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Diverging Identification of the Poor: A Non-random Process. Chile 1992–2017

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Abstract
This paper investigates the degree of association in the identification of the poor between the standard monetary FGT measure and the Alkire-Foster Multidimensional Poverty Index. For this purpose, we use a measure of redundancy between the two poverty measures (R^0). In Chile, over the past 25 years, R^0 has declined at a rate of 1.5% per year. The decline is unimportant during the 1990s, a decade of rapid economic growth, while it is notable thereafter, in a period characterized by modest economic growth and the progressive introduction and deepening of social policies. The conditional correlation between socioeconomic and demographic characteristics with R^0 is examined at the province and household levels. After controlling for household non-eligibility across some of the indicators of the Multidimensional Poverty Index, we find that the divergence in the identification of the poor can be explained by improvements in education, increasing urbanization, and a reduction in the household size. Consequently, the divergent identification of the poor seems to be a real process, which is not randomly distributed across the population. On the basis of our results, we hypothesize that this divergence is a general phenomenon that tends to occur in countries undergoing demographic transition, urbanization, and progress in education. If so, and given the fact that poverty alleviation strategies are adopted partly on the basis of poverty statistics, the diverging identification of the poor might have distributive consequences for the poor themselves.

Keywords: Multidimensional poverty; monetary poverty; poor identification, measures of association.

JEL classification: D63, I32

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The Oxford Poverty and Human Development Initiative (OPHI) is a research centre within the Oxford Department of International Development, Queen Elizabeth House, at the University of Oxford. Led by Sabina Alkire, OPHI aspires to build and advance a more systematic methodological and economic framework for reducing multidimensional poverty, grounded in people's experiences and values.

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1. Introduction

The measurement of wellbeing and poverty have traditionally and prominently taken place in the utilitarian space.[1] Two types of utilitarian poverty measurements have become widely available. On the one hand, there is the direct measurement of consumption levels, the main appeal of which is that it is closely related to welfare or utility. It also has the advantage of being robust when changes in resources are transitory (see Hurd and Rohwedder, 2006; Mayer, 1993; Meyer and Sullivan, 2003; and Slesnick, 1993, 2001).[2] On the other hand, the lack of consumption data in many countries has opened the space to income-based poverty measures, in which poverty is defined as the inability to have at their disposal the income needed to reach a minimum level of consumption (Slesnick, 2001).[3]

Although the utilitarian view has played, and continues to play, a key role in the measurement of poverty, this approach is still subject to criticism. For instance, there is no convincing explanation of why all individuals need to have the same utility function. Moreover, fundamentally, what do we understand by utility and which function of social welfare should be used when assessing social outcome (i.e. the average utility principle or the total utility principle; see Sen and Williams, 1982).[4] This question has also been raised by Sen (1993), with reference to the *capability* framework (discussed later in this paper); he argues that: 'two persons with identical commodity holdings may have very unequal freedoms to lead the lives they value'.[5] Moreover, Sen (1970), discussing the impossibility theorem put forward by Arrow (1951), also argues that it is impossible to give intrinsic value to utility, and, at the same time, to endorse certain liberal values. Nozick (1974) believes that humans are in fact hardly utilitarian at all, as the mental state of

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1 Measures in the utilitarian space are a combination of welfarism, the principle of sum-ranking, and act consequentialism (Sen, 1979a). See Sen (2009) for an updated normative discussion on the space where poverty should be measured. See Baujard (2016) for a review of different utilitarian approaches to ethics and their influence in welfare economics.

2 Hurd and Rohwedder (2006) find that households use wealth to smooth/sustain consumption when income decreases. Consequently, an income-based measure of wellbeing could yield misleading results for many households, especially those which consist only of elderly members. One of the main disadvantages of consumption-based measures is that they require substantial amounts of resources and survey time.

3 There is evidence that different welfare distributions within the utilitarian space produce significantly different patterns in the identification of the poor. For instance, in cross-sectional perspective, Meyer and Sullivan (2012) find a significant mismatch in the identification of the poor for the US when using two income-based poverty measures (the official poverty measure and the supplementary poverty measure). Noll and Weick (2007) find the same pattern in Germany.

4 Moreover, the diversity of views regarding the concept of utility is important. One can favour the traditional view of utility (the 'hare's view'), with its emphasis on desires and their fulfilment, or the related choice-based understanding of utility by Harsanyi, or the interpretation by Mirrlees, who stated that utility directly describes wellbeing rather than a conception of it (Sen and Williams, 1982, p.64). On the other hand, there is the Benthamite utility conception, which relies on the concepts of pleasure and pain and is less acceptable now.

5 In words of Sen (1993): 'A disabled person with the same commodity bundle may be just as rich as another, but still lack the capability to move about freely and to achieve other functionings that are affected by that disability.'

happiness is not the only thing that people value.[6] In the same vein, considerations of agency, sympathy, and commitment imply that the assessment of choices and welfare encompass more considerations than the personal command over commodities (Laderchi, 1997).[7]

In a more applied context, the mainstream income-poverty tradition turns out to be problematic as resources are not a perfect proxy for inherently valuable states and activities (Sen, 1985, 1992, 1999). Markets often do not exist, or else they function imperfectly (Bourguignon and Chakravarty, 2003; Thorbecke, 2013). Moreover, there is the possibility that income is not broadly used in achieving a good quality of life (Atkinson, 1989; Townsend, 1979; Sen, 1983, 1984; Thorbecke, 2013) or expanding key capabilities (Laderchi et al., 2003; Sen, 1980). Consequently, the relationship between income and the ability to use it is crucial in developing countries, in which, at least for a portion of the population, having enough income does not guarantee the ability to purchase baskets of goods that are consistent with achieving a good quality of life (see Streeten, 1981).

Although there is a wide recognition that poverty is a multidimensional phenomenon, unidimensional utilitarian measures can account for the multidimensionality of poverty. In fact, income poverty represents a multidimensional concept in which the many dimension weights are based on relevant goods expenditures at the level of subsistence (Ravallion, 2011). However, given the aforementioned shortcomings of this approach, some alternative theoretical frameworks have been developed which emphasize the necessity to consider a plurality of values when assessing wellbeing (Baujard, 2016).[8] One of the most relevant and prominent alternative views is the capability approach, advocated by Sen (1985, 1992, 1999), which is based on two different concepts of freedom, process freedom, and opportunity freedom, and rejects the commodity space as the space in which freedom has to be judged (Sen, 1993).[9] Sen (1989) argues that the problem of assessing the quality of life consists in deciding which doings and beings (functionings) are valuable and also in evaluating the capability to function. Then, capability takes the form of a set of feasible n-tuples of functionings (Sen, 1985, 1992), and judgements about capability

6 Sen (1979b, 1980) claims that utilitarianism neglects any other values by reducing (social) wellbeing only to individual utility information (welfarism) representing a totally inadequate framework for analysing issues of distribution.

7 Other critiques of utilitarianism were made by Yaari and Bar-Hillel (1984) showing that the assessment of income distributions is based on needs rather than tastes or beliefs, and more recently, Hausman (2011) claims that individuals may behave against their own interest, which is a contradiction under the utilitarian framework. In a review of the historical deployment of the utilitarian ideas, Baujard (2016) considers all versions of utilitarianism as fundamentally welfarist.

8 For instance, approaches based on the importance of basic goods (Rawls, 1971), basic needs (Hicks and Streeten, 1979; Streeten, 1984; Stewart, 1985), social inclusion (Atkinson and Marlier, 2010), social protection (Barrientos, 2010, 2013), complex equality (Walzer, 1983), Ubuntu (Metz and Gaie, 2010), human rights (CONEVAL, 2010), livelihoods (Bowley and Burnett-Hurst, 1915), Buen Vivir (Hidalgo-Capitán et al., 2014), and the Catholic social teaching (Curran, 2002).

