossert & D'Ambrosio, 2013; Hacker et al., 2014; Rohde et al., 2014).

Second, I propose indicators for these two dimensions of economic insecurity to be implemented in middle-income countries, especially those in Latin America, delivering a measure of well-being that contemplates the possibility of future events, which complements the forward-looking measures of vulnerability to poverty used in these countries. Until now, all measures of economic insecurity at the household or individual level have been applied using data from developed countries.

My third contribution is the application of the MEII to Chile for the period 2007-2017. I study economic insecurity in a nation characterised by i) a significant reduction in absolute poverty coupled with a significant increase in vulnerability to poverty (Prieto, 2019); ii) an unemployment insurance system that has not yet managed to cover the workers who have greater job instability (Sehnbruch, Carranza, & Prieto, 2018); iii) an increase in consumer debt that has been accompanied by mental health problems in households facing over-indebtedness (Hojman, Miranda, & Ruiz-Tagle, 2016); and iv) a high proportion (75 per cent) of households experiencing asset-based poverty according to the OECD measure (Balestra & Tonkin, 2018), placing Chile, in this aspect, within the most economically vulnerable OECD countries.

This chapter is organised as follows. In Section 2, I summarise the most salient theoretical approaches and empirical findings related to economic insecurity. In Section 3, I describe the SHF data and dimensions and indicators of economic insecurity used in my research. In section 4, I show the evolution of economic insecurity in Chile for each indicator. In section 5, I explain how I construct the index of economic insecurity. In Section 6, I discuss the downsides of multidimensional indexes of well-being and how to deal with them. In Section 7, I show and discuss the empirical results. In Section 8, I present the conclusions.

4.2 Background

During the last decade, new approaches have been proposed to measure the social and economic well-being of the population. These approaches go beyond gross domestic product (GDP) to measure welfare, acknowledging that production is not an appropriate indicator of individual and social well-being (Adler & Fleurbaey, 2016; D'Ambrosio, 2018; Kakwani & Silber, 2007; Stiglitz et al., 2018, 2009). One of the new well-being metrics that has been studied theoretically and empirically at both levels is economic insecurity (Hacker, 2018; Osberg, 2018; Rohde & Tang, 2018). The notion of economic insecurity refers to "the adverse well-being effect of (involuntary) exposure to uncertainty in enduring an uninsured financial shortfall" (Rohde & Tang, 2018, p. 303). The idea behind it is that economic insecurity has a subjective component and is a forward-looking measure since stress and anxiety are associated with financial uncertainty. This measure assumes that changes in the subjective levels of anxiety in regard to lacking economic safety are highly correlated with changes in the objective risk (Osberg, 1998; Osberg & Sharpe, 2014).

Economic insecurity versus vulnerability to poverty

These characteristics distinguish economic insecurity from other welfare concepts such as income poverty, multidimensional poverty, vulnerability to poverty, and income mobility. However, economic insecurity may overlap in some respects and to varying degrees with some of the measurements mentioned above, especially with vulnerability to poverty, which is also a forward-looking measure related to the risk of income shortfall.[56] In the economic literature, vulnerability is used as a synonym of insecurity, and throughout this chapter, I use these terms interchangeably. However, there is a clear distinction between the concept of vulnerability to poverty, defined as the risk faced by a proportion of the population of falling into poverty in the near future, and economic insecurity, which refers to the risk of facing an economic shock without being financially prepared, that affects (with different degrees) the entire population .

[56] Although both vulnerabilities to poverty and economic insecurity look forward at future hazards, the measures of vulnerability are built using backwards-looking data on individuals' past experiences (Cafiero & Vakis, 2006). Thus, any operationalization of both concepts must assume that the economic conditions where the vulnerability measures were estimated in the past remain unchanged in the present and the future.

Also, there are three specific elements of economic security that distinguish it from vulnerability to poverty (Osberg, 2010; Rohde, Tang, Osberg, & Rao, 2017). First, the fear of experiencing a significant income drop matters more for health than the fear of being poor. Second, economic insecurity measures not only include household income (like the vulnerability to poverty approach) but also the buffering role of the wealth of the household, together with information on it (e.g. unforeseen medical expenditure or debt service burden), which allows for understanding the concept of economic insecurity as a multidimensional phenomenon. Third, the economic insecurity concept incorporates a subjective dimension regarding the perception of buffers, level of indebtedness or expectations regarding future shocks, which allows for capturing the idiosyncratic characteristics of individuals.

Economic insecurity as a measure of well-being

The importance of economic insecurity as a measure of well-being is recognised in the Human Development Report (HDR) by the United Nations Development Program (1994), which states that economic security "requires an assured basic income for individuals, usually from productive and remunerative work, as a last resort, from a publicly funded safety net" (HDR, p. 25). Beyond this formal recognition, the value of measuring economic insecurity is that provides estimates on two key welfare costs associated with it. First, economic insecurity makes difficult for households with children to plan for the future, resulting in psychological distress in the household environment and in diminished well-being, human capital investment, and development of the children in the household (Hardy, 2014; Hill et al., 2013; Western, Bloome, Sosnaud, & Tach, 2016).

Second, economic insecurity can influence complex psychological processes that cause an increase in health problems throughout people's lives (McEwen & Gianaros, 2010). Several studies have found that the physical and mental health of household members is affected by different downside risks of future economic events, such as sharp income drops or unemployment (Adda, Banks, & Von Gaudecker, 2009; Caroli & Godard, 2016; Ferrie, Shipley, Newman, Stansfeld, & Marmot, 2005; Kopasker, Montagna, & Bender, 2018; Smith et al., 2009).

Studies have shown that households that experience difficulties in raising emergency funds when facing an unexpected economic shock are associated with poor health outcomes (e.g. Rohde, Tang, Osberg, & Rao, 2016). More specifically, households lacking access to health insurance, and households financially fragile due to high indebtedness show higher prevalence of physical and mental health problems such as obesity, anxiety and depression (Clayton, Liñares-Zegarra, & Wilson, 2015; McWilliams, 2009; Münster, Rüger, Ochsmann, Letzel, & Toschke, 2009; Sweet, Kuzawa, & McDade, 2018; Sweet, Nandi, Adam, & McDade, 2013).

A direct association between economic insecurity and subjective well-being has also been found, for example, the negative relationship between job insecurity and life satisfaction in countries such as Australia, Germany and the United Kingdom (Clark & Georgellis, 2013; Green, 2011; Otterbach & Sousa-Poza, 2016), and the positive correlation between the universal coverage of health insurance in one of the states in the U.S.A. and the levels of happiness of the affected population (Kim & Koh, 2018).

There are several ways to build economic security indicators for these two dimensions. For a comprehensive review of the methods implemented recently, see Hacker et al. (2018) and Osberg (2018). However, the concept of economic insecurity has some methodological challenges in its operationalisation (Hacker, 2018; Rohde & Tang, 2018). First, it is difficult to know whether the economic shocks experienced by a household are unexpected or the result of a household decision. Second, although economic insecurity is a phenomenon that deals with unobservable and forward-looking expectations, most of the measures are based on retrospective information. Third, although several studies have shown a high correlation between both subjective and objective measurements (e.g. knowledge of future job loss (Hendren, 2017), it is reasonable to think that two individuals with similar characteristics may have very different perceptions about the future. Hence, under the same conditions, one individual can feel much more insecure than the other.

Although economic insecurity has serious implications for well-being, there is no commonly accepted framework for its analysis. This can be explained by the methodological challenges in its operationalisation. First, it is difficult to know whether the economic shocks experienced by a household are unexpected or the result of a household decision. Second, economic insecurity is a phenomenon that deals with unobservable and forward-looking expectations rather than retrospective information. Third, it is reasonable to think that two individuals with similar characteristics may have very different perceptions about the future. Hence, under the same conditions, one individual can feel much more insecure than the other.

As a consequence, the empirical studies that have been carried out in developed countries up to now have proposed their own definitions of economic insecurity along with an ad hoc methodology for their measurement (Hacker, 2018; Osberg, 2018; Rohde & Tang, 2018). These insecurity measures, although they sometimes overlap, can be classified in three ways, according to: i) the unit of analysis (aggregate measures versus individual-level measures); ii) the nature of the dimensions (observed measures versus subjective measures); and iii) the number of dimensions considered (multidimensional measures versus unidimensional measures).

Aggregate measures of economic insecurity

When making comparisons across countries, the aggregated national indices allow for analysing trends in economic insecurity based on the combination of a variety of economic risk indicators. The two main macro indexes of economic insecurity are the Index of Economic Security (IES) proposed by Osberg & Sharpe (2014), and the International Labour Organization's (ILO) index of economic security (ILO, 2004). The IES comes from the 'named risks' approach, which examines four downside economic risks named in Article 25 of the UN Universal Declaration of Human Rights (i.e., unemployment, family breakup, medical costs, and poverty in old age).

Osberg & Sharpe (2014) applied an IES adjusted to 70 countries and found substantially different levels of economic insecurity across rich and developing countries. The ILO index uses aggregated data from countries to measure seven forms of labour security (income, labour market, employment, work, skills, job, and voice representation). This index is currently applied to 90 countries, covering 86 per cent of their population (Rohde & Tang, 2018). It is important to mention that these measures do not allow for measuring the subjective and idiosyncratic characteristics of insecurity. As discussed below, econometric measures based on household-level surveys allow for studying the effects and distribution of the insecurity features at the household or individual level, although this requires making assumptions on which there is still no consensus.

Individual-level measures of economic insecurity

Subjective measures versus observed measures

At the individual level, measures of economic insecurity can be obtained directly through subjective questions included in the surveys (e.g. general assessments of the economy, perceptions of buffers, and expectations regarding future shocks) (Espinosa, Friedman, & Yevenes, 2014; Hacker, Rehm, & Schlesinger, 2013; C. F. Manski, 2004; Rohde et al., 2015; Romaguera de la Cruz, 2017). The assumption behind these subjective measures is that people can make reasonably good forecasts of the economic risks they face. Although the economic literature has generally been sceptical about this type of premise (Bertrand & Mullainathan, 2001),[57] Hendren (2017) has shown that individuals can more or less correctly anticipate an economic shock in the near future. These findings suggest that perceived, and observed safety measures may be correlated, at least when individual responses are averaged over larger groups. However, several authors have opted to measure economic insecurity at the individual level using objective measures also obtained from surveys.

Unidimensional measures versus multidimensional measures

Using a one-dimensional-micro-based measurement approach, economic insecurity has been conceived of as i) job insecurity (Keim, Landis, Pierce, & Earnest, 2014; Rehm, 2016b), ii) a large income loss experience or a downward deviation from trend income (Hacker et al., 2014; Hacker, Huber, Rehm, Schlesinger, & Valletta, 2010; Rohde et al., 2014; Western et al., 2016), iii) financial difficulties (over-indebtedness and arrears) (Anderloni, Bacchiocchi, & Vandone, 2012; Azzopardi et al., 2019; Białowolski, 2018), and iv) an inadequate private wealth buffer stock against shocks (Balestra & Tonkin, 2018; Bossert & D'Ambrosio, 2013).

[57] The main arguments of those who ask for caution against using subjective measures are: i) their sensitivity to non-observable transient influences (e.g. the state of mind of the person responding to a life satisfaction measure (Krueger & Schkade, 2008); ii) bias due to cognitive factors (e.g. subjective data may vary according to the phrasing of the questions, location in the survey and type of scale used (Tourangeau, Rips, & Rasinski, 2000)); and iii) the fact that they are not always correlated with the objective variable of interest (e.g. perception of criminal victimization and perception of corruption versus reality (Ambrey, Fleming, & Manning, 2014; Olken, 2009). However, studies that have recognised these weaknesses in their analysis have also found that specific subjective measures show a highly positive correlation with the latent variable of the phenomenon to be measured (Oswald & Wu, 2010), and that by not having perfect information about the variable of interest with objective measures, subjective measures can work better due to their ability to measure the unobservable characteristics (Jahedi & Méndez, 2014).

Most of these measures of economic insecurity have focused on the United States, showing a significant increase in recent decades, with peaks in the years 1998 and 2007. Nevertheless, integrated measures fail to include important dimensions of economic insecurity in their construction, focusing on large income loss or the buffering role of private wealth or income volatility (Osberg, 2018). For example, they fail to capture the social protection that the state can provide (e.g. eligibility for unemployment insurance benefits or severance payments) or do not incorporate subjective measures on the perception of the economic situation that reflect the anxiety and concern of individuals in a direct way (Espinosa et al., 2014).

In recent years authors have wondered whether economic insecurity is also increasing in other developed countries. Rohde et al. (2015) analysed the case of Australia using indicators of objective and subjective economic insecurity (job insecurity, financial dissatisfaction, emergency funds, unemployment risk, expenditure distress and income drop) and found that these are correlated with the country's unemployment rate and GDP growth rate. At the same time, they proposed a measure of economic insecurity using a multidimensional index that combined all of the unidimensional measures into a single indicator using the principal components method. The rationale behind this multidimensional measure is that an appropriate concept of economic insecurity should be able to capture all types of economic stress explained by the risk of a negative financial future. In this way, economic insecurity can be conceptualised as a latent variable that can be inferred by the exposure to specific types of potential economic hazard (Rohde, Tang, & Osberg, 2017, p. 1669).