9 Following Drèze and Sen (2013, 43), the capability approach sees human progress, ultimately, as 'the progress of human freedom and capability to lead the kind of lives that people have reason to value'.

orderings take place in the multidimensional functioning space. In this context, poverty is ultimately a matter of capability deprivation (Drèze and Sen, 1995).[10]

Unlike the unidimensional approach to poverty measurement, multidimensional measures use joint deprivations across dimensions to determine the poverty status of the units. They do this by comparing deprivations across dimensions and seeking to respect the unit of measurement of each indicator. Venn diagrams, the dominance approach, statistical approaches, fuzzy sets, and the axiomatic approach are methods for measuring multidimensional poverty which are compatible with theoretical frameworks that consider a plurality of values when assessing wellbeing (see Alkire et al., 2015, for a detailed review of these multidimensional methods).

The most influential of the alternatives to the methods that adopt a social welfare function approach, concentrate on the counting of deprivations in the multiple dimensions of welfare. They have been particularly relevant to poverty alleviation policies and have been implemented in several contexts. Worth mentioning are UNICEF's Multiple Overlapping Deprivation Analysis for children (MODA), based on child rights, and the Multidimensional Poverty Index (MPI) which is being currently calculated in Chile. Both methods build upon the capability approach and follow the Alkire-Foster method (Alkire and Foster, 2007, 2011; de Neubourg et al., 2012).

If different frameworks for poverty measurement (namely, the utilitarian and capability approaches and their associated measurement technologies) produced similar identification outcomes, then there would be no point in asking how to identify the poor. During the 1990s, researchers tended to overlook this question, as influential literature claimed the existence of a close correlation between income achievements and non-income achievements (Anand and Ravallion, 1993; Pritchett and Summers, 1996; Anand and Bärninghausen, 2004). Such evidence motivated Devarajan et al. (2002) to conclude that rising incomes would be enough to achieve the Millennium Development Goals that weren't directly related to income. The lack of an even closer correlation between income and non-income achievements drew attention to the provision of public services, income poverty and income inequality (Sen, 1988; Anand and Ravallion, 1993; Lipton and Ravallion, 1995; McGillivray, 2005). However, and more recently, several studies have found that income poverty is in fact not strongly correlated with achieved functionings in key wellbeing indicators. For instance, Klasen (2000) found that, for the worst-off sections of society, there was only a weak correlation between expenditure poverty and a composite non-monetary deprivation index in South Africa. Whelan et al. (2004) showed that the level of poverty identification mismatch in Europe existed in

10 The capability approach does not impose restrictions on the nature of utility functions and the functional form for their aggregation. It allows the existence of public goods and externalities, and does not have any preconception about the transformation of resources into wellbeing.

both the cross-sectional and the longitudinal data structure. They suggested that (capability) deprivation was more affected by factors related to socioeconomic disadvantage, whereas income poverty was more influenced by income stream, but did not necessarily impact on living standards. Bourguignon et al. (2010) find no association between the alleviation of monetary poverty and a decrease in non-monetary deprivations, except for underweight (see Klasen, 2008). Wang et al. (2016), using the 2011 China Health and Nutrition survey, show that about two out of three multidimensionally poor individuals are non-income poor. In a developed country setting, Suppa (2016) compares Germany's official income-based poverty measurement with a multidimensional poverty index and finds a significant mismatch which is robust when stricter poverty lines are used. Alkire et al. (2017) indirectly show that multidimensional and income poverty trends may diverge for a group of 34 countries.

The current evidence on how the two different approaches identify the poor may have consequences for the design of poverty alleviation strategies as well as for their success. Addressing this issue, this paper makes three main contributions to the literature in this field. Firstly, it provides a 25-year overview of the association between two poverty measures in Chile representing complementary views on poverty (the utilitarian and the capability views).[11] The utilitarian approach bases its identification of the poor on the standard and officially recognized monetary poverty measure. The capability framework is usually applied using the Alkire-Foster method, and in this case, based on this method, we calculated a Historical Multidimensional Poverty Index (HMPI), to cover the 25 years between 1992 and 2017. The Alkire-Foster MPI was selected to assess the poverty overlap due to its widespread use worldwide, as well as its advantages over other multidimensional poverty measures.[12] In this transition country, in 2011 international dollars, the GDP per capita PPP rose from 10.438 in 1992 to 22.767 in 2017. To the best of our knowledge, the present paper is the longest trend comparison of the identification outcomes reached by such alternative approaches. Our second contribution is to exploit this time variability to provide evidence about the nature of the association between income poverty and multidimensional poverty, as well as its determinants, exploring the role of household composition and characteristics at different aggregation levels allowing the use of panel data. Thirdly, following Dotter and Klasen (2014), the non-eligibility of certain parts of the population in a subset of indicators of the MPI can be an important

11 In this transition country, in 2011 international dollars, the GDP per capita PPP rose from 10.438 in 1992 to 22.767 in 2017. Data from the World Development Indicators.

12 The MPI produces a multidimensional single summary measure of poverty (as shown in the Stigliz Sen Fitoussi Commission Report – Stiglitz et al., 2009) and is based on the counting approach (as recommended by the Atkinson Commission Report, 2017, rec 19). In contrast to the multidimensional alternatives, this index identifies the poor and provides a single cardinal index to assess the degree of poverty in the population. The fuzzy sets and axiomatic methods are exceptions to this rule, but, to the best of our knowledge, there are no current poverty estimates for Chile calculated using these methods.

empirical issue.[13] To address this issue, we provide 25 years of novel evidence on the impact of the non-eligible populations on the identification mismatch between the multidimensional and income-poverty measures.

The paper is organized as follows. The next section is devoted to presenting the data and analytical strategy for drawing up an HMPI for Chile for the period 1992–2017. For the same period, Section 3 describes the trends in poverty, and the evolution of the two-way poverty classifications of households, the poverty overlap trends and the shares of HMPI non-eligible populations. Section 4 outlines the results of our conditional analyses at the province and household levels. Finally, conclusions are presented in Section 5.

2. Data and Analytical Strategy for the Historical Multidimensional Poverty Index (HMPI)

2.1 The Data

This study employs data from all twelve waves of the Chilean household survey ('Encuesta Nacional de Caracterización Socio Económica' – CASEN) for the years 1992, 1994, 1996, 1998, 2000, 2003, 2006, 2009, 2011, 2013, 2015 and 2017. The twelve complex household surveys are representative at the country, regional and urban/rural levels of aggregation, covering the full population of the country, which was 13.5 million inhabitants in 1992 and 17.8 million inhabitants in 2017. All estimations in this study provide unbiased analytical standard errors that account for the complex survey design of CASEN.

2.2 Methodology to Identify the Monetarily Poor

To determine income poverty, the CASEN household survey relies on a food poverty line to estimate the poverty line (by scaling up the food poverty line). The two lines allow the identification of the severely income-poor and the income-poor, respectively. Although the identification methodology underwent some changes in 1996 and 2013, for the empirical purposes of comparing the identification of the poor using the two approaches (income and multidimensional), we consider the official identification of the income-poor as given and as officially reported by the CASEN household surveys.[14]

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13 Non-eligible households are those households lacking information on an indicator (e.g. school attendance, because it contains no school-age children) who are then assumed to be non-deprived in that dimension in the MPI. Over a period of 25 years, this issue is highly relevant, as demographic changes may confound the way in which we assess the identification overlap figures using different poverty measures.

14 It is impossible to reverse the methodology changes in 1996 and 2013. Regarding the urban/rural definition, before 1996, all localities with more than 2,000 inhabitants were considered urban. Thereafter, localities with 1,000 to 2,000 inhabitants were considered urban if at least 50% of the active population was employed in the secondary or tertiary economic sectors. Since 2013, the urban--rural divide has been disregarded when calculating the poverty line. From 1992 to 2011, the calorie intake threshold was set at 2,176 Kcal in urban areas and 2,236 Kcal in rural areas. Starting in 2013, the threshold was set at 2,000 Kcal per person. Finally, the Orshanksy coefficient rose from 2 to 2.42, in 2013, the year in which the food basket

2.3 Methodology to Identify the Multidimensionally Poor

A population of interest of n individuals $(i = \{1, \dots, n\})$ is measured across d achievement indicators $(j = \{1, \dots, d\})$. Each indicator j has a corresponding deprivation cutoff z_j. An individual is deprived in indicator j if his/her achievement in that indicator is below z_j (that is, $x_{ij} < z_j$). w_j is the weight of indicator j and the sum of the d indicators equals the unity. The deprivation matrix $g^0 = [g^0_{ij}]$ defines each entry as equal to w_j if $x_{ij} < z_j$ and 0 otherwise. The method does not impose the restriction of equal weights across dimensions. Here, higher weights imply a greater dimensional deprivation relative value. A deprivation score vector can be calculated for each person as $c_i = \sum_{j=1}^{d} g^0_{ij}$. c_i contains the sum of his/her weighted deprivations. The identification of the poor relies on a poverty cutoff denoted by k and on an identification function ρ_k. Then a multidimensionally poor individual has a deprivation score which is higher than k. That is, $\rho_k = 1$ if $c_i \geq k$ and $\rho_k = 0$ otherwise.