The proposal of a multidimensional index to measure economic insecurity is not new. Bucks (2011) measured economic insecurity in the United States using twelve household-level measures of i) vulnerability to health, employment, or income shocks, ii) adequacy of household savings and income, and iii) borrowing constraints. His index is based on the methodology proposed by Alkire & Foster (2011) for measuring multidimensional poverty. Unlike Hacker et al. (2014), Bucks (2011) did not find a significant increase in economic insecurity except during the Great Recession (2007-2009).

A third country where economic insecurity has been measured from a multidimensional perspective is Spain. Romaguera de la Cruz (2017) constructed an index from a modified version of the objective and subjective indicators used by Rohde et al. (2015) and an adjusted version of Alkire & Foster's methodology (2011). The estimates show that after the Great Recession, economic insecurity in Spain fell (in the year 2011), but since then the economic insecurity has been continually increasing. However, multidimensional measures that capture the insecurity of a household or individual in a single statistic have an important disadvantage. They are less clear and more sensitive to the choice of dimensions and weights in the construction of the index than an integrated measure (Hacker, 2018).

Economic insecurity measures in the Global South

Although Osberg & Sharpe's IES proposed a multidimensional measure at the aggregate level to compare both Global North and Global South countries, indices of economic insecurity at the individual or household level allow for comparative analysis between different groups within each country, making them a key tool for the design of social protection policies that can offer a better safety net to protect households from the stress or anxiety caused by not being economically prepared to face different economic shocks in the future.

It is worth mentioning that economic insecurity measures at individual-level have not been developed in the Global South. In these countries vulnerability to poverty is the concept that is most often examined. It has helped in thinking about how to protect people from the risk of a decline in their well-being (López-Calva & Ortiz-Juarez, 2014). Specifically, in Latin America, vulnerability to poverty is the concept that has been used to study the income dynamics of households with a focus on income drops (Ferreira et al., 2013; Stampini, Robles, Sáenz, Ibarrarán, & Medellín, 2016b).

In Global South countries, vulnerability to poverty and economic insecurity are forward-looking concepts that overlap in their goal of informing the design of policies focused on preventing households facing unexpected income falls. The complementarity between these two measures makes them applicable to nations beyond the developed world, that is, countries characterised by a large reduction in absolute poverty is accompanied by an increase in the number of households that have a high risk of falling into poverty again, weak social protection systems, an expansion in access to credit (depicted as a boom) and high exposure to aggregate shocks.

4.3 Data and measures of economic insecurity

SHF data

I use data from the Chilean Survey of Household Finances (SHF) carried out by the Central Bank of Chile in 2007, 2011, 2014 and 2017. The SHF is representative of urban private households. It collected information on income, expenditure, household characteristics, household assets and debts with a high degree of detail.[58] The SHF used a stratified, multi-stage probability sample selected from the population Census (2002 and 2012) sampling frame and included an oversample of well-off households using taxpayer information from the Chilean Internal Revenue Service (SII for its acronym in Spanish). The SHF design is similar to that of the U.S.A. Survey of Consumer Finances (Kennickell & Woodburn, 1999), as well as of the Household Finance and Consumption Survey coordinated by the European Central Bank (HFCN, 2016).[59]

I use the SHF household-level data, which not only contains variables on financial and non-financial assets and debts, but also include socioeconomic and demographic variables. The size of the sample in 2007 was 3,827 households. The 2011 sample comprised 4,057 households and the samples in 2014 and 2017 comprised 4,502 and 4,449 households respectively.

In summary, the economic insecurity variables obtained from the SHF are i) employment status and type of contract of household members; ii) retrospective questions related to significant unexpected expenses or substantial unexpected income drops faced by the households in the last two years; iii) information on the burden that debt imposes on the income of household; and iv) household assets such as non-housing wealth.

I use the Chilean national poverty line defined by the Ministry of Social Development (2015), which measures poverty in absolute terms. This threshold is based on the cost of a basic food bundle. I construct post-transfer household income as the sum of income from labour, imputed

[58] The SHF methodological documents, reports and databases can be accessed through the following link: https://www.bcentral.cl/financiera-de-hogares

[59] These characteristics have made it possible to include the Chilean SHF in the OECD Wealth Distribution Database, which has been used for comparative studies on households' wealth inequality (Balestra & Tonkin, 2018; Murtin & d'Ercole, 2015; OECD, 2013b).

rent, and private transfers plus public transfers. Because I use assets as a stock of material resources that can support the current consumption of a household, it is appropriate to equivalise it in the same way as household income is equivalised (OECD, 2013b, p. 141). Therefore, to account for different disposable income and asset requirements for different family sizes, I equivalise both income and assets using the scale that is equivalent to the household size to the power of 0.7.[60]

I break down my estimates of the Multidimensional Economic Insecurity Index by individual characteristics such as gender, age and education level and household characteristics such as family type (couple or single, with or without children, or lone person), size of the household, housing (outright owner or owner with mortgage or tenant) and location (regions).

Measures of economic insecurity

To measure economic insecurity requires quantifying the level of stress or anxiety of a household attributed to an uncertain financial future. Given that stress or anxiety is not directly observable in the data sources that sociologists and economists usually work with, sources of economic insecurity rely on proxies. I classify these proxy measures into two dimensions. The first dimension is the risk of the household experiencing potential events related to negative economic consequences such as unemployment, losses in asset values, or unexpected medical expenses. The second dimension is the lack of household economic buffers, which generates stress such as not having enough assets to face an event that decreases incomes or increases expenses, or not having access to social protection mechanisms to offset these economic losses.

Following an approach focused on the household-level measures, due to the existence of a shared decision-making process, my work uses four sources of stress distributed across two dimensions of the economic insecurity. As mentioned above, the first dimension is vulnerability to economic loss. I consider in this dimension a measure of unexpected large income loss or unanticipated expenses (known as downside income insecurity). The lack of household buffers is the second dimension. It includes three measures: i) unprotected employment or non-workers in the household, ii) over-indebtedness, and iii) asset poverty.

[60] The use of equivalence scales for the estimation of household income in Chile began in 2013. The value of the equivalence elasticity was defined by an Expert Advisory Committee to update the poverty line (Ministerio Desarrollo Social, 2015).

My starting point in the selection of these indicators is that the level of stress or anxiety of an individual or household depends on the combination of these four sources of economic insecurity. For example, a family facing a decrease in their income (e.g., losing their job without access to unemployment insurance) might spend their savings or borrow money. However, families that have low levels of savings, or that have a limited ability to borrow, or are already allocating a large portion of their income to servicing a debt, may have trouble addressing this unexpected drop in earnings and be forced to give up food or fail to pay their debts or other receipts.

Sometimes these situations overlap or combine with aggregated shocks like economic crises or natural disasters, which cause households to face an enormous wealth loss. An example is Latin America, where a large proportion of the population live in informal settlements located on residual land (e.g. ravines and river shores) making them particularly vulnerable to the frequent occurrence of natural disasters (earthquakes and floods). This reality has a negative impact on the value of the real assets of households (e.g. dwellings or vehicles) affecting the long-term economic security of these families (Baez, Fuchs, & Rodriguez-Castelan, 2017). These situations are associated with an increase in the level of stress or anxiety of the head of household and other members.

In the following section, I justify the selection of the four sources of economic insecurity. For that, I rely on the empirical evidence offered by the health economics literature. Several investigations have linked these economic vulnerabilities with health problems, in particular with the stress of the home and its members. I describe the operationalisation of the indicators for each source of economic insecurity based on the information provided by the SHF.

<u>Household risk to an unexpected economic event</u>

Income insecurity refers to the risk of large income drops or unexpected expenses faced by families should they encounter unpredictable events of social life (Western, Bloome, Sosnaud, & Tach, 2012). In addition to unemployment risk, the common triggers of income insecurity are family breakdown and illness. Concerning health problems, these not only cause losses in household income (e.g. independent or informal workers with no protection for this type of incidents) but also unanticipated costs whereby part of the household income has to be used for medical expenses (Adda et al., 2009). Studies have shown that household experiences of income instability are associated with situations of stress in parents and children, and increase the likelihood of indebtedness of the household, inconsistency in consumption, and underinvestment in children (Hill et al., 2013; Western et al., 2016; Yeung, Linver, & Brooks–Gunn, 2002).

The indicator I propose to measure income insecurity is based on the following SHF retrospective question: "Have you faced either unexpected expenses of significant magnitude or an income drop of significant magnitude during the last year?".[61] Although it is not an objective measure such as a household disposable income fall, it does ensure that the economic shock is considered as unexpected and not a household decision. I change this dichotomous indicator for a measure of risk attached to each household making out-of-sample predictions. I use a probit model, in which the dependant variable takes the value 1 if the household faced any economic event that triggered a sharp drop in income or a sharp increase in their expenses in $t-1$, and 0 otherwise. Both household head characteristics and household characteristics at t, are used as covariables, including gender, age, labour status, educational level, type of households, number of children, number of workers, housing and household income. See the model on Table A.1, in the appendices.

Assuming the relation stays the same for the next period, I attached to each household the predicted probability calculated using the characteristics at the current period and coefficients from the regression of that year. I classify a household as income insecure if the risk of an unexpected economic event is situated above a threshold. I establish the 70th percentile of predicted probabilities as a threshold because it is the cut-off that is closest to the observed values after doing sensitivity analyses for different thresholds. In this way, I differ from authors who have measured a similar economic insecurity dimension (a drop in household income) in their multidimensional index following the proposal of Hacker et al. (2010). Bucks (2011), Rohde et al.(2015) and Romaguera de la Cruz (2017) operationalise the income insecure dimension as a binary indicator of whether households experienced a large income drop in the last year, not the risk of facing it. By doing this, in addition to having an ex-post measure instead of a looking-forward measure, they cannot classify as vulnerable households that have not experienced such an economic shock in the previous year.

[61] In 2007 the SHF did not include this question. Therefore, I used as a proxy the SHF 2007 question if household had expenses larger than its income in the last year.

As mentioned above, both job loss and serious illness are among the major event of unexpected economic shock. There is an extensive literature that measures when out-of-pocket exceed a cut-off such as 10 or 25 per cent of household income for consumption-known as a catastrophic expenditure (e.g. Thomson, Cylus, & Evetovits, 2019; Wagstaff, Eozenou, & Smitz, 2020). Studies have shown an association between health outcomes and households that do not know how to pay a medical bill in case of severe disease (e.g. because they do not have health insurance) (Adda et al., 2009; McWilliams, 2009).

For job insecurity, studies are even more abundant. It was first defined by Greenhalgh & Rosenblatt (1984, p. 484) as the "perceived powerlessness to maintain desired continuity in a threatened job situation". Since then, a series of studies have analysed the levels of anxiety (Cheng & Chan, 2008; Huang, Lee, Ashford, Chen, & Ren, 2010; Keim et al., 2014) and health physical and mental problems generated by workers' concerns about losing their jobs (Caroli & Godard, 2016; Green, 2011; László et al., 2010; Muenster, Rueger, Ochsmann, Letzel, & Toschke, 2011; Watson & Osberg, 2018).[62]

I do not include both out-of-pocket health spending dimension and job insecurity dimension in my framework because the SHF data does not allow me to do so. Regarding the former dimension, the SHF does not collect information on household consumption. Therefore, I cannot calculate any measure of catastrophic out-of-pocket expenses. Regarding the latter dimension, the SHF asks for the interviewee's perception about the future stability of his / her current job. However, these questions are not comparable between 2011 and 2014 and were not included in 2007. Although the SHF has a panel sub-sample that could allow estimating the risk of losing a job at the individual level, there is a significant proportion of individuals who were not interviewed in the next round. The follow-up rules of the panel focused on contacting households, not households' members. Therefore, individuals who left their original household were not followed.

[62] See Lee et al. (2018) for a complete review of the research on job insecurity.

Lack of buffers to offset potential economic loss

a) Unprotected employment or non-workers in the household

Although I do not include an indicator that would account for the risk that a household has of an economic shock due to a job loss, I do consider the current employment situation of the household members in regard to facing an event of this type in the future. The term informal employment is used to refer to a lack of economic protection in the case of dismissal or a work accident. Salaried workers that do not have health and social security contributions as part of their labour relationship with their employer have an informal occupation. Self-employed workers and employees who are part of the informal sector (that is, their businesses are not registered in the Internal Revenue Service) are informal workers (ILO, 2013).

The SHF collects information on the occupational category and the type of contract of all the members of the household that are working at the time the survey is applied. Also, it asks whether or not household members pay social security contributions. This information allows me to construct a variable that distinguishes an informal worker from a formal one. I start from the assumption that formal jobs normally offer economic protection in the case of dismissal.

For households without any labour market attachment, I consider that they are also unprotected against an unexpected economic shock. This consideration is important because these types of households could be classified as economically secure as they do not have informal workers. Thus, the objective indicator of economic insecurity for each household works as follows: I classify a household as economically insecure if i) none of the workers in the household has access to unemployment insurance benefits or would receive any sort of compensation in the event of their dismissal, or ii) the household does not have members working. This indicator takes the value of 1 when all workers are informal workers or there are non-workers in the household.

b) Over-indebtedness

Several researchers have shown that over-indebtedness can lead to financial difficulties (e.g., unsuitable debt or debt arrears) that cause a series of adverse psychological effects (such as distress, anxiety, reduction of life satisfaction and depression) in the members of the household, mainly the head of household (Białowolski, 2018; Białowolski & Weziak-Bialowolska, 2014; Bridges & Disney, 2010; Brown, Taylor, & Wheatley Price, 2005; Hojman et al., 2016; Selenko & Batinic, 2011; Sweet et al., 2013). Although it is not possible to know exactly whether the over-indebtedness was due to an unexpected event, or a risky planned decision, a household with a high default risk experiences a stressful situation because it is highly sensitive to any future economic loss, even if this is not a significant loss.