The MPI requires deprivations of those already identified as multidimensionally poor to be aggregated across dimensions, while neglecting the deprivations of those deemed non-poor (with $c_i < k$). The censored deprivation score vector $c_i(k)$ preserves the entries of c_i when $c_i > k$ and takes the values of zero for all individuals when $c_i < k$. The multiplication of each row in g^0 by identification function ρ_k corresponds to the censored deprivation matrix $g^0(k)$, in which all the entries of g^0 are made equal to zero for those non-poor individuals. In the aggregation step, the MPI (or M_0) is obtained by the multiplication of the mean $g^0(k)$ and the number of deprivations d. Analytically, $M_0 = \mu(g^0(k))$ is the MPI, which is the mean of the censored deprivation matrix. Note that M_0 is also the multidimensional headcount ratio (H) adjusted by the deprivation intensity (A) suffered by the poor, or $M_0 = H \times A$ (see Alkire and Foster, 2011, and Alkire et al., 2015 for more details related to the Alkire-Foster method).

This counting methodology employs a dual cutoff approach to the identification of the poor. Firstly, it considers dimension-specific cutoffs (z), fulfilling the requirement of having deprivation cutoffs for each dimension of an individual's wellbeing (see Bourguignon and Chakravarty, 2003). Then, it aggregates to identify the poor on the basis of the count of weighted deprivations, given a poverty threshold (k). The aggregation step does not lose information on dimension-specific deficits. The dual cutoff approach is a

was updated, economies of scale were introduced ($n^{0.7}$), and incomes ware no longer adjusted to national accounts. Finally, there were more sources for imputing rental income (see CASEN, 2013).

general framework when identifying the poor, in which the intersection approach (deprivation in all dimensions, $k = d$) as well as the union approach (deprivation in any dimension $k = 1$) are special cases.[15]

Two important features of the MPI are the subgroup's decomposability (using population share as weights) and the possibility of breaking down the index by dimension (and by indicator within the dimensions).[16] Both features together allow us to understand the poverty patterns across population subgroups.[17]

Although the MPI has desirable features, it requires researchers to take the responsibility for their decisions regarding dimensions, weights and cutoffs. There are also some empirical issues related to its formulation. For instance, it neglects inequality amongst the poor, while it unequally treats deprivations below the second threshold as substitutes and above this threshold as complements (Rippin, 2012; Dotter and Klasen, 2014). The strict separation between identification and aggregation, is less compelling than in the case of unidimensional poverty measurement, as the deprivation counting of poor households can be already seen as a form of aggregation. In the same way, it is possible to see the identification process not as a dichotomy but as a question of degree (Rippin, 2012; Dotter and Klasen, 2014). While the dual cutoff approach does not rule out the possibility of potential trade-offs between deprivations (Ravallion, 2011, 2012), it has empirical advantages over the intersection and union approaches when the number of indicators is large enough. It can be fed with an unlimited number of indicators, thereby supporting a much broader definition of poverty, including culturally specific concepts of poverty, which also makes it less sensitive to misclassifications and mismeasurement (Dotter and Klasen, 2014).

2.4 A Historical Multidimensional Poverty Index for Chile 1992–2017

In the construction of an HMPI for 1992–2017, we adopt the same dimensions, dimension-specific cutoffs (z), and weights (w), and the same poverty cutoff (k) that the Ministry of Social Planning (Ministerio de Desarrollo Social) used in its official estimation of multidimensional poverty in 2013. The disadvantage of doing this is that it reduces the amount of information necessary to create the achievement matrix X while reproducing the ineligibility problem across indicators. However, the advantage of this approach is that it

15 One advantage of the MPI over MODA is that it does not rely on the union approach and consequently it is more flexible when identifying the poor in a context of numerous dimensions.

16 The subgroup's contribution to overall poverty can be calculated as the subgroup poverty level divided by the overall poverty level. Similarly, the percentage contribution of each dimension to total poverty corresponds to the weighted censored headcount ratio divided by the overall poverty level as the MPI is equal to the weighted average of the censored headcount ratios (the average of the mean of the columns of the censored deprivation matrix).

17 Alkire and Seth (2011), in a cross-country comparison, show that while the Indian region of Madhya Pradesh and the Democratic Republic of the Congo share the same MPI (0.39), the dimensional contributions strongly differ between both populations. For instance, the contribution of nutrition to overall poverty in Madhya Pradesh reaches 21.6% while in the Democratic Republic of Congo it reaches only 7.2%.

makes achievements strictly comparable for the whole period 1992–2017 and thus, normative judgements about our Chilean HMPI can be avoided.[18]

The 2013 estimation of the Chilean MPI relies on the four dimensions of education, health, employment and social protection, and living standards. Each dimension consists of three indicators. The weights structure attaches equal importance to all dimensions, and within each dimension, it is assumed that each indicator is also equally important. Consequently, each dimension has a weight of 0.25 and each indicator within each dimension, has $\left(w_j = \frac{0.25}{3}\right)$ as its weight. Finally, the poverty cutoff was set at $k = 0.25$, implying that if a household is deprived in 3 out of 12 indicators, its members are classified as multidimensionally poor.[19]

Table 1 shows the structure of the index, including dimensions, definitions of deprivation by indicators, and weights as used here. It also includes the definition departures of the indicator's definitions from the official 2013 MPI. This guarantees a time-consistent estimation of the HMPI for the period 1992–2017.

Table 1. Historical Multidimensional Poverty Index (HMPI) for Chile 1992–2017: Dimensions, deprivation indicators, weights, and definition departures from the official 2013 MPI

Dimensions	**Deprivation indicators (People who live in households with the following characteristics)**	**Weights (%)**
	Education	**25**
Children's school attendance	Households where there is at least one child or adolescent aged 4– 18 not attending school and who has not yet graduated (after completing 12 years of schooling). **Departure from the 2013 indicator definition:** The information regarding school absence for an extended period (permanent absence) for those aged 4–26, was excluded because of a lack of information in this variable across the 1992, 1994, 1996, 1998, 2000, 2003 CASEN waves.	25/3
Schooling gap	Households where there is at least one person aged 21 or below in primary/secondary education who is at least two years below his/her corresponding school level. **There is no departure from the original 2013 MPI definition.**	25/3
Adult schooling achievement	Households where there is at least one person whose level of education falls below the legal minimum for their cohort. These are as follows: those born between 1920 and 1929: 4 years of schooling; between 1930 and 1965: 6 years of schooling; and between 1966 to 2002: 8 years of schooling. From 2003 onwards, the legal minimum was 12 years of schooling. **There is no departure from the original 2013 MPI definition.**	25/3
	Health	**25**
Nutrition	Households where there is at least one child aged 0–5 who is undernourished, at risk of undernourishment or obese. **Departure from the 2013 indicator definition:** in 1992, 1994, 1996, 1998, 2000, 2003, and 2006, the key variable refers to children aged 0–5, while in the rest of the surveys,	25/3

[18] To assess the normative definitions is beyond the scope of this study, which is focused on the matches and mismatches in identifying the poor using two officially accepted and implemented estimation methodologies.

[19] For robustness purposes, we use the alternative poverty cutoffs $\left(k = \frac{4}{12}\right)$ and $\left(k = \frac{5}{12}\right)$ to study the matches and mismatches between the two identification approaches.

	it refers to children aged 0–6. Thus, children aged 0–5 are the common denominator.	
Insurance	Households where there is at least one person who does not have any health insurance, either public or private (including complementary insurance). **Departure from the 2013 indicator definition:** the information on complementary health insurance is excluded because in 1992, 1994, 1996, 1998, 2000, 2003, 2006, 2009, CASEN does not provide such information.	25/3
Access	Households where there is at least one woman aged 21 or above who has not completed a pap test during the past 3 years. **Departure from the 2013 indicator definition:** the original 2013 definition considers households to be deprived if there is at least one household member who suffered a health problem in the last 3 months and did not receive treatment, or if in the last 12 months he/she has been receiving health treatment but this has not been covered by the health system's warranty (AUGE-GES). This complex definition is impossible to reproduce, as the relevant programmes were created in 2005 and the recall time has changed continually since 2000. The solution was to select the pap test indicator for this dimension, as it can be consistently estimated from 1992 to 2017.	25/3
	Employment and social protection	**25**
Employment	Households with at least one member aged 18 or above being unemployed and not attending school. **There is no departure from the original 2013 MPI definition.**	25/3
Pension system contribution	Households with at least one working member aged 15 or above who is not contributing to the pension system and has not had any tertiary education. **There is no departure from the original 2013 MPI definition.**	25/3
Pension or retirement income	Households with at least one female member aged 60 or above, or a male member aged 65 or above, who is not receiving a pension or any retirement income. **There is no departure from the original 2013 MPI definition.**	25/3
	Living standards	**25**
Overcrowding	Households in which the average number of household members sharing a room is higher than 2.5. **There is no departure from the original 2013 MPI definition.**	25/3
Housing materials	A house whose floor, roof, or walls in bad shape, or the house is made of unsound materials. **There is no departure from the original 2013 MPI definition.**	25/3
Basic services: Drinking water and sewage waste	A house without interior piped water supply (urban areas) or access to safe water supply (rural areas), or lacking a WC or septic tank (rural and urban areas). **There is no departure from the original 2013 MPI definition.**	25/3

Source: Ministry of Social Planning, Chile.

2.5 Measures of Overlap between the Income and Multidimensional Poverty Approaches

To assess the matches and mismatches between the monetary and multidimensional approaches to the identification of the poor, we use a measure of association or redundancy dubbed overlap R^0 measure (see Alkire et al., 2015). The way this is calculated is illustrated in the two-way contingency table below (Table 2). Entries $\mathbb{P}_{00}^{jj'}$ and $\mathbb{P}_{11}^{jj'}$ show the percentages of people being classified simultaneously as non-poor and poor by both methods, respectively. $\mathbb{P}_{10}^{jj'}$ and $\mathbb{P}_{01}^{jj'}$ show the percentages of the population classified as monetarily poor but not multidimensionally poor and vice versa, respectively. The marginal distributions are $\mathbb{P}^{\cdot j}_{1+}$ for the monetarily poor, $\mathbb{P}^{\cdot j}_{0+}$ for the monetarily non-poor, $\mathbb{P}^{\cdot j'}_{+1}$ for the multidimensionally poor and $\mathbb{P}^{\cdot j'}_{+0}$ for the multidimensionally non-poor.

Table 2. Two-way contingency table for monetary and multidimensional poverty

		Multidimensional poverty (j')		
		Non-poor	**Poor**	**Total**
Monetary poverty (j)	Non-poor	$\mathbb{P}^{jj'}_{00}$	$\mathbb{P}^{jj'}_{01}$	$\mathbb{P}^{\cdot j}_{0+}$
	Poor	$\mathbb{P}^{jj'}_{10}$	$\mathbb{P}^{jj'}_{11}$	$\mathbb{P}^{\cdot j}_{1+}$
	Total	$\mathbb{P}^{\cdot j'}_{+0}$	$\mathbb{P}^{\cdot j'}_{+1}$	**1**

Source: Alkire et al. (2015).

If poverty measures are not independent, and at least one of the headcount ratios is different from zero, this measure depicts the poverty identification matches as a proportion of the minimum of the marginal poverty rates.

$$R^0 = \frac{\mathbb{P}^{jj'}_{11}}{min[\mathbb{P}^{\cdot j'}_{+1}, \mathbb{P}^{\cdot j}_{1+}]} \tag{1}$$

By construction, R^0 takes values from zero to the unity. For instance, if the monetary poverty headcount ratio is 10% and the multidimensional poverty headcount ratio is 22%, R^0= 0.4 implies that 40% of the income-poor population is simultaneously multidimensionally poor.[20]

3. Poverty Trends, Poverty Overlap Trends and HMPI Household Non-eligibility

3.1 Poverty Trends

Figure 1 depicts the headcount poverty trends in Chile over the period 1992–2017. The poverty trends calculated using our HMPI tally with the official MPI estimates for the period in which both multidimensional indices are available (2013–2017).[21] The stagnation of the multidimensional poverty headcount between 2015 and 2017 drew public attention, owing to the fact that in the same period, income poverty showed an impressive reduction from 11.7% to 8.6%. Such strong divergence in terms of poverty headcounts derailed the public debate as it was not clear how to interpret such dynamics or what index

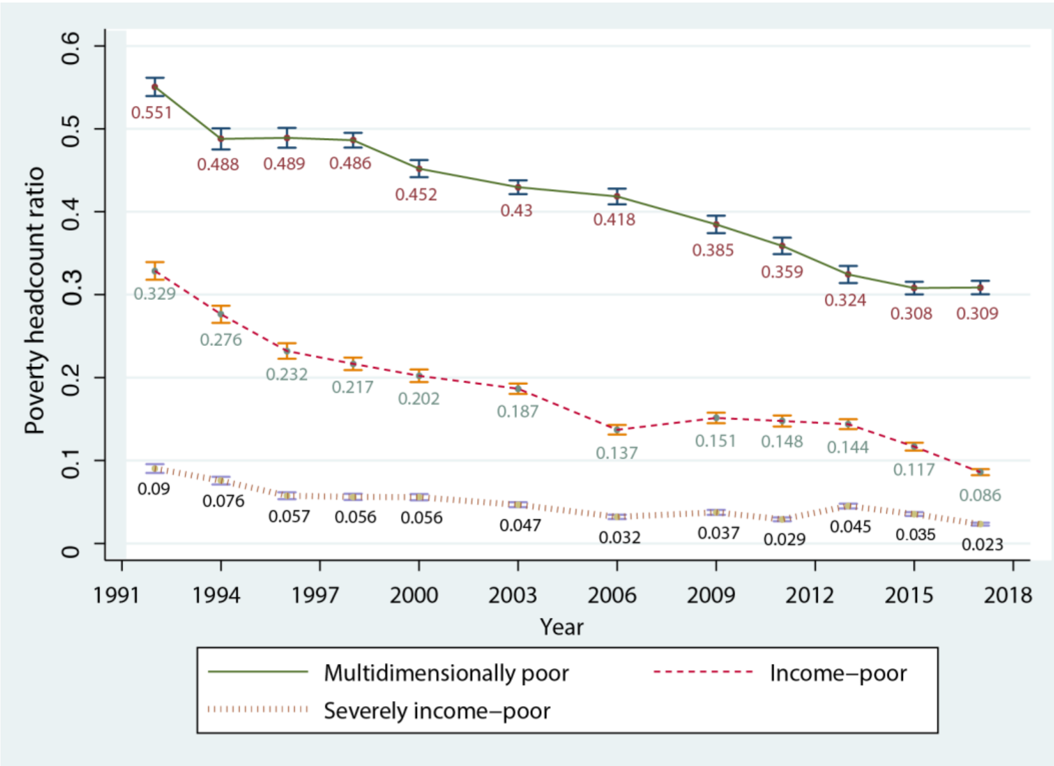
20 An alternative interpretation of this overlap measure is that 60% of those who are income-poor are classified as non-multidimensionally poor.

21 At the country level, multidimensional poverty declined between 2013 and 2015 and stagnated between 2015 and 2017.

should be considered for the purposes of social planning.[22] It is worth nothing that both official poverty measures are published by the government on the same day.

Using the calculation method shown in the two-way contingency table (Table 2), Figure 2 shows the how the shares of the population have fared according to their income and multidimensional poverty status. The share of population, which is unambiguously non-poor increased steadily after 1992 and even faster after 2011. By contrast, the share of population classified as unambiguously poor decreased steadily over the same period but at a declining rate. Interestingly, the share of population whose poverty status is ambiguous seems to follow more stable trends, with a combined reduction of about ten percentage point over the whole 1992–2017 period.