In the SFH, various questions address the level of indebtedness and debt problems that the households interviewed have experienced. The indicator of vulnerability that I use measures the debt service to income ratio. It provides information on the burden that the debt imposes on the household's current income, and it is estimated as the ratio of the monthly payment of the debt to the disposable income of the household. Although in the SHF the interviewee is asked about his/her perception of the level of household indebtedness, I use only the information observed about this source of economic insecurity. In this way, I avoid introducing potential subjective bias related to the idiosyncratic characteristics of individuals in the construction of the indicator.

c) Asset poverty

A household that does not have an adequate buffer (wealth) against major economic shocks is aware of its economic vulnerability generating stress and anxiety among its members (Bossert & D'Ambrosio, 2013). The economic literature focused on the lower part of the income distribution has measured this economic disadvantage as asset poverty (Brandolini, Magri, & Smeeding, 2010). A household is considered to experience asset poverty if its assets (e.g. net worth, non-housing wealth or liquid assets) are insufficient to keep it above the poverty line for a specific period of time (e.g. 3 or 6 months) (Haveman & Wolff, 2004).[63] I use non-housing wealth as household assets, which refers to the difference between total assets and total liabilities, without considering any wealth or debt related to the primary residence. I consider three months as the least amount of time that a household should be able to stay out of poverty

[63] The OECD has used this definition of asset poverty to compare the levels of economic vulnerability of member countries (Balestra & Tonkin, 2018). Economically vulnerable households are those that are not income poor but asset poor. The wealth concept used is liquid financial wealth (e.g., bank accounts and other financial assets) because it can be easily monetised, and the period of time is 3 months. The income poor are those with an equivalised income below 50 percent of the median income (OECD, 2017, p. 89).

if it liquidates all of its non-housing wealth.

Although several works use liquid assets in the asset-poverty operationalisation (Balestra & Tonkin, 2018; Hacker et al., 2014) I decided not to use this for Chile for two reasons. First, when applying the liquid assets measure to Chile, 9 out of 10 households fall into asset-poverty in the 10-year period analysed (2007/2017). Hence, this definition provides little information for middle-high income country contexts like Chile. Second, including real assets such as vehicles in the operationalisation of asset-poverty allows for considering selling the vehicle to be a concrete and feasible strategy for the household to address an income shock in this type of national context.

Table 4.1: Dimensions, indicators and cut-offs of the economic insecurity sources

Dimensions	Indicators	Household is vulnerable if…
Household risk to an unexpected economic event	Unexpected economic shocks	the risk of experiencing an unexpected decrease in incomes or an unexpected increase in expenses in the next year is greater than the 70th percentile risk of all households
Lack of buffers to offset potential economic loss	Unprotected employment or non-workers	its workers have not a labour contract and none pay social contributions, or it does not have workers
	Over-indebtedness	the ratio of the monthly payment of the debt to the disposable income of the household
	Asset poverty	assets are insufficient to keep it above the poverty line for three months

Note: All variables are dichotomous.

In total, I generate four measures of economic insecurity at the household level. For the dimension on the household risk to an unexpected economic event, I use one indicator and for the dimension on the lack of household economic buffers, I use three indicators (Table 4.1). This allows me to have a set of indicators that captures vulnerability in different ways. While none of the indicators perfectly captures all aspects of each economic insecurity dimension, taken together, they can be used to identify most of the major sources of stress or risk.

4.4 Economic insecurity in Chile: an overview

In this section, I provide a descriptive analysis of the four indicators of economic insecurity to contextualise economic insecurity in Chile between 2007 and 2017. Table 4.2 shows the behaviour of the insecurity measures constructed with the SHF data. In aggregate, the indicators deliver a broad and clear definition of economic insecurity. When combining all of the years, 8 out of 10 households are classified as economically insecure in at least one of the four measures during the decade studied. Half of the population is classified as economically insecure when considering two or more vulnerabilities. When using a more demanding criterion, that is, three or more vulnerabilities, 13.9 per cent are economically insecure, and only 1.6 per cent of households are in a situation of insecurity in the four indicators.

Table 4.2: Shares of households classified as economically insecure in Chile, 2007-2017

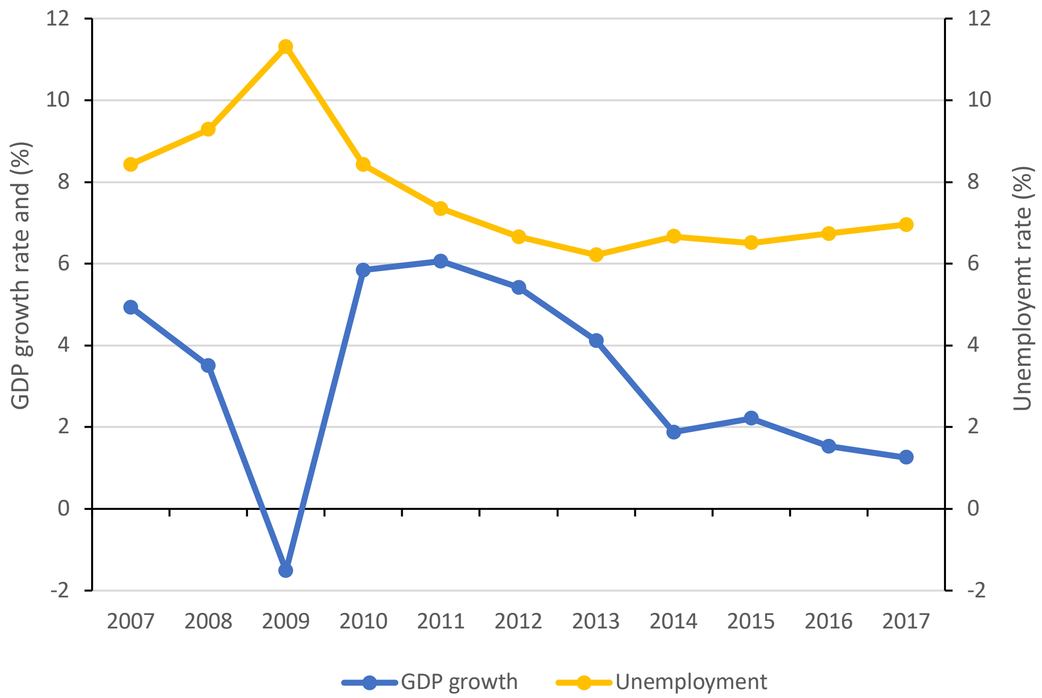
Dimensions and indicators	Headcount ratio: 2007-2017	SHF cross-section survey year				Time trend: 2007-2017
		2007	2011	2014	2017	
Household risk to an unexpected economic event						
Unexpected economic shocks	37.9	43.7	37.9	31.5	38.5	-5.3**
Lack of buffers to offset potential economic loss						
Unprotected employment or non-workers	30.0	34.0	37.6	23.8	24.5	-9.5 **
Over-indebtedness	15.4	15.1	13.5	15.2	17.6	2.6 *
Asset poverty	62.8	67.2	72.7	56.2	55.1	-12.1 **
Households by number of vulnerabilities						
One (any) vulnerability	81.0	84.6	86.8	75.1	77.7	-6.9 **
Two or more	49.5	55.4	56.9	40.6	45.1	-10.3 **
Three or more	13.9	18.0	16.0	9.9	11.6	-6.4 **
Four	1.6	1.9	2.1	1.1	1.3	-0.6 *
Number of households		3,827	4,057	4,502	4,549	

Source: Author's calculations based on the Chilean Survey of Household Finances (2007, 2011, 2014 and 2017).

The estimated trends are shown in the last column of Table 4.2. The indicator that measures the risk of households facing an economic shock presents a significant negative tendency during the period analysed, despite the increase from 31.5 per cent to 38.5 per cent between 2014 and 2017. This indicator appears coupled with the changes in national unemployment and GDP growth rates.

Figure 4.1 shows that after the economic crisis in 2008, the annual unemployment rate rose to 11.3 per cent in 2009, and then began to decline during the economic expansion period, reaching 6.2 per cent in 2013. Since then the rate of unemployment has slightly increased. Likewise, the economic growth recovered by 2010, reaching similar rates to that before the financial crisis; it then fluctuated at around 5.5 per cent per year until 2013, after which time there was a substantial decline (about 1.7 per cent annually).

Figure 4.1: Evolution of economic growth and unemployment in Chile, 2007-2017

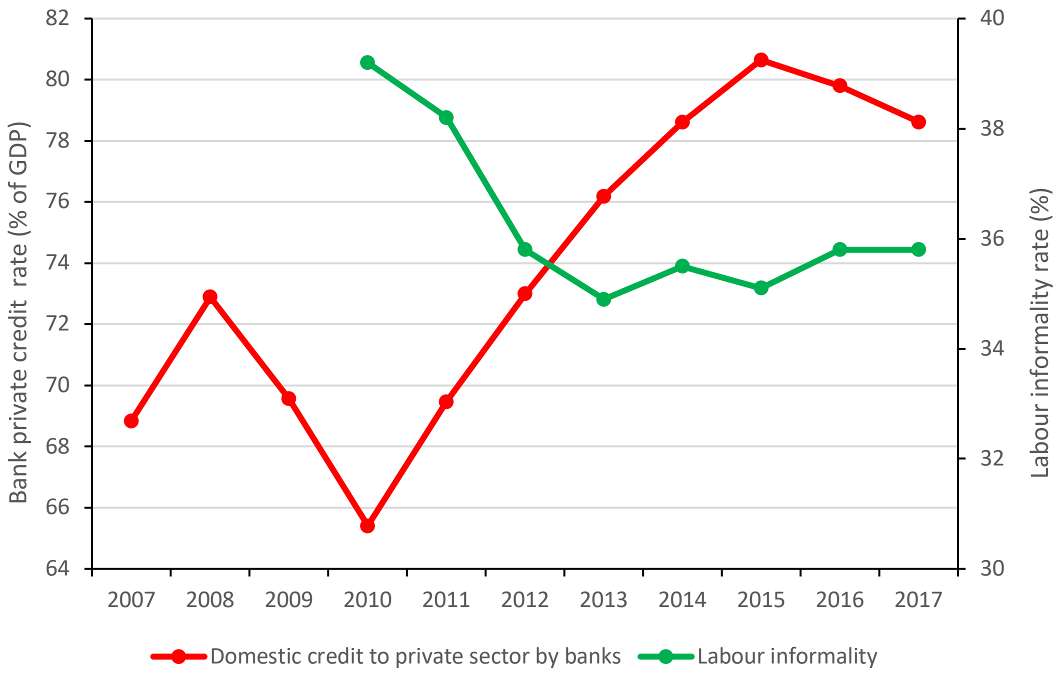


Sources: For GDP growth, data from OECD Economic Outlook 102 database, and for unemployment data from International Labour Organization, ILOSTAT database.

Concerning the lack of protection of households to offset an economic loss, significant improvements are observed. The proportion of households with workers without access to social protection mechanisms or non-workers decreased from 34.0 per cent in 2017 to 24.5 per cent in 2007. Likewise, the proportion of households without enough private assets to face an event with negative economic consequences fell from 67.2 per cent in 2017 to 55.1 per cent in 2007. The highest levels of economic insecurity were reached in 2011 when 37.6 per cent of households were either in unprotected jobs or had non-worker members, and 72.7 per cent of households were asset poor. Only the over-indebtedness of households significantly increased during the period studied. In 2017, 17.6 per cent of households showed a high risk of default.

The tendencies of these three measures of household buffers to offset an unexpected economic loss can be somewhat contrasted with macro indicators. For instance, the asset poor households follow the macro changes in the economy and labour market (Figure 4.1). In the case of households with unprotected employment, it is not evident that this is related to a decrease in unemployment. This can be associated with either an increase in informal jobs or with an increase in the rate of labour-protected jobs. Figure 4.2 clarifies this point. Between 2010 and 2013, the proportion of informal work fell from 39.2 per cent to 34.9 per cent in the Chilean labour market. However, in the following years, the informality rate increased slightly, reaching 35.8 per cent in 2017. As to the level of households' over-indebtedness, this indicator follows the trend of financial resources allocated by domestic money banks. Figure 4.2 shows that between 2010 and 2017, the bank private credit rate increased by 13.2 per cent, peaking at 80.6 per cent in 2015.

Figure 4.2: Evolution of bank credit to GDP and labour informality in Chile over time



Sources: For labour informality data from New National Employment Survey (known as NENE in Spanish which began to be applied on 2010), and for domestic credit to private sector by banks, data from World Bank, databank.

Table 4.3 shows the association between economic insecurity measures. A third of households with unprotected workers or non-workers are at risk of facing an unexpected economic shock.

In the case of the over-indebtedness indicator, 46 per cent of households have a high probability of experiencing an event that generates an economic loss. As to the asset poverty indicator, 44.5 per cent of households in this situation are at risk of having a significant income drop or higher expenses in the near future. It is worth noting that none of the correlation coefficients between the indicators is greater than 0.3 (see Table A.2 in the appendix). This minimises the problem of double counting, which, as I will discuss in the next section, is one of the critiques to multidimensional approaches.

Table 4.3: The joint distribution between economic insecurity indicators in Chile, 2007-2017

Indicators	Per cent of households in row meeting column criterion (%)			
	Unexpected economic shocks	Uninsured employment	Over-indebtedness	Asset poverty
All households	37.9	30.0	15.4	62.8
Unexpected economic shocks	-	25.9	18.6	73.5
Unprotected employment or non-workers	32.9	-	15.1	70.2
Over-indebtedness	46.0	29.5	-	72.7
Asset poverty	44.5	33.5	17.9	-

Source: Author's calculations based on the Chilean Survey of Household Finances (2007, 2011, 2014 and 2017).

4.5 A multidimensional measure of economic insecurity

Although the sum of the vulnerabilities presented in Table 4.2 reveals, with a single measure, the proportion of households that are in a situation of economic insecurity, the index of economic insecurity is not sensitive to changes in the vulnerabilities of the households that are above or below the threshold used. In formal terms, this type of index does not satisfy the properties of dimensional monotonicity. For example, if one were to consider a household economically insecure when it shows two vulnerabilities, the headcount ratio of economically insecure households would not change if a household experiencing three types of vulnerabilities increased to four.

Using the adjusted headcount ratio to measure multidimensional economic insecurity

There are several approaches that have been developed to aggregate and summarise information on multidimensional phenomena such as poverty and inequality (Aaberge & Brandolini, 2015). One of the best known is Alkire & Foster's Multidimensional Poverty Index (MPI) (2011) based on the counting approach (Atkinson, 2003). Alkire & Foster (2011) propose an adjusted headcount ratio as a MPI that is sensitive to changes in the dimensions of the phenomenon that households are facing over time. My empirical strategy is to adapt their approach to the construction of a multidimensional index of economic insecurity.

It is worth mentioning that Alkire & Foster (2011) MPI has been calculated in 104 countries to identify multiple deprivations at the household level (Alkire & Santos, 2014), and their adjusted headcount ratio has been used in other multidimensional concepts such as job quality. For instance, García-Pérez et al. (2017) for Spain and Sehnbruch et al. (2020) for nine Latin American countries. Economic insecurity also has been measured from a multidimensional perspective following Alkire & Foster (2011) approach in north-western countries. The first time was in the U.S. using cross-sections and panel data from the Survey of Consumer Finances between 1989 and 2009 (Bucks, 2011), and recently in 28 EU countries, using longitudinal EU-SILC data from 2009 to 2016 (Cantó, García-Pérez, & Romaguera de la Cruz, 2019b).[64]

The approach that I follow has three parts: i) the identification of households that are economically insecure, ii) the aggregation of the different indicators into a scalar value, and iii) the selection of dimensional weights for each indicator.

Identifying economically insecure households

As I described above, I have selected the two dimensions and their indicators which, in my framework are related to household risk to an unexpected economic event and lack of buffers to offset a potential economic loss. Also, I identified economic insecurity for each of the indicators using specific thresholds (see Table 4.1). The next step is to determine if a household has enough vulnerabilities to be considered economically insecure.

To do this, I build the variable EI, which summarizes the total number of economic vulnerability indicators. It is a weighted sum of vulnerabilities in the indicators that define economic

[64] Cantó el al. (2019b) research is based on the Romaguera de la Cruz (2017) work who built an economic insecurity index using an adaptation of Alkire & Foster's (2011) model proposed by García-Pérez et al. (2017).

insecurity. For a household i it is calculated as follows:

$$EI_i = \sum_{j=1}^{V} w_j I_{ij} \quad i = 1, \dots, n \tag{1}$$

where I_{ij} is a variable that takes the value 1 if the household i is vulnerable in the indicator j and 0 otherwise, V is the total number of vulnerabilities analysed, w_j is the wight assigned to each indicator and n is the total of number of households. The weights are standardised so that their sum equals the total number of indicators, V. Therefore, EI_i will take values between 0 and V, where 0 is associated to a household that is not considered to be economic insecurity in any indicators and V is associated to a household i that is considered to be economic vulnerable in all of them.

Once I calculated the EI value for each household, I identify a household as economically insecure from a multidimensional perspective if EI is greater than or equal to the cut-off k ($EI_i \geq k$). And then, the sum of the economically insecure households of n households of the total population is given by q_{EI} ($q_{EI} = \sum_{i=1}^{n} I_{\{EI_i \geq k\}}$).

Aggregate economic insecurity measures

From an aggregate perspective, I can summarize the information on the economic insecurity of households by one scalar known as 'adjusted multidimensional headcount ratio' (M_0).[65] As mentioned the M_0 increases/decreases when the number of economic vulnerabilities increases/decreases, therefore it satisfies the properties of dimensional monotonicity (Alkire & Foster, 2011, p. 481). The M_0 calculates the total weighted sum of economic vulnerabilities divided by the maximum number of vulnerabilities that all households (nV) could have experienced. Formally, this expression is:

$$M_0 = \frac{\sum_{i=1}^{n} EI_i I_{\{EI_i \geq k\}}}{nV} \tag{2}$$

From the perspective of policy analysis the Alkire & Foster (2011) adjusted headcount ratio has two characteristics that make it an appropriate measure. First, it simultaneously measures both

[65] Alkire and Foster (2011) also propose measures of intensity (M_1) and inequality (M_2) that are not used in my proposal because my indicators of economic insecurity are dichotomous, and cardinal data is required for their calculation.

the incidence (proportion of economically insecure households) and the intensity of the economic insecurity (number of vulnerabilities affecting it). Second, it can be decomposed by population subgroup (e.g. income decile groups or geographic area) and economic insecurity indicators (e.g. unexpected economic shocks, unprotected employment, over-indebtedness, and asset poverty).

Regarding the former, I can calculate the (M_0) using the product of both the incidence (H) and the intensity (A) of the economic insecurity phenomenon.

$$M_0 = HxA \tag{3}$$

To measure the incidence of economic insecurity in the population, I calculate the 'multidimensional headcount ratio' as follow:[66]

$$H = \frac{q_{EI}}{n} \tag{4}$$

Then I measure the intensity of economic insecurity as the average of the vulnerabilities faced by economic insecure households standardised ($u_{EI}^{q_{EI}} = \sum_{i=1}^{n} EI_i I_{\{EI_i \geq k\}} / q_{EI}$) by the total number of indicators of economic vulnerability V.

$$A = \frac{u_{EI}^{q_{EI}}}{V} \tag{5}$$

Replacing H and A in Eq. 3, I get Eq. 2 since $q_{EI} u_{EI}^{q_{EI}} = \sum_{i=1}^{n} I_{\{EI_i \geq k\}}$

$$M_0 = \frac{q_{EI}}{n} \frac{u_{EI}^{q_{EI}}}{V} \tag{6}$$

Regarding the latter, the M_0 is additively decomposable by population subgroup, and also by vulnerabilities (Alkire & Foster, 2011). Therefore, the M_0 can be expressed as a weighted sum of the adjusted headcount ratios of each of the S subgroups:

$$M_0 = \sum_{l=1}^{S} \frac{n_l}{n} M_{0_l}$$

where n_l is the size and M_{0_l} is the the adjusted headcount ratio of subpopulation l.

[66] The application of this measure, considering that each of the four indicators of economic vulnerability has equal weight, can be seen in the last lines of Table 4.2.

The M_0 can also be decomposed by vulnerabilities as follows:

$$M_0 = \sum_{j=1}^{V} \frac{H_j}{V}$$

where H_j is the proportion of the total number of economically insecure households with elements of vulnerability on dimension j.

The H, A and M_0 estimates were computed in Stata (Release 15.0, Stata Corporation) using the *mpi* command (Pacifico & Poege, 2017).

Using a normative approach to define the weighting structure

Using an appropriate weighting scheme for any compound index is crucial. Weights have critical importance in the construction of a measure of wellbeing because they determine the trade-off between the dimensions and/or indicators, which can significantly affect the conclusions derived from the index (Decancq & Lugo, 2013; Ravallion, 2012b). The weights given to the different sources of stress that the household has due to economic vulnerabilities are a determining factor in the definition of the index I propose.[67] There are several approaches to setting weights, which can be grouped into two types. The first are the data-driven approaches, which let the data 'speak for themselves' and depend solely on the distribution that the data being analysed provides. That is, data-driven weights are not based on either theoretical criteria or value judgements regarding what the trade-offs should be between the dimensions and indicators. The second are the normative approaches, which define the weights based only on value judgements or conceptual frameworks of the dimensions of the phenomenon studied rather than the information that the distribution of the data matrix can provide.

There are two reasons for not using data-driven weighting strategies such as the principal component analysis (used by Rhode et al. (2015) to build the multidimensional index of economic insecurity in Australia) or frequency-based weights (used by Romaguera de la Cruz (2017) in her index for Spain). First, as mentioned in the previous section, the indicators that I

[67] The decision on which cut-off to use to aggregate the vulnerabilities also has consequences for the results of the application of the index. However, unlike the weight structure, there is no clear cut-off rule to determine the appropriate cut to use in the index. The recommendation is to perform sensitivity analyses to find the proper value for k.

use for Chile do not have a high correlation with each other, minimising the problem of double counting, which can capture the same latent dimension for two highly correlated indicators. The use of techniques based on principal component analysis has some drawbacks such as the difficulty in interpreting the combination between the indicators of the index, and in assigning a low weight to the dimensions that show a weak correlation, relying on mechanic justifications rather than theoretical ones (Decancq & Lugo, 2013).

Second, in countries like Chile that show a high percentage of economic vulnerability in all the indicators, using frequency-based weights has no justification. The reason for using frequency-based weights is that households attach greater importance to vulnerabilities that do not affect most households. Besides, there are situations in which one dimension may have a significant impact on the population, but this does not mean the others with a lower impact are less important. For example, Brandolini (2007) found this type of inconsistency between dimensions such as health and education when using frequency-based weights to calculate a well-being index in Italy.

Within the normative approach, the equal weighting is the most commonly used approach to build multidimensional indices of well-being (e.g. Human Development Index (UNDP, 2018)). Its use is recommended when the dimensions used in the index are considered equally important or when the dimensions included do not overlap. In my framework, the dimensions have both characteristics. First, the vulnerability indicators are not highly correlated (see Table A.2 in the appendix). Second, each dimension has an adverse effect on the well-being of a household, and, to the best of my knowledge, there are no studies that have determined that an economic vulnerability (e.g., over-indebtedness) causes more stress or anxiety in the household members than another (e.g., unprotected employment). Therefore, by applying the same weight to each indicator of economic insecurity, I can treat them in the same way.

Thereby, I assign the weights using a normative approach to define two economic insecurity indices. The first uses uniform weights, that is, the index of economic insecurity that has four indicators (treated as dimensions) whose weight (w_j) takes the value of 1 for each of them. I call this measure the Multidimensional Economic insecurity index (MEII), which has the following expression:

$$MEII_i = \begin{cases} 1\ if\ \sum_{j=1}^{V} w_j I_{ij} \geq k \quad \text{where } w_j = 1 \text{ and } V = 4 \\ \text{0 otherwise} \end{cases} \tag{7}$$

The second index also uses uniform weights. It classifies households as economically insecure using predefined combinations of two dimensions using three indicators (it does not include the over-indebtedness indicator). I have called this index the Integrated Economic Insecurity Index (IEII). I explain the IEII in detail below.

4.6 Drawbacks of multidimensional indexes of well-being

The development of multidimensional indexes of well-being has been accompanied by criticisms related to the methodology (Ravallion, 2011). However, the focus of the questioning has never been about the multidimensionality of phenomena such as poverty. The point in question is whether this multidimensionality can be adequately measured in a single index. There are many ways to build what Ravallion (2012a) calls mash up indices or ad-hoc aggregation depending on the available data and the distribution of the weights chosen by the researcher. For example, if the objective is to monitor and evaluate antipoverty programmes, and improve the targeting of social benefits, it is not clear how it is of added value to measure the dimensions in a scalar value versus the alternative of focusing on monitoring and improving the measurement of separate dimensions (e.g. consumption poverty, health poverty or education poverty). The main criticism to this approach is that the meaning, interpretation and robustness of these indices are often unclear.

A similar and more recent discussion has focused on the measurement of economic insecurity (Hacker, 2018; Osberg, 2018). Although the academic debate acknowledges that economic insecurity is a multidimensional phenomenon (Bucks, 2011; Osberg & Sharpe, 2014; Rohde et al., 2015; Romaguera de la Cruz, 2017) most of the analyses focus only on one of the dimensions of economic insecurity (Anderloni et al., 2012; Balestra & Tonkin, 2018; Białowolski, 2018; Bossert & D'Ambrosio, 2013; Keim et al., 2014; Rehm, 2016b; Rohde et al., 2014; Western et al., 2016).