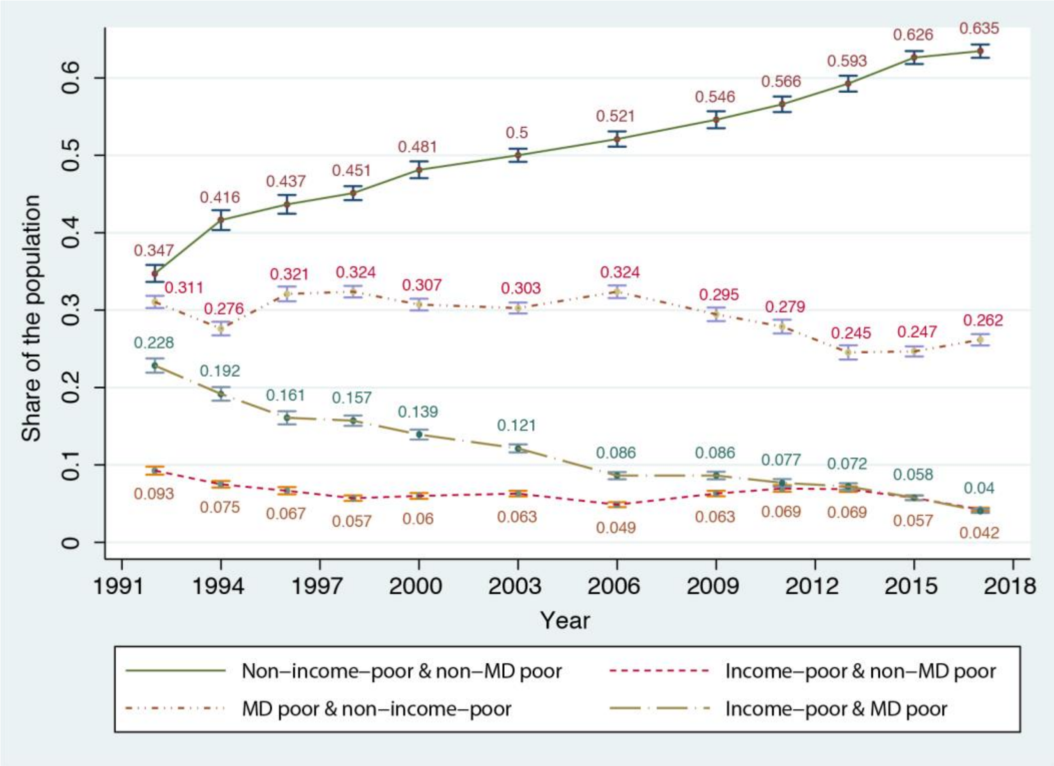
Figure 1. Poverty headcount ratios, Chile, 1992–2017



Note: 95% confidence intervals.
Source: Own elaboration based on CASEN household surveys.

22 See 'The 'Politicization of the CASEN survey', by Ignacia Fernández, Executive Director of the Latin American Center for Rural Development (Rismip), https://www.elmostrador.cl/noticias/opinion/2018/08/23/la-politizacion-de-la-casen/.

Figure 2. Two-way poverty classification trends, 1992–2017



Note: MD = multidimensionally.
Source: Own elaboration based on CASEN household surveys.

3.2 Household Characteristics and Demographics and the Two-Way Poverty Status

In this subsection, we look at the characteristics of households by their poverty classification. Table 3 presents summary information on the household characteristics and demographics of those households classified as poor, both ambiguously and unambiguously. For the four cohorts presented in Table 3, a greater gap in mean characteristics and demographics is observed amongst the income-poor households, depending on their multidimensional poverty status. The socio-demographic gaps between the two groups of multidimensionally poor households (the income-poor and the non-income-poor) are less pronounced. In other words, amongst the same group of (ambiguously and unambiguously poor) households, we observe a higher unconditional correlation between multidimensional poverty and household characteristics and demographics. Then, the multidimensional poverty approach seems to identify households with a priori more adverse non-income circumstances. This finding is highly relevant for the design of poverty alleviation policies, as it shows that targeting programmes solely at income-poor households can leave behind the worst-off families while inadvertently focusing on the less deprived ones.

Table 3. Characteristics of households according to their poverty classification, 1992, 2000, 2009, and 2017

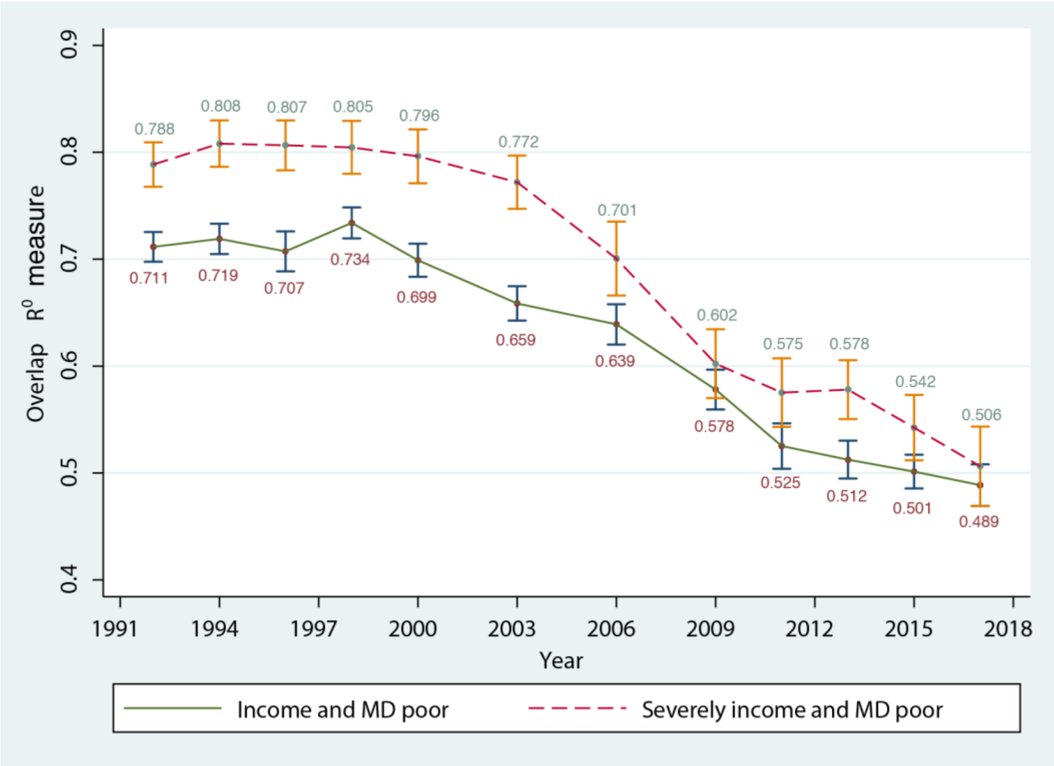
Household characteristics and demographics	Multidimensionally poor								Income-poor and multidimensionally non-poor			
	Income-poor				Income non-poor							
	Mean	Lin. Std. Err.	[95% Conf. Interval]		Mean	Lin. Std. Err.	[95% Conf. Interval]		Mean	Lin. Std. Err.	[95% Conf. Interval]	
1992												
Household size	5.73	0.05	5.64	5.83	5.09	0.04	5.01	5.16	4.60	0.05	4.51	4.69
Adults' education (avg. years)	7.15	0.05	7.06	7.24	7.89	0.05	7.80	7.99	9.62	0.06	9.50	9.74
Years of educ. of HH head	6.15	0.06	6.03	6.26	6.65	0.07	6.52	6.78	9.23	0.09	9.06	9.40
HH head is single	0.20	0.01	0.19	0.22	0.23	0.01	0.22	0.24	0.18	0.01	0.16	0.20
HH head is female	0.18	0.01	0.17	0.20	0.19	0.01	0.18	0.20	0.16	0.01	0.14	0.17
HH head is elderly	0.17	0.01	0.16	0.18	0.31	0.01	0.30	0.33	0.08	0.01	0.07	0.09
2000												
Household size	5.86	0.05	5.76	5.97	5.09	0.03	5.02	5.16	4.69	0.05	4.59	4.78
Adults' education (avg. years)	7.65	0.05	7.56	7.74	8.45	0.04	8.36	8.54	9.79	0.07	9.66	9.93
Years of educ. of HH head	6.56	0.07	6.43	6.69	7.11	0.06	6.99	7.23	9.32	0.10	9.12	9.52
HH head is single	0.22	0.01	0.21	0.24	0.23	0.01	0.22	0.25	0.17	0.01	0.15	0.19
HH head is female	0.24	0.01	0.22	0.26	0.22	0.01	0.21	0.23	0.18	0.01	0.16	0.20
HH head is elderly	0.16	0.01	0.14	0.17	0.33	0.01	0.32	0.35	0.06	0.01	0.05	0.07
2009												
Household size	5.54	0.08	5.38	5.70	4.93	0.03	4.87	5.00	4.31	0.05	4.22	4.40
Adults' education (avg. years)	8.30	0.06	8.19	8.41	8.95	0.05	8.85	9.05	10.15	0.07	10.02	10.29
Years of educ. of HH head	7.01	0.09	6.84	7.19	7.70	0.08	7.55	7.86	9.69	0.09	9.51	9.86
HH head is single	0.34	0.01	0.31	0.36	0.28	0.01	0.27	0.29	0.39	0.01	0.36	0.41
HH head is female	0.39	0.01	0.36	0.41	0.31	0.01	0.30	0.32	0.40	0.01	0.38	0.43
HH head is elderly	0.25	0.01	0.23	0.27	0.38	0.01	0.36	0.39	0.15	0.01	0.14	0.17
2017												
Household size	4.61	0.06	4.49	4.73	4.56	0.03	4.50	4.63	3.84	0.04	3.77	3.91
Adults' education (avg. years)	8.67	0.07	8.53	8.81	9.58	0.04	9.50	9.66	10.74	0.07	10.61	10.88
Years of educ. of HH head	7.73	0.11	7.51	7.94	8.47	0.06	8.35	8.59	10.31	0.09	10.13	10.48
HH head is single	0.37	0.01	0.35	0.40	0.32	0.01	0.31	0.33	0.46	0.01	0.43	0.49
HH head is female	0.46	0.01	0.43	0.49	0.41	0.01	0.40	0.43	0.52	0.01	0.50	0.54
HH head is elderly	0.24	0.01	0.22	0.26	0.44	0.01	0.43	0.45	0.14	0.01	0.13	0.15