In this context, Hacker at al. (2014, 2010) have made a significant contribution by proposing a hybrid measure to build an index that relates downside income insecurity to an insufficient financial safety net to buffer an unexpected economic loss. This measure, the Economic Security Index (ESI), offers policymakers a fully comprehensive measure of economic insecurity. To use the authors' own words, the integrated index is defined as "an annual index that represents the share of individuals who experience at least 25 per cent decline in their inflation-adjusted 'available household income' from one year to the next (except when entering retirement) and who lack an adequate financial security net to replace this income until it returns to its original level" (Hacker et al., 2014, p. 8).

This measure has been criticised for only considering private wealth as a buffer stock protection against an economic shock without including in the measurement the protective role of the state through social assistance or social insurance (e.g. the benefits of unemployment insurance or workers' compensation) (Osberg, 2018). Two additional criticisms that Hacker (2018) himself has raised regarding this index have to do with problems usually present in one-dimensional income insecurity measurements that use a retrospective approach. First, these measures cannot identify whether the income drop is a voluntary decision made by the household (e.g. an early withdrawal by the head of household) or rather the result of unforeseen events faced by it.

Second, a measure based primarily on changes in household income omits aspects of economic insecurity that do not imply economic instability. For example, Hacker et al.'s (2014) index can indicate that a household is not financially insecure because it did not experience a large drop in income despite having a very low income, high indebtedness and very limited liquid financial wealth. This point acquires relevance in middle-income countries where a high proportion of the population can experience several economic vulnerabilities simultaneously, even if they have not experienced a recent fall in their income.

Building upon the discussion presented above, I propose an Integrated Economic Insecurity Index (IEII) to complement the Multidimensional Economic Insecurity Index (MEII) and, at the same time, to be considered as a reference to define the multidimensional threshold value (k) used in the MEII.

An integrated measure of economic insecurity

Another way to think about the hybrid measure that Hacker et al. (2014) propose to measure economic insecurity in the U.S. is the multidimensional approach. As mentioned before, the

ESI measures the proportion of households that experienced a large drop in income or a large increase in out-of-pocket medical expenses and lacked liquid financial wealth to offset the economic loss. In the multidimensional approach, this measure is equivalent to a multidimensional economic insecurity rate (H) that has two indicators of vulnerability (V=2), using *uniform* weights, and a threshold set at two (k =2). The specifications of this simplified multidimensional index do not require estimating a multidimensional adjusted headcount ratio (M_{EI}) because in this particular case, the properties of dimensional monotonicity are fulfilled. For example, a household initially classified as economically insecure will be considered secure if it ceases to be vulnerable in either of the two dimensions.

The IEII that I propose also derives from the multidimensional approach. The IEII allows for classifying a household as economically insecure in two scenarios. The first scenario is when the household has a high risk of experiencing a large income drop or a large expense increase and lacks at least one buffer to offset the economic loss (unprotected job or asset-poverty). This scenario is similar to the one proposed by Hacker et al. (2014, 2010) except for two features. First, it does not include voluntary economic losses (see section on the construction of indicators) and second, it considers social protection mechanisms of the welfare state by incorporating as a buffer the level of protection of the household's workers.

The second scenario is when the household lacks buffers that can protect it from an economic loss (that is, a household with unprotected workers that is also asset-poor). This scenario addresses the critique that Hacker (2018) himself poses to his index being unable to adequately distinguish households that are economically insecure in the lower part of the income distribution. For example, Hacker et al.'s (2014) index does not consider as economically insecure households that do not have a high risk of experiencing a significant income shock although they live in conditions of high vulnerability due to the lack of buffers to face economic losses. It is worth noting that unprotected work is highly correlated with low-income households; therefore, by including this buffer, I will be measuring a source of economic insecurity characteristic of this group of the population.

The measurement of this second scenario does not include over-indebtedness as a buffer. There are two reasons for not doing so: first, so as not to complicate the IEII and, second, to avoid including a criterion that is highly demanding in regard to classifying households as economically insecure. In other words, I want to prevent the IEII from considering households as financially secure when they are not over-indebted while they are asset-poor, and when their members are workers without labour protection. Besides, the smallest contribution of over-indebtedness in the measure of multidimensional insecurity is in the lower part of the income distribution (see Table 4.5). A classification that includes this indicator along with the other two buffers would report a lower proportion of economically insecure households in that part of the income distribution, compromising the goal of improving the measurement of economic insecurity among low-income households.

The IEII classification enables me to represent in a single scale the risk of unbuffered economic loss from two major dimensions of economic well-being: i) household risk to an unexpected economic event, and ii) lack of buffers to offset the potential economic loss. This definition of economic insecurity offers a more comprehensive interpretation than that of the MEII, at the cost of not including the over-indebtedness indicator in the index, thus losing the information that this source provides about households' stress.

In formal terms, the IEII is a uniform weighting structure with equal values for the weights and a fixed k. The weights values and the threshold are chosen so that the index can classify the households according to the two scenarios of economic insecurity predefined in the integrated measure. In this way the IEII is defined by the following expression:

$$IEII_i = \begin{cases} 1\ if\ \sum_{j=1}^{V} w_j I_{ij} \geq 2 \quad \text{where } w_j = 1 \text{ and V} = 3 \\ \qquad\qquad 0 \text{ otherwise} \end{cases} \tag{8}$$

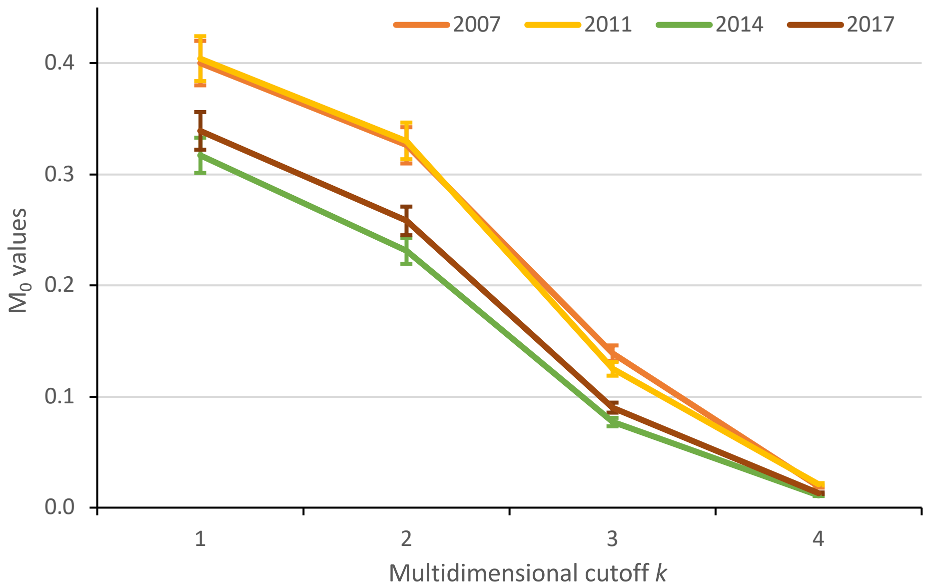
With these specifications, a household is economically insecure if it has i) a high risk of facing an economic shock and lacks at least one of the two buffers or ii) lacks the two buffers.

4.7. Results

General analysis of economic insecurity measures

Here I present the results at the household level of the economic insecurity measures that I have proposed, and I discuss why these results justify using the MEII over the IEII to understand the economic insecurity in Chile. Figure 4.3 shows the aggregate measure (M_0) of the MEII for different thresholds (k). For the years 2007 and 2011, the confidence intervals overlap for each of the cut-offs, thereby presenting no significant differences in the M_0. For $k = 1$, the value of M_0 for those two years is 0.4, reaching 0.02 when the household experiences the four vulnerabilities at the same time. When analysing the period 2014-2017, the values of M_0 are statistically different when the cut-off corresponds to two vulnerabilities ($k = 2$). This shows that the economic insecurity behaviour follows a U shape, that is, there is a significant drop in economic insecurity between 2011 and 2014, which is then followed by an increase in the MEII between 2014 and 2017.

Figure 4.3: Adjusted multidimensional economic insecurity rate (M_0) using uniform weights by number of k cut-off (Chile, 2007-2017)



Source: Author's calculations based on the Chilean Survey of Household Finances (2007, 2011, 2014 and 2017).

To calculate the MEII I use $k = 2$, a threshold that, as shown in Figure 4.3, distinguishes significant changes in the economic insecurity of Chilean households after the Great Recession in 2008/2009. These changes range from an M_0 of 0.330 in 2011 to 0.258 in 2017, where the lowest level of economic insecurity was observed in 2014, with a value of 0.231.

Table 4.4: Measurements of economic insecurity in Chile, 2007-2017

Index defined by weights and threshold	Year	H (incidence of economic insecurity)	Std. Err.	A (intensity of economic insecurity)	Std. Err.	M_0 (adjusted multidimensional economic insecurity rate)	Std. Err.
MEII (Multidimensional Economic insecurity index)	2007	0.554	0.012	0.590	0.005	0.326	0.007
	2011	0.569	0.009	0.579	0.004	0.330	0.006
	2014	0.406	0.012	0.568	0.005	0.231	0.007
Four dimensions, uniform weights and k=2	2017	0.451	0.010	0.571	0.004	0.258	0.006
	Δ 2007-2017	-0.103	**	-0.019	*	-0.068	**
IEII (Integrated Economic insecurity index)	2007	0.505	0.012	0.740	0.005	0.374	0.009
	2011	0.526	0.010	0.728	0.004	0.383	0.007
	2014	0.348	0.011	0.710	0.004	0.247	0.008
Two dimension and three indicators, uniform weights and k=2	2017	0.384	0.010	0.713	0.004	0.274	0.007
	Δ 2007-2017	-0.121	**	-0.027	*	-0.10	**

Source: Author's calculations based on the Chilean Survey of Household Finances (2007, 2011, 2014 and 2017).

Table 4.4 compares the MEII values for $k = 2$ with the aggregate measures for the IEII (H and M_0). In both measures, a similar trend was observed during the decade, but with values slightly higher in the MEII than the IEII. This difference can be seen in 2014 and 2017, where the incidence in the MEII is approximately 15 per cent higher than in the IEII. It is important to note that the MEII outcomes for other values of k are quite different from the IEII outcomes (see table A2 in the annexes), being the cut-off of two vulnerabilities the one that constructs a multidimensional measure with values similar to those of IEII.

A second difference between the two measures of economic insecurity is that the MEII seems to be a more smoothed measure than the IEII in both the incidence and the adjusted multidimensional economic insecurity rate. This is most clearly seen between 2011 and 2014, where both measures capture the sharp decline in economic insecurity, yet the IEII incidence presents a reduction of 36 per cent, whereas the MEII indicates that the fall was 30 per cent.

The third difference between the two measures of economic insecurity, already mentioned above, lies in their interpretation. While the MEII aggregate measures are constructed from the combination of one, two, three and four vulnerabilities (depending on the cut-off (k) chosen), the IEII informs us more comprehensively about the relationship between the three economic insecurities of the household. For the IEII, households are vulnerable for two reasons: i) having a high risk of facing an economic shock without having at least one of the two buffers to offset the economic loss, or ii) experiencing the lack of these two buffers at the same time (unprotected employment and asset poverty). However, when the MEII uses the cut-off of two vulnerabilities ($k = 2$), this not only contains the two mentioned scenarios of the IEII but also allows over-indebtedness to be included as an indicator. The MEII provides greater flexibility than the IEII by applying a cut-off of two vulnerabilities to the four indicators. This makes it possible to classify economic insecurity more adequately for households in the lower part of the income distribution. For example, the MEII classifies a household as economically insecure if its workers are not protected from dismissal and are asset-poor without necessarily being over-indebted.

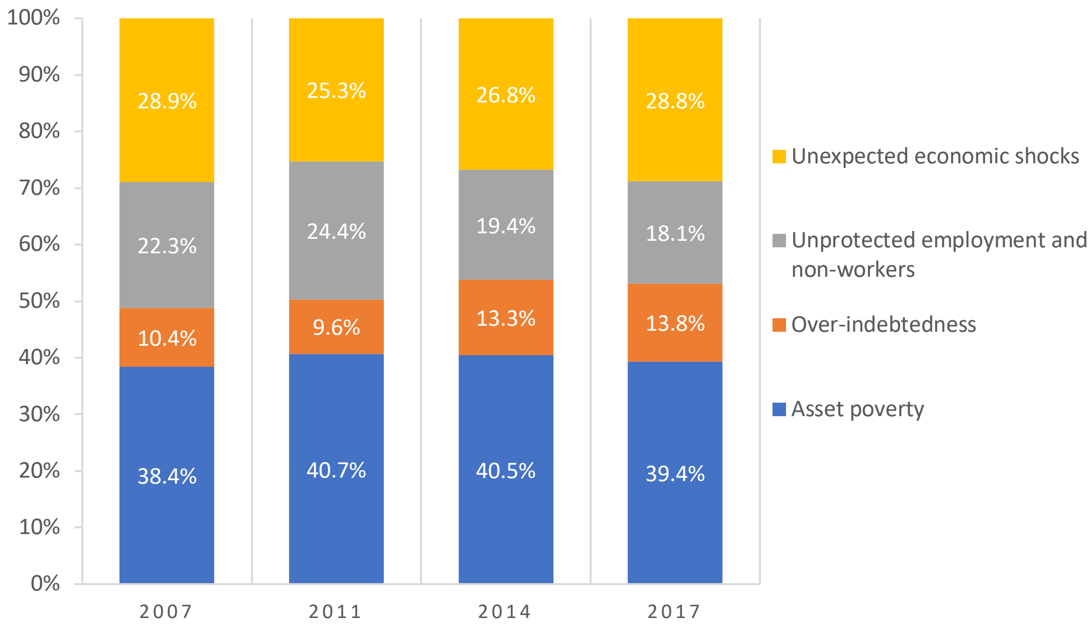
All three differences discussed above allow me to suggest that an MEII with a multidimensional cut of two ($k = 2$) is the most appropriate measure of economic insecurity to apply to Chile. The analyses that follow make use of the decomposition benefits of the aggregate measure M_0. From now on I will only refer to the aggregated results (H, I, and M_0.) delivered by this measure.

Disaggregated analysis by dimensions, income decile groups and family types

Table 4.4 shows that the changes in the adjusted multidimensional economic insecurity rate (M_0) are explained more by variations in the incidence (H) (over 12 per cent between 2007 and 2017), than by changes in the intensity (I) of the vulnerabilities (less than 3 per cent for the same period). This result raises the question of what the contribution of each of the indicators is to M_0, and how this contribution changed over the decade studied.

Figure 4.4 illustrates the evolution of the composition of M_0. In the four measurements obtained between 2007/2017, asset poverty is the dimension that contributes the most to economic insecurity, with an average of 40 per cent. The second most important component of the M_0 for all households is unexpected economic shocks, with an average of 28 per cent. In third place is unprotected employment, with an average of 21 per cent. Finally, the component with the lowest contribution to the aggregated measure of the MEII is over-indebtedness, at 11 per cent. Yet, it is worth noting that this dimension is the only one out of the four dimensions considered that increased its contribution over the decade (from 10.4 per cent in 2007 to 13.8 per cent in 2017). The increase over time of economic insecurity in households due to over-indebtedness opens an important discussion about the lack of financial education in Chile as well as why households must increasingly resort to formal or informal credit to cover their expenses both scheduled as unexpected. The changes in the compositions of the other three dimensions become more apparent from 2011 onwards; the contribution of economic shocks increases, and the lack of buffers (asset poverty and unprotected employment) decreases. In 2017 the relative M_0 composition of these three dimensions was 28.8, 39.4 and 18.1 per cent respectively.

Figure 4.4: Evolution of the relative composition of MEEI (M_0) in Chile, 2007-2017

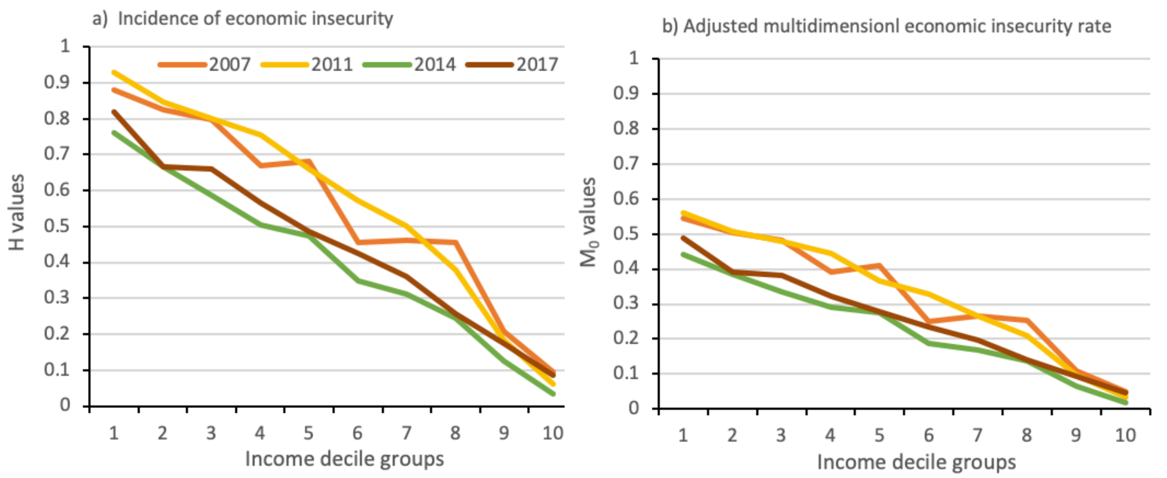


Source: Author's calculations based on the Chilean Survey of Household Finances (2007, 2011, 2014 and 2017).
Notes: The MEII (Multidimensional Economic insecurity index) uses uniform weights and k=2

Figure 4.5 shows the aggregate MEII measures for the years 2007, 2011, 2014, 2017 by income decile group. The results show two relevant phenomena. First, economic insecurity affects the whole population. The results show high levels of economic insecurity across the entire income distribution. Although the economic insecurity is much higher in the lower part of the income distribution, the incidence in the decile groups of the upper part of the distribution is relatively high as well. Panel A in Figure 4.5 shows that during the years 2007 and 2011 the average incidence of the MEII was around 80 per cent for the first two income decile groups, while in the two highest income decile groups (9 and 10) was 12 per cent. This contrasts with the results from the only study that has carried out a similar analysis using a multidimensional index (Romaguera de la Cruz, 2017). This author found that in Spain, the M_0 for deciles 9 and 10 was less than 1 per cent. Although this comparison is not strictly accurate since the period analysed was between 2009/2015 and the index was not built with the same indicators, it allows for emphasising the fact that economic insecurity in Chile is not bounded to the lower income groups.

This result is particularly interesting when comparing the concept of economic insecurity with that of vulnerability to poverty (risk of falling into poverty). Poverty vulnerability analyses indicate that in Chile, only the highest income decile groups (9 and 10) have a near zero risk of falling into poverty. This means that a low risk in terms of vulnerability to poverty does not exempt households or individuals from the risk of curtailing their well-being, a risk that is associated with significant stress at the household level.

Figure 4.5: Aggregate measures of MEII by income decile groups in Chile, 2007-2017



Source: Author's calculations based on the Chilean Survey of Household Finances (2007, 2011, 2014 and 2017).

The second phenomenon that the results show is that although in Chile the levels of economic insecurity are high, these decreased significantly between 2011 and 2014. Figure 4.5 shows that this reduction is reflected throughout the first eight income decile groups in both aggregated measures (H and M_0). The highest income decile groups (9 and 10) show no significant changes. As noted, this decrease in economic insecurity is coupled with good macroeconomic performance between those years: economic growth of 4.4 per cent on average and a decrease in informal work of almost 5 per cent.

Table 4.5: Relative contribution to M_0 by income decile group in Chile, 2017

Income decile groups	M_0 (adjusted multidimensional economic insecurity rate)	Relative contribution to M_0			
		Unexpected economic shocks	Unprotected employment or non-workers	Over-indebtedness	Asset poverty
1	0.490	0.178	0.346	0.078	0.397
2	0.390	0.257	0.253	0.097	0.393
3	0.383	0.304	0.169	0.131	0.396
4	0.322	0.319	0.143	0.137	0.401
5	0.278	0.366	0.097	0.157	0.380
6	0.235	0.364	0.107	0.158	0.371
7	0.198	0.355	0.060	0.174	0.412
8	0.139	0.351	0.076	0.164	0.409
9	0.092	0.197	0.057	0.338	0.408
10	0.046	0.199	0.156	0.312	0.333

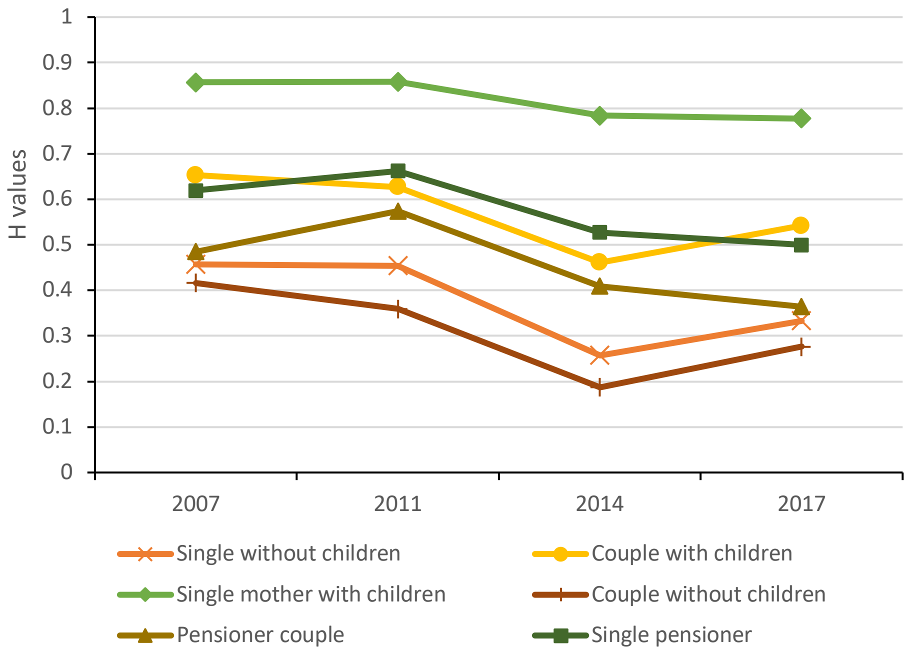
Source: Author's calculations based on the Chilean Survey of Household Finances 2017.

Taking advantage of the decomposition properties of one of the MEII's aggregated measures, I analyse the contribution of the dimensions to economic insecurity according to households' position in the distribution of income. And, more specifically, I analyse whether the composition of the four dimensions in the index differs between the extremes of the income distribution. Table 4.5 shows the adjusted multidimensional economic insecurity rate (M_0) for the year 2017 by income decile group.

For the year 2017, the contribution of unexpected economic shocks is higher between deciles 3 and 8 than at the extremes of the income distribution. In the case of asset poverty, the contribution is relatively constant. It does not seem to be related to income decile, except in the highest income decile group (10), where the contribution falls to 33 per cent. The indicator unprotected employment or non-workers in the household is important in the lower part of the income distribution, and its contribution falls in the highest deciles. Conversely, over-indebtedness is more relevant for households at the top of the distribution, which reveals that over-indebtedness, falling revenues or increased expenditure are sources of greater stress among households with a higher income in Chile.

The breakdown of the MEII aggregate measures into subgroups of the population also makes it possible to identify the types of families with the highest levels of economic insecurity. From the perspective of public policy design, this information is relevant because it allows for identifying where and how to focus public resources to reduce household stress due to economic vulnerabilities, thus complementing other welfare measures that are traditionally used in the targeting of social policies.

Figure 4.6: Incidence of economic insecurity (*H*) by family type in Chile, 2007-2017



Source: Author's calculations based on the Chilean Survey of Household Finances (2007, 2011, 2014 and 2017).

Figure 4.6 shows the incidence of economic insecurity in Chile between 2007 and 2017, broken down by population subgroup. The three groups with the highest rate of economic insecurity are households composed by i) a single mother with children; ii) couple with children, and iii) a single pensioner. Around 8 out of 10 single mother with children households experienced economic insecurity during the decade analysed. The other two subgroups show rates close to 65 per cent in 2007. Although by 2017 these rates had declined to around 52 per cent. The high economic insecurity of these three types of families correlates with other welfare deprivation measures such as vulnerability to income poverty (López-Calva & Ortiz-Juarez, 2014). In this way, the application of the MEII informs policymakers that more than half of these households have been under economic stress during the last decade in Chile.

Understanding the determinants of the economic insecurity in Chile

In this last section of the results, I analyse the relationship between economic insecurity and some significant households' characteristics variables. I use a probit model to estimate the probability of a household being economically unsafe. The dependent variable is the definition of the MEII for a cut-off of two vulnerabilities. The multivariate model was applied to pooled data from SHF household samples for the years 2007, 2011, 2014 and 2017. Specifically, my interest is in identifying the average marginal effect (AME) that each of the socioeconomic characteristics of the household has on economic insecurity for the studied period. Table 4.6 shows these estimates

Regarding the features of heads of households, i.e. gender, age and education, the results show first, that households headed by women are more vulnerable than households headed by men (7.7 per cent). An explanation of this result could be the gender inequalities that the Chilean labour market exhibits (participation, stability and wages). Second, the age of the head of the household was not a significant variable. This result shows that the economic insecurity throughout the decade was transverse to the life cycle of households. Finally, it is worth noting that households with heads of households that have a university degree have a significantly reduced risk of being economically vulnerable. The AME for heads of households with a university degree was 26.0 per cent.[68]

As to the variables related to households' characteristics, i.e. type of family, number of children, number of members working, the results in Table 4.6 show that two types of households have a higher risk of being economically insecure compared to households with couples without children. In the case of households with a single mother with children, the risk is 27.3 per cent, while for couples with children is 11.8 per cent. These results are aligned with those presented in Figure 4.6, providing significant evidence of the need to direct support through tailored policies to these types of families to alleviate the stress and anxiety they experience. It is important to mention that during the last decade, Chile increased the cash transfer through its family benefit programs, reaching 0.7 per cent of GDP in 2015 (Tromben & Podestá, 2019, p. 59). This percentage is still below the average of 1.2 percent from OECD countries.

[68] In other words, in average the probability of these households is around 25 per cent higher than of head of households that only completed secondary school.