Source: Own elaboration based on CASEN household surveys.

3.3 Poverty Overlap: Multidimensional and Income poverty

While informative, the dynamics in Figure 2, do not say anything about whether those households identified as poor or non-poor by each method are to the same ones or not. To investigate this, Figure 3 shows the trends of the overlap R^0 measures (multidimensional poverty against income and severe income poverty).[23]

Figure 3: Overlap R^0 trends, Chile, 1992–2017



Note: 95% confidence intervals. MD = multidimensionally.
Source: Own elaboration based on CASEN household surveys.

During the 1990s, a decade characterized by high rates of market-driven economic growth and declining rates of income poverty, the level of overlap between the two poverty identification methods remained almost unchanged. From 2000 onwards, a period characterized by slower economic growth but accompanied by more comprehensive social policies, the overlap declined unambiguously and independently of the considered poverty measure.

As the monetary poverty headcount ratio is strictly smaller than the multidimensional headcount over the whole period 1992–2017, the overlap R^0 measure represents the percentage of those monetarily poor

[23] For robustness purposes, in the appendix Table 1.A, we report the Cramer's V coefficient of association. It is defined as the product of the matches minus the product of the mismatches divided by the square root of the product of the marginal distributions. We conclude that the declining association is robust to the selection of the association coefficient.

people who are at the same time multidimensionally poor. From 1992 to 2000, the overlap remains unchanged at the same level, around 70%. This implies that about 70% of those deemed monetarily poor were also multidimensionally poor. That is, about 30% of those deemed monetarily poor were not multidimensionally poor. The same dynamic is true for the overlap between multidimensional poverty and severe income poverty, at a level of about 80%.

The pattern changes dramatically during the 2000s, as already in 2009, the same redundancy measures reached 58% (monetary and multidimensional poverty) and 61% (severe monetary and multidimensional poverty), respectively. The poverty overlap reduction continued until 2017, a year in which only about 49% of both the income-poor and the severely income-poor were simultaneously identified as multidimensionally poor.

To address the concern that the poverty overlap trends in Figure 3 can be affected by compositional changes within the population identified as income-poor, we raise the income poverty line to match the monetary poverty headcount ratio to the multidimensional poverty headcount ratio. We do this in Table 4, dividing the whole period in three sub-periods, namely 1992–2000, 2000–09 and 2009–17.[24] While the overlap levels are somewhat different, the declining trend holds.

Table 4. Poverty overlap trends and annualized rates of growth, Chile, 1992–2017

	Overlap R^0 measure (standard errors in parenthesis)				Annualized rate of growth		
Year/Period	1992	2000	2009	2017	1992–2000	2000–09	2009–17
Overlap R^0, MD and income poverty	0.711 (0.0071)	0.699 (0.0079)	0.578 (0.0095)	0.489 (0.0099)	-0.213%	-2.328%***	-2.112%***
Overlap R^0, MD and severe income poverty	0.788 (0.0106)	0.796 (0.0129)	0.602 (0.0164)	0.506 (0.0189)	0.126%	-3.056%***	-2.148%***
Overlap R^0, MD and adjusted income poverty	0.673 (0.0060)	0.623 (0.0061)	0.518 (0.0067)	0.439 (0.0058)	-0.960%***	-2.030%***	-2.047%***

Note: *** Significance at 1% level; MD = multidimensionally.
Source: Own calculations based on CASEN household survey.

In order to explore whether the observed trend in the overlap R^0 measure between income and multidimensional poverty varies across population subgroups, Table 5 shows its annualized relative rate

24 Such partition is arbitrary but consistent with the observed overlap trends as well as with the structural changes that have happened to the Chilean economy over the past 25 years. Table 2.A shows the same information for the overlap R^0 measure between severe income poverty and multidimensional poverty.

Table 5. Annualized relative rate of change in overlap R^0 measure between income-poor and multidimensionally poor households, Chile, 1992–2017

Aggregation level	Whole period 1992–2017	Washington consensus period 1992–2000	Period of slowing growth and the introduction of social policies 2000–09	Period of slow growth and more comprehensive social policies 2009–17
Country level	-1.49	−0.21	-2.09	-2.07
		Geographic location		
Urban areas	-1.68	-0.22	-1.93	-2.84
Rural areas	-1.39	-0.02	-1.77	-2.32
Region I	0.27	3.38	-3.28	1.29
Region II	-1.36	-0.80	-0.17	-3.22
Region III	-0.42	-0.15	-0.63	-0.44
Region IV	-1.86	-1.01	-1.65	-2.95
Region V	-1.25	1.09	-1.78	-2.95
Region VI	-2.33	-0.36	-3.07	-3.44
Region VII	-2.18	-1.09	-4.06	-1.13
Region VIII	-2.53	-1.60	-2.17	-3.85
Region IX	-0.88	-0.15	-2.06	-0.28
Region X	-1.57	-0.65	-0.70	-3.45
Region XI	-0.69	-1.03	-2.04	1.21
Region XII	-1.17	0.50	0.22	-4.33
Region XIII (metropolitan)	-1.10	0.31	-2.05	-1.42
		Household type		
HH head is not elderly	-1.63	-0.25	-2.29	-2.24
HH head is elderly	-1.21	0.23	-2.41	-1.28
One-person HH	-1.69	0.89	-7.49	2.58
Two-person HH	-1.62	0.60	-5.22	0.32
HH consists of three or more people	-1.38	-0.25	-1.82	-2.00
		Average education amongst adult household members		
Less than 8 years	-0.78	-0.21	-1.14	-0.92
8 years or more	-1.13	0.57	-1.80	-2.05

Source: Ownelaboration based on CASEN household survey.

of change for a set of population subgroups based on household composition and its spatial distribution.[25] We find that the declining association of the poverty identification measures happens in all population subgroups for the whole period 1992–2017, being more pronounced from 2000 onwards. Although some heterogeneity is observed during the 1990s, the evidence supports the idea that the declining poverty overlap is a general dynamic, with speeds of reduction varying somewhat across population subgroups.

3.4 Multidimensional Poverty and Non-Eligible Households

A significant empirical concern relates to fact that the poverty overlap can be affected by the presence of non-eligible households within some HMPI indicators (see Dotter and Klasen, 2014). The official MPI is built upon 12 indicators and, in 8 of them, there are households which are by default treated as non-deprived because they have no eligible members. The household non-eligibility across HMPI indicators varies according to changes in the demographic structure of the population. For instance, Table 6 shows that the non-eligible population in the nutrition indicator, that is the proportion of households without children aged 0–5, increases from 49.8% in 1992 to 71.3% in 2017. Consequently, the likelihood of classifying a random household as deprived in this dimension has decreased sharply over the past 25 years. Changes in the nutrition indicator not only convey information on improved nutrition but also on the increasing non-eligibility in this indicator. An inverse demographic shift affects the non-eligibility in the indicator of pension benefit. As the population gets older, a higher proportion of eligible households are expected. In the mid-1990s about 75% of the population lived in ineligible households for this indicator. The figure reached almost 65% in 2017.

A second related issue is that the non-eligibility can happen in many indicators simultaneously. For example, households with no members aged 18 or below are by default classified as non-deprived in the school attendance, schooling gap and nutrition indicators. The eligibility problem gets even worse for households that additionally have no elderly members, as they are non-deprived in one-third of the indicators. In fact, the median household is ineligible in two indicators, and the population share which is ineligible in three or more indicators has increased steadily since 2000. Surprisingly, a modest 3% to 4% of the population is fully eligible and consequently, our analysis needs to control for the fact that the declining poverty overlap may reflect demographic changes rather than diverging poverty identification processes.

25 Currently, the country is divided into 16 regions. However, to maintain the time comparability, we based the whole study on the 13 administrative regions that existed in 1992. The population subgroups under consideration are the zone (urban/rural), the 13 old administrative regions, whether the household head is elderly, the size of the household, and the education profile of the adult household members.

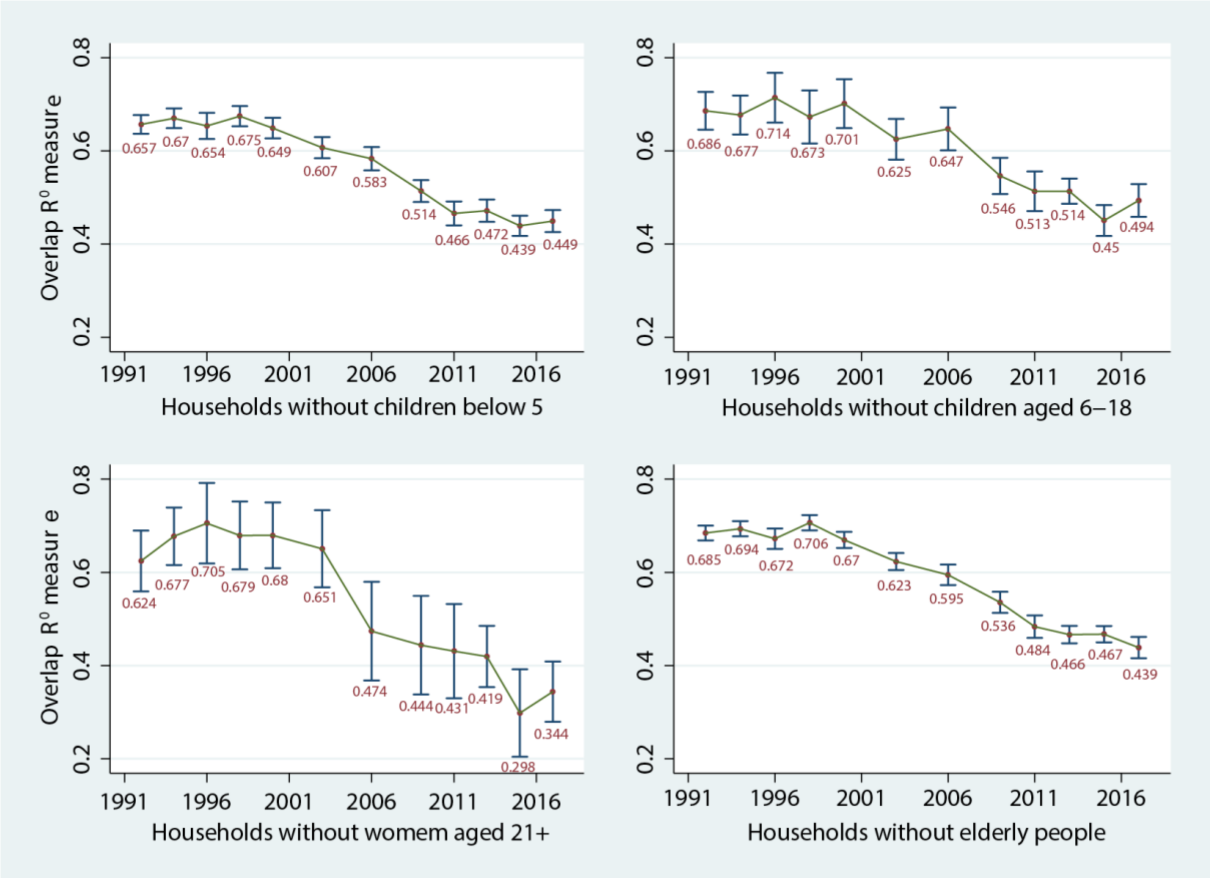
Table 6: Share of non-eligible population, by indicator and accumulated indicator non-eligibility, Chile, 1992–2017 (%)

		Year											
	HMPI indicator	1992	1994	1996	1998	2000	2003	2006	2009	2011	2013	2015	2017
Share of population not eligible, by indicator	Children's school attendance	44.5	28.2	26.8	26.8	26.6	28.2	29.8	34.4	37.4	39.4	40.9	44.9
	Schooling gap	48.7	39.7	36.6	36.1	35.3	35.7	37.7	41.7	45.3	47.3	48.3	51.7
	Adult schooling achievement	2.33	0.06	0.01	0.01	0.02	0.03	0.02	0.01	0.01	0.01	0.02	0.02
	Nutrition	49.8	55.9	57.0	58.5	60.0	63.0	65.3	67.3	66.8	67.6	68.4	71.3
	Health insurance	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
	Access to healthcare	17.5	3.3	2.6	2.8	2.8	2.9	3.0	3.5	3.6	3.9	4.0	4.5
	Employment	24.8	6.6	5.8	5.9	6.1	6.1	6.3	8.1	8.6	8.8	8.6	9.1
	Pension system contribution	27.3	8.6	7.6	9.5	9.8	9.1	8.2	10.8	10.6	10.7	10.7	11.4
	Pension or retirement income	42.6	75.4	75.4	75.9	75.2	75.0	71.3	69.2	68.6	68.4	67.2	65.4
	Overcrowding	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
	Housing materials	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
	Basic services	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Share of population not eligible (N is the number of indicators)	N=0	3.7	3.9	3.9	3.7	3.8	3.4	4.0	3.6	3.3	3.5	3.4	3.2
	N=1	29.5	28.2	29.9	29.0	28.6	27.7	27.4	25.0	24.1	23.0	23.0	20.5
	N=2	35.6	35.7	36.0	36.4	36.6	37.2	35.5	33.1	31.7	30.6	29.8	28.5
	N=3	16.6	17.0	16.3	15.9	16.0	15.4	16.1	18.0	19.5	19.7	20.2	21.7
	N=4	9.9	10.0	9.4	10.1	9.8	10.9	11.4	12.8	13.5	14.5	14.8	16.2
	N=5+	4.7	5.2	4.5	5.0	5.2	5.4	5.6	7.4	7.9	8.7	8.9	9.9

Source: Own elaboration based on CASEN household surveys.

To assess the degree to which this measurement constraint affects the overlapping trend between the poverty measures, we follow two complementary procedures. In the first one, we divide the population according to its demographic composition, which means that some households are non-eligible in certain indicators. Then, we calculate the overlap R^0 measure for the same type of non-eligible household over time.

Figure 4. Multidimensional and income-poverty overlap R^0 trends for groups of non-eligible households, Chile, 1992–2017



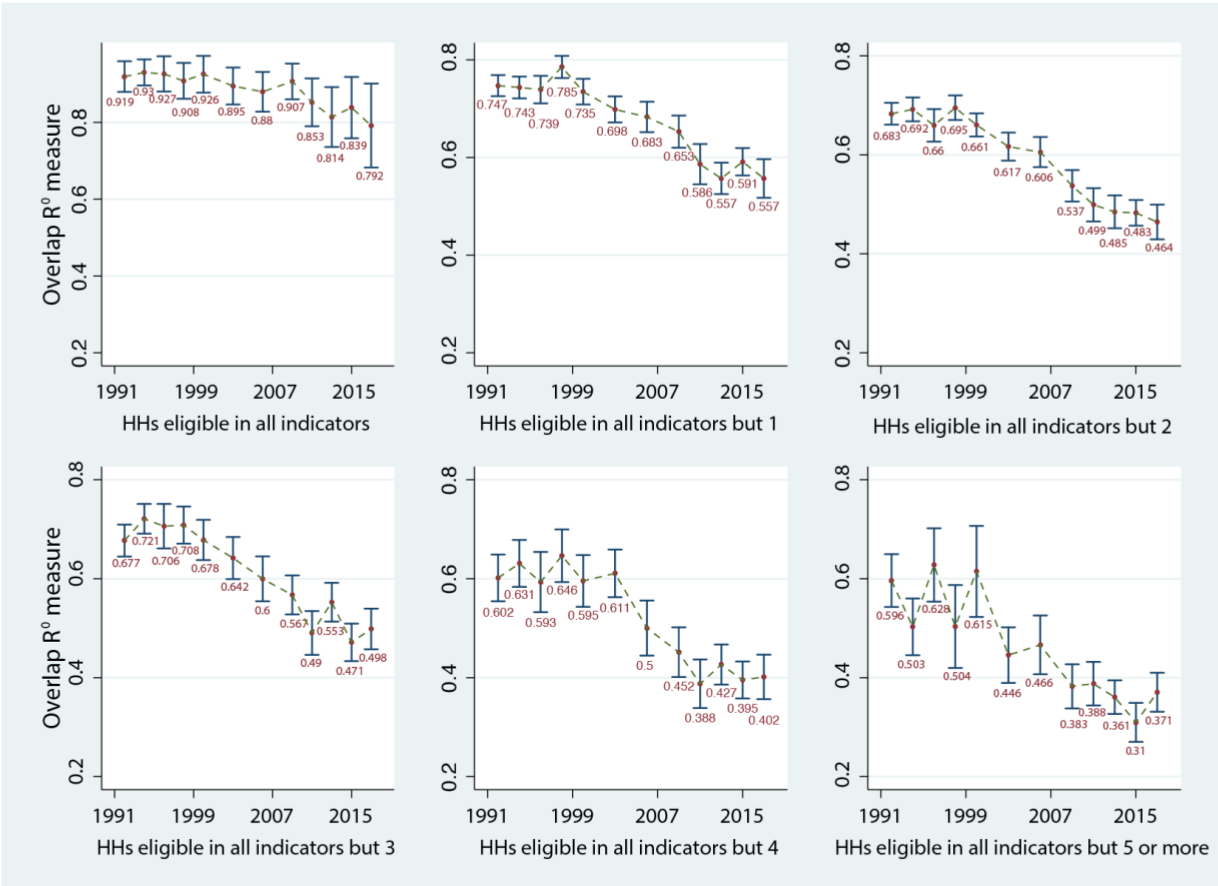
Note: 95% confidence intervals.
Source: Own elaboration based on CASEN household surveys.

Figure 4 shows overlap R^0 measures between income and multidimensional poverty for households without children aged five or under (top left), households without children aged 6–18 (top right), households without women aged 21 or above (bottom left), and households without elderly people (bottom right).[26] 95% confidence intervals show that the declining overlap between multidimensional and income poverty follows almost the same pattern in households with different sources of non-eligibility. That is, the overlap measure remains stable during the 1990s and early 2000s, and then it decreases sharply.

26 Figures 1.A and 2.A show the overlap trends between severe income poverty and multidimensional poverty according to the source and depth of non-eligibility, respectively.

The second way of addressing this issue consists of depicting the poverty overlap trends according to the degree to which the households are non-eligible across indicators; that is, the number of indicators in which households are non-eligible. Figure 5 shows the poverty overlap trends for mutually exclusive households, from fully eligible households (top left) to those which are non-eligible in five or more indicators (bottom right).

Figure 5. Multidimensional and income-poverty overlap R^0 trends by depth of non-eligibility, Chile, 1992–2017



Note: 95% confidence intervals.
Source: Own elaboration based on CASEN household surveys.

A visual inspection shows the same pattern for the periods 1992–2000, and 2000 onwards. Fully eligible households follow the same pattern even though, due to reduced population share, 95% confidence intervals are quite large. However, the difference in the overlap R^0 measure between 1992 and 2017 is statically significant at the 2% level, and between 2009 and 2017 it is statistically significant at the 3% level.[27] The next section presents the conditional analysis aiming to identify the factors behind the observed overlap dynamics.

27 P-values are based on two-sample one-sided *t* test with unequal variances.

4. Determinants of the Poverty Overlap

4.1 Two-Way Fixed-Effect Regression of Poverty Overlap on Education, Demographic Variables, and Type and Depth of the Non-eligibility at the Province Level

In this section, we employ a two-way fixed-effect regression at the province level to detect the factors associated with the observed variability of the overlap R^0 measure. As explanatory variables, which correspond to the province population-weighted means, we considered household characteristics, household composition, rurality, and non-eligibility. Household characteristics are represented by the years of education of the head of the household. The demographic variables are the proportion of one-person households, the proportion of adults in the households, the proportion of female-headed households and the household size. Rurality is measured by the proportion of rural households. The controls for non-eligibility aim to capture the depth and quality of the household non-eligibility. The depth measure corresponds to the average number of indicators in which provincial households are non-eligible. The quality of non-eligibility is captured by the proportion of households with a demographic profile that makes them non-eligible in different indicators.

The results in Table 7 show that all considered variables are correlated with the unconditional poverty overlap variation across provinces. However, models (9) and (10) show that when considered all together, only the education of the household head, rurality and household size are significant. Regarding the household head's education, we find that higher education reduces the poverty overlap. This is expected, as education should be positively correlated with other functionings, while the correlation with income seems weaker; moreover, it is directly included as an indicator in the MPI. By contrast, rurality seems more likely to generate low incomes and functionings, as markets are incomplete and the availability of public goods is poorer than in urban areas. Thus, income poverty and multidimensional poverty are more likely to go hand-in-hand there. This evidence is also found in Klasen (2000) for South Africa during the 1990s (see also Lipton, 1977; van de Walle and Nead, 1996). Following Libois and Somville (2018), the complex relationship between fertility and household size can explain the non-significant coefficient of the proportion of adults in the households, as higher birth rates are associated with larger household sizes. However, the idea that larger families are on average poorer and less able to invest in education, as well as being less capable of functioning, is confirmed at this aggregation level. Thus, we confirm the positive linkage between demographics (household size) and poverty (Lipton, 1983; Klasen, 2000; Merrick, 2002). In Chile, the ongoing demographic changes are characterized by an increase in the number of small households, a shrinking rural population, and increasing levels of education. Consequently, at this level of aggregation, the overlap between multidimensional poverty and income poverty is expected to decline further.[28]

Neither non-eligibility indicators nor the mean provincial per capita income variable appears to be significant, the only exception being the fact that non-eligibility is associated with the health access indicator (percentage of households without women aged 21 or above). By design, this indicator differs from the 2013 MPI indicator in terms of non-eligibility. Therefore, this result is not surprising.

In summary, our results show that amongst income-poor households, small, better-educated households in urban areas are less likely to be multidimensionally poor than their less-educated