Second, regarding the number of children in the household, an additional child increases the probability of a household being economically insecure by 3.1 per cent. Third, the number of workers in the household has a reverse effect and is significant. When a member of the household gets a job the probability of the household being economically insecure decreases by 11.0 per cent. Finally, when a household rents their home this increases their probability of being economically vulnerable by 17.9 percent compared to a household that owns their home. Since housing was not included as a measure of asset poverty, this result does not have a mechanical explanation but rather directly relates this characteristic of the household to the level of insecurity that it experiences.

Table 4.6: Average marginal effects on probability of a household being economic insecure for significant variables

Variables	Pooled data	
	AME	Std. Dev.
Household head characteristics		
Female	0.077 ***	(0.017)
Age: Ref.45 to 54 years		
Under 35 years	-0.024	(0.022)
35 to 44 years	-0.010	(0.021)
55 to 64 years	-0.025	(0.024)
65 years and more	0.049	(0.051)
Education: Ref. Secondary school		
Primary school	0.079 ***	(0.020)
University degree	-0.260 ***	(0.014)
Household characteristics		
Household type: Ref. Couple with children		
Single without children	0.016	(0.023)
Single mother with children	0.118 ***	(0.029)
Couple without children	0.273 ***	(0.040)
Pensioner couple	-0.081	(0.050)
Single pensioner	-0.093 *	(0.050)
Number of children < 15	0.031 **	(0.014)
Number of workers	-0.110 ***	(0.007)
Housing: Ref. Own housing (no mortgage)		
Own housing, mortgage	0.179 ***	(0.016)
Rent	0.012	(0.021)

Source: Author's calculations based on the Chilean Survey of Household Finances (2007, 2011, 2014 and 2017).

Notes: I present average marginal effects for probit estimations in which the dependent variable is the Multidimensional Economic Insecurity Index (MEII). *** significance at 1 percent; ** significance at 5 percent; * significance at 1 percent.

4.8 Conclusions

In this chapter, I have studied both the nature and evolution of economic insecurity in Chile over the last ten years (from 2007 to 2017). To carry out this analysis, I have constructed the Multidimensional Economic Insecurity Index (MEII) combining four sources of economic insecurity causes stress and anxiety: unexpected economic shocks, unprotected employment, over-indebtedness and asset poverty. In this way, the MEII offers a measure at the household level that directly relates economic uncertainty to stress due to the lack of both social protection and buffers to face unexpected economic shocks.

Until now only integrated measures of economic insecurity, such as that proposed by Hacker et al., (2014) have used this two-dimensional conceptual framework in the construction of an index. Other indices have focused on the objective and subjective dimensions of economic insecurity or only on one of its dimensions, such as large income drops or level of household wealth. The MEII that I propose incorporates sources of stress and anxiety that are characteristic of households located at the two ends of the income distribution in middle-income countries. This is the case for the unprotected jobs at the bottom of the distribution, and the over-indebtedness at the top. In this way, the MEII becomes a more versatile and useful tool for the diagnosis and design of social policies for the reality of countries such as Chile and others that are similar in the Latin American region. Furthermore, using a multidimensional approach to construct the MEII not only allows me to analyse the incidence and intensity of economic insecurity but also to decompose the index by dimension or subpopulation.

After selecting the appropriate vulnerability cut-off to the MEII and validating its results with an integrated index *à la* Hacker et al., (2014) I propose a cut-off of two vulnerabilities and four indicators with uniform weights to analyse the level and intensity of economic insecurity in Chile. Applying this measure to the data from the Household Financial Survey shows that during the decade studied, economic insecurity, on average, affected almost 50 per cent of urban households in Chile, with an intensity of 2.3 out of 4 indicators. By taking into account both incidence and intensity, I obtain an adjusted rate of average economic insecurity of 0.286. Although in the period of the economic crisis the level of insecurity did not change (measures taken in 2007 and 2011), its evolution in the subsequent years shows U-shaped behaviour where a significant fall in economic insecurity between 2011 and 2014 is followed by an increase between 2014 and 2017. This result shows a negative correlation with the country's economic cycle. Other macroeconomic indicators also correlate with some of the indicators that make up the MEII, for example, the reduction of the levels of labour informality with the unprotected unemployment indicator, and the constant increase in the bank private credit rate with the over-indebtedness indicator.

When considering the entire population, asset poverty is the indicator that contributes the most to economic insecurity. The other indicators follow in this order: unexpected economic shocks, unprotected employment, and over-indebtedness. Although insecurity is present throughout the income distribution, the composition of the four indicators varies according to the position of the household in the income deciles. Thus, although the asset-poverty contribution is similar throughout the income distribution, unprotected employment is more relevant in the lower deciles, while unexpected economic shocks and over-indebtedness make a more significant contribution in the higher deciles.

The main determinants of economic insecurity are households headed by women who have children. Also, heads of households with low educational levels who work without a contract increase the household's risk of being affected by economic insecurity. The number of workers in the household is the most critical determinant to predict their economic insecurity. These results are similar to studies that have used other economic welfare measures such as vulnerability to poverty. This allows for relating these forms of socioeconomic disadvantage to exposure to economic stress. In this way, one could argue that policies that seek to reduce the economic risk in the poorest households fulfil several desirable objectives simultaneously.

The most significant difference between these welfare measures is that economic insecurity affects the entire income distribution, while the other measures do not provide relevant information on the highest deciles. The high economic insecurity experienced by all income groups finds an explanation in two critical and intertwined conditions: firstly, the low level of income and wealth collected through household surveys, even of those in decile groups 9 and 10, which are not enough to protect individuals from the stress of future economic shocks; and secondly, the weak social protection system, which is incapable of working as a buffer to offset households' economic insecurity. It is worth noting that in 2015 the OECD ranked Chile as having the greatest economic vulnerability among its members, for almost 8 out of every 10 Chileans did not have liquid financial wealth to face a sudden adverse economic shock. In that same year a new reform was made to the unemployment insurance system based on individual savings to increase insurance coverage for a greater proportion of the unemployed.

By identifying the groups of households most affected by economic insecurity and its trend in recent years, the application of the MEII in countries such as Chile provides relevant information to monitor, evaluate and improve social safety nets together with labour market regulations. Although this welfare measure has been criticised for not considering the fact that the perception of economic vulnerability varies among households, it is important to acknowledge that the contexts in which households decide to avoid or increase their economic risks are determined and informed by the support scheme offered through social policies. The question that arises is, what is the base level of hazard that as a society we want to have? In the case of Chile, to a certain extent, the state shares with people the financial risk of hazards such as unemployment or illness, through programmes such as unemployment insurance or public health insurance. Households decide how to cope with the additional costs of an illness or unemployment taking into consideration information about programme benefits (if eligible) and their own resources. However, regardless of the level of risk aversion on the part of the household, social policies should be able to effectively address economically insecure households, generating a more complete social welfare system than the current one.

4.9 Appendices

Table A.1: Average marginal effects on the probability of a household facing a large drop in income or a sharp increase in its expenses for significant variables

Variables	Pooled data: 2007-2011-2014-2017		
	AME		Std. Dev.
Household head characteristics			
Female	0.020	**	(0.008)
Age (years)	0.005	***	(0.001)
Age^2 (years)	-0.001	**	(0.001)
Education: Ref. Secondary school			
Primary school	0.021	**	(0.011)
University degree	0.002		(0.013)
Labour status: Ref. Unoccupied			
Formal employed	0.004		(0.011)
Informal employed	0.036	***	(0.012)
Household characteristics			
Household type: Ref. Couple without children			
Single without children	-0.033	**	(0.015)
Couple with children	0.053	***	(0.015)
Single mother with children	-0.020		(0.015)
Pensioner couple	-0.024		(0.020)
Single pensioner	-0.069	***	(0.022)
Number of children < 15	0.026	***	(0.007)
Number of workers	0.015	***	(0.005)
Housing: Ref. Own housing (no mortgage)			
Rent	0.043	***	(0.009)
Own housing, mortgage	0.025	**	(0.011)
Income: Ref. Decile 6-8 income group			
Decile 1-5 income group	0.030	***	(0.010)
Decile 9-10 income group	-0.078	***	(0.010)
Year: Ref. 2017			
2007	0.026	**	(0.011)
2011	0.002		(0.010)
2014	-0.085	***	(0.010)

Source: Author's calculations based on the Chilean Survey of Household Finances (2007, 2011, 2014 and 2017).

Notes: I present average marginal effects for probit estimations in which the dependent variable is a large drop in household income or a sharp increase in its expenses. *** significance at 1 percent; ** significance at 5 percent; * significance at 1 percent.

Table A.2: Correlation between economic insecurity indicators in Chile, 2007-2017

Indicators	Per cent of households in row distributed in each indicator (%)			
	Unexpected economic shocks	Uninsured employment	Over-indebtedness	Asset poverty
Unexpected economic shocks	1			
Unprotected employment or non-workers	0.047	1		
Over-indebtedness	0.144	-0.003	1	
Asset poverty	0.213	0.141	0.096	1

Source: Author's calculations based on the Chilean Survey of Household Finances (2007, 2011, 2014 and 2017).

Chapter 5

Conclusion

In the last decade, middle-income countries with fast-growing economies have been able to reduce the poverty levels of their populations significantly. Traditional measures of income poverty or multidimensional poverty continue to be relevant for the design of social policies focused on those who remain deprived. However, in contexts of high-income inequality and weak social protection systems, new approaches are needed to understand this new reality and thus design better social policies for the new income groups. I propose three new measures of social and economic well-being using different approaches. These measures are applied to Chile using two household surveys: the Panel CASEN and the Financial Survey.

Each empirical chapter or paper addresses one of these measures. In the second chapter, I measured the persistence at the bottom and at the top of the income distribution using transition matrices. Also, I used a REDOP Model to measure whether position in the income distribution this year affects the chances of leaving poverty or remaining someone's at the top of the income distribution next year. In the third chapter, I proposed a strategy to identify degrees of vulnerability-to-poverty that relates the risk of falling into poverty to household income. Using a low-income dynamics approach, I generate two lines of vulnerability-to-poverty. One distinguishes the income-secure middle class from the vulnerable to poverty group. The other distinguishes between the vulnerable who have a high risk of falling into poverty and those with a moderate risk. In the fourth chapter, I propose an integrated economic insecurity index from a multidimensional approach. The index allows us to classify a household as economically insecure for two dimensions of economic insecurity: i) household risk to an unexpected economic event, and ii) lack of household buffers to face an economic shock.

Altogether the contribution of these three chapters is twofold. They enable a better understanding of the economic well-being of the new income groups (low income household who are not poor) from a longitudinal perspective, and they provide a concrete tool for the design, monitoring and evaluation of social policies focused on this new social reality. In this chapter I summarise the main findings of this study, provide hypotheses that could explain these findings, present implications for social policies, and offer recommendations for future research.

5.1 Main findings and contributions

Low-income and high-income persistence

The second empirical chapter provides interesting inputs to a discussion of individuals' mobility within the income distribution in Chile. First, the descriptive results show that the persistence at these two extremes of the income distribution in Chile is much higher than the expected, showing signs of high economic insecurity.

Thus, the evidence to support the thesis of a sticky floor at the bottom of the distribution that prevents people from scaling the income ladder seems to be less strong for Chile. The high mobility at the bottom of the income distribution is probably related to a right-skewed distribution. This means that since the boundaries between the income quintile groups 1 to 4 were being close to each other, changes in the positions in the income distribution do not necessarily represent significant changes in individuals' income. Therefore, although Chile has decreased its levels of absolute poverty, there is still a high turnover of households around the poverty line. Although this characteristic is true for most countries, a comparative study of income distribution shapes among countries showed that the case of Chile is more evident (Chauvel, 2018).

Likewise, the evidence to support the idea of a glass floor, 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 form 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 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 wealthiest 5 per cent of the population).

When analysing income persistence, the models show evidence that experiencing high (or low) income last year increases the probability of remaining in the same income position this year. Furthermore, not only do the observable and unobservable variables explain the persistence in these positions in the income distribution, but the impact of state dependence is also more significant for the affluent than for the poor. Therefore, the influence of time on remaining in the same position is more important in the richest tenth than in the lowest part of the income distribution. Understanding which mechanisms explain affluent traps in Chile are new questions posed by this research.

In summary, as expected, in both the lower and upper parts of the income distribution, there is a higher likelihood not to change position. State dependence was found to be a mechanism that explains that persistence. In the affluent group, past high-income experience is greater than past poverty experience in the poor. However, when compared to OECD member countries, Chile appears to be a fluid society throughout its income distribution, even at both ends of the distribution. This means that the entire population is vulnerable to downward from their positions. Hence, 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 likely to be because the income mobility is mostly bounded to short-range movements.

My findings provide three new elements for discussion on income mobility. The first is related to the characteristics of the affluent. The Chilean case shows that the highest decile group has the particularity of combining two conflicting characteristics. On the one hand, it shows signs of fluency with the middle class, and on the other hand, it shows signs of income persistence explained by the state dependency mechanism. This particularity could be related to the level of heterogeneity of this group, which justifies an in-depth analysis of this segment of the population.

The second element is related to the concept of poverty dynamics. The Chilean case shows that poverty reduction is accompanied by a high turnover around the poverty line, giving rise to a new class: people who are vulnerable to poverty. This poses the challenge of measuring and understanding better the determinants of this emerging group.

Finally, the third element for the debate relates the scopes and limits of mobile societies. As my results show, Chile is an unequal and mobile society where position changes in the income distribution appear more linked to insecurity and instability than to progress and better life chances throughout individuals' lifetime. My findings provide evidence that justifies delving deeper into the role of economic insecurity in people's well-being across the income distribution.

Vulnerability to poverty

In the third empirical chapter, I estimated two vulnerability lines that measure the risk of falling into poverty in the next period, using the World Bank's poverty line for upper-middle-income countries. This measure of economic well-being allows identification of three types of household. The first group are the 'highly vulnerable'. These are households that have an income below US$9.9 per person per day (pppd) at 2011 PPP, and whose probability of falling into poverty in the next year is equal to or greater than 17.1 per cent. These households are the ones that need the most support from social policies to stay out of poverty. This high vulnerability line is closely associated with the average risk of falling into poverty for decile groups 4 and 5 of the income distribution. Therefore, using this vulnerability line, one could say that 40 per cent of the population in Chile were highly vulnerable during 2006 and 2009.

The second group are the 'moderately vulnerable'. These are households whose income is between US$9.9 and US$20 pppd (both cut-offs in 2011 PPP terms). The low vulnerability line is associated with an average probability of falling into poverty of 4.6 per cent, which relates to the risk of falling into poverty for decile groups 8 and 9 of the income distribution. This means that one-third of the population in Chile (between decile groups 5 and 8) were moderately vulnerable during the period studied. From a comparative perspective, it is important to say that this cut-off is close to the poverty line used to compare absolute poverty among high-income countries (Jolliffe & Prydz, 2016).

These results have high relevance for the design of social policies because they show that a large part of the Chilean population is at risk of falling into poverty without being protected by the social security system and with access to low quality social services through the co-financing of benefits. This is due to the subsidiary rationale of the Chilean social policy, which focuses on and prioritises support for the low-income population.

My findings imply that two vulnerability lines that I propose can be used in countries that only have cross-sectional household data. This allows for measuring the size of the three groups according to their degrees of vulnerability to poverty. Although several studies have used the World Bank vulnerability line to compare countries in Latin America, a new comparative study in the region using my two vulnerability lines is an important line of research to explore.

Two limitations of the vulnerability lines proposed should be mentioned. The absence of longitudinal data on households in Latin America does not allow for updating the vulnerability lines as time goes by. My data, although more up to date than those used by the World Bank, are from the period 2006-2009. The other limitation – that also applies for the World Bank vulnerability line – is that the estimation of the risk of falling into poverty depends on the form of the income distribution. Not all countries necessarily have an income distribution with similar characteristics to the Chilean case. Therefore, these considerations must be taken into account when applying these lines of vulnerability in contexts other than Chile.

The values of the vulnerability lines that I propose allow for anticipating some results. A high proportion of the population that would be classified as middle class using the World Bank's vulnerability line are households that, according to my approach, face a considerable risk of falling into poverty. Therefore, I would argue that the previous research has underestimated how many people in Latin America are vulnerable to falling into poverty and overestimated the growth of the middle class. The formation of a new and extensive social group in the Latin American region whose vulnerability to poverty is its main characteristic is one of the important conclusions of this chapter.

Economic insecurity

In my fourth chapter, I propose an economic insecurity measure (MEII) that incorporates sources of stress and anxiety that are characteristic of households located at the two ends of the income distribution in middle-income countries. This is the case with unprotected jobs at the bottom of the distribution, and over-indebtedness at the top. These features make the MEII a more versatile and useful tool for the diagnosis and design of social policies for countries such as Chile, and other similar countries in Latin America and the Global South.

My results show that the income mobility affecting the entire income distribution in Chile (discussed in chapter two) is more associated with the high economic insecurity of the population than with a fluid society where there are no barriers to upward social mobility. During 2007 and 2017, for all income decile groups, urban households in Chile experienced economic insecurity due to the lack of both social protection and buffers to face unexpected economic shocks. The incidence of economic insecurity was around 80 per cent for the first two income decile groups, while in the two highest income decile groups (9 and 10) was 12 per cent.

When considering the entire population, the MEII shows that asset poverty is the indicator that contributes the most to economic insecurity. The other indicators follow this order: unexpected economic shocks, unprotected employment, and over-indebtedness.

The people who are most exposed to economic insecurity are households headed by women who have more than one child, and households whose head of household has a low level of education and/or whose work is informal. The number of workers in the home is the most important predictor of economic insecurity. These results are consistent with those found in chapter three on vulnerability to poverty. Thus, it could be argued that policies that seek to reduce economic risk (vulnerability to poverty) for the poorest households meet several desirable objectives simultaneously, like for example, reducing the exposure to economic stress (economic insecurity). The most significant difference between the vulnerability to poverty and economic insecurity measures is that economic insecurity affects the entire income distribution, while vulnerability to poverty does not provide information on the highest income groups.

The high economic insecurity experienced in Chile by all income groups finds an explanation in two critical and intertwined conditions. The first is the low level of income and wealth in absolute terms even of those in groups of deciles 9 and 10, which are not enough to protect people from the stress of future economic shocks. The liquid financial wealth of about 8 out of 10 Chileans is less than three times the national income poverty line. In 2015, the OECD ranked Chile as having the greatest economic vulnerability among its members (Balestra & Tonkin, 2018). The second is the weak social protection system, which is unable to work as a buffer to compensate for household economic insecurity. At present, the Chilean state and the households themselves share the financial risk of events such as one of their members becoming ill or unemployed through programmes such as unemployment insurance and public health insurance. However, these programmes, which are not universal, leave out a significant proportion of the population. In the case of unemployment insurance, those who have informal jobs, and in the case of health, those who do not belong to the lowest decile groups of the income distribution are not eligible. Therefore, these households rely on their own resources when their members are faced with unemployment or health problems.

5.2 Policy implications

Although the three welfare measures that I have proposed use different approaches (income persistence, vulnerability to poverty and economic insecurity) and two households surveys with different periods of analysis, the empirical findings are entirely consistent. In the case of Chile, economic insecurity is highly correlated with vulnerability to poverty. This finding contributes to a deeper understanding of the levels of well-being (in terms of stress and anxiety due to economic uncertainty) of those who have managed to get out of poverty but have a significant risk of falling into it again.

Also, the high levels of economic insecurity, even in the top decile groups show that high income mobility in Chile along the entire income distribution that is far from positive. There is no evidence that this dynamism is associated with an improvement in people's life prospects, i.e. social mobility, compared to a more rigid society. The high mobility of income in Chile presents a rather negative aspect, since a significant proportion of households are exposed to fluctuations in their income and lack minimum social protections that would help them to face situations of economic loss better.

Thus, the conclusions of my three empirical chapters have several implications for the design of social policies in countries such as Chile, in particular for policies related to monitoring social progress and improving the economic well-being of people from a social security perspective. Next, I present what I think are the most relevant elements to be considered in the design and implementation of social policies in Chile. To some extent, they are also applicable to other upper middle-income countries in the Global South which do not have data to make similar well-being economic measurements.

First, the evidence found in the second chapter on the importance of past income position to explain the current position of income distribution shows that supporting households to prevent them from falling into poverty is an effective social policy. Since being poor in one period causes an increase in the risk of being poor in future periods, social programmes that aim to reduce the persistence of poverty should include in their strategies ways to prevent people and households facing an adverse economic situation from falling into poverty again.

Second, the proposal to measure degrees of vulnerability to poverty developed in the third chapter contributes to the design of this type of policy. Vulnerability to poverty lines offer the government a concrete way to improve the targeting accuracy of programmes that seek to reduce absolute poverty. The distinction between poor households and households with varying degrees of vulnerability to poverty (high, moderate and low) should enable the design of programmes specific to each target group. The extension of social protection coverage to these new social groups should be accompanied by the comprehensive design of social security programmes that consider vulnerability to poverty as part of economic welfare measures to assess social progress. In this way, the approach to vulnerability to poverty that I have proposed should fulfil a dual role: targeting and monitoring these new social groups.

Third, in the multivariate analyses of the three chapters of this thesis, a change in the number of workers in the household is one of the most relevant variables for explaining income mobility, vulnerability to poverty and economic insecurity. This is not surprising since the participation of women in the Chilean labour market is particularly low. Faced with this panorama, family-oriented policies that encourage or protect women's participation in the labour market could be of great help. In this regard, policies such as the promotion of full-time nurseries go in this direction if they succeed in encouraging dual salaries in the household and minimise disruptions in women's careers.

Fourth, if economic insecurity is deemed a measure of economic well-being that can inform us about the level of development of countries, then Chile certainly has a lot of work ahead.[69] The fourth chapter showed that widespread economic insecurity affects a large part of the population. This finding has profound implications for the evaluation of the current social protection system and the design of a potential new social security system. Although Chile was classified as a high-income country a few years ago on the basis of its GDP per capita, the reality is that it still lacks a protection system that is capable of lessening households' anxiety and stress due to not being able to cope with an economic loss, illness, death, disability or an involuntary loss of employment.

In welfare states such as Chile, social policies aim to primarily support lower income households

[69] It is currently being debated whether or not the Human Development Index should include a dimension of economic stability of the population (Levy, 2019).

to meet their basic needs through small and highly focused cash transfer programmes.[70] This principle explains the non-coverage of the 40 per cent of the population who are at high risk of falling into poverty, let alone those with moderate vulnerability to poverty. It is worth remembering that in Chile, during the period studied, only 20 per cent of the population had a risk of falling into poverty of less than 4.6 per cent. This situation makes apparent the need to evaluate a coverage extension of the current social policy to minimise the economic instability of those who have managed to exit poverty.

Financing and designing new social policies that aim to grow public social security networks should be part of the social development agenda in the coming years. The need to protect this segment of the population – vulnerable to poverty or economic insecure – is starting to rise on the public agenda. The current government administration in Chile launched this year a programme called 'Protected Middle Class', which considers all households that are not income poor, thereby targeting the group of households that I have identified as vulnerable to poverty.[71] However, the policies and strategies of that programme so far are a combination of the already existing programmes, except for one new health insurance for catastrophic diseases; hence its effectiveness and impact still need to be tested.

The question that arises is whether an extension of the coverage of social programmes based on money transfers is sufficient to give economic stability to households that are vulnerable to poverty. It is known that a gradual growth in social security programmes is a feature of the economic progress of countries (Chetty & Looney, 2007). However, there are several reasons to go beyond an extension of the subsidiary state and to raise the idea of moving towards a welfare state where universal social insurance is the fundamental pillar (Levy, 2019).

From a social welfare point of view, there are three reasons for moving towards a universal social protection model. The first is the high proportion of households in Chile – and other countries in the Latin American region – that are vulnerable to poverty. The second is the fact that households support and value measures that reduce their exposure to adverse economic

[70] This social policy is based on two principles: i) ensuring efficiency in the use of resources that a small State can devote to social spending and ii) avoiding adverse incentives to work and the accumulation of assets by beneficiary households (Repetto, 2016). Although the second principle is a valid concern, studies that have sought to demonstrate this adverse effect have not been able to prove it (Alzúa, Cruces, & Ripani, 2013; Banerjee, Hanna, Kreindler, & Olken, 2017; Carneiro, Galasso, & Ginja, 2015).

[71] See details in the following link: https://clasemediaprotegida.gob.cl/sobre-clase-media-protegida

shocks compared to other social demands. A recent study in the United States shows that households value the achievement of economic stability more than ascending the income scale (Morduch and Schneider 2017). The third is the failure of the current social security system, both in Chile and in the region more widely, which does not adequately protect workers from the risks that affect the economic well-being of their families.[72] At present, the social security system provides low benefits to low-wage workers who face illnesses, dismissal or retirement and does not protect a large group of workers (e.g. informal workers and short-term workers). Considering Latin America as a whole, in 2016, only 46.9 per cent of the workforce were covered by these programmes (ILO, 2017).

One of the most important arguments against a universal security system relates to the increase in social spending, since it is funded through tax rises, which affect economic growth. Yet the evidence collected from the current system proves that a social security system based on the contributions that companies make to the social security of their workers can affect countries' productivity (OECD, 2019). Two arguments support this point. First, companies can change the nature and duration of the contracts they offer to their workers to avoid paying social security contributions. Although these contracts are not the most appropriate for their business model, companies might find it profitable to do so if cost savings compensate for productivity losses (Levy, 2019). Second, companies that do not pay social contributions to their workers often generate inefficiencies, since they limit their size to a scale lower than their optimum efficiency to avoid control (Dabla-Norris, Gradstein, & Inchauste, 2008).

Undoubtedly, improving a measure of economic well-being by resorting to other measures besides or instead of GDP, such as economic insecurity or vulnerability to poverty, represents a major challenge for several reasons. First, it means recognising the limits of the current social policy model, which focuses on the poorest and delivers limited social security and, is therefore unable to meet the need of economic stability required by the new social groups in the region. Secondly, it entails moving towards a new universal security model focused on reducing the vulnerability to poverty and economic insecurity of the population, and in some cases, mitigating inequalities in income distribution.

[72] Social insurance is financed mainly by companies, which are required by law to pay a social security contribution that is proportional to the wages paid to their workers. These contributions are channeled into a common fund that is used against various contingencies faced by the worker.

It is time for evaluating the implementation of universal social insurance in Global South countries, which would mean changing and redirecting the path followed until now towards one leading to greater social progress and well-being in these countries.

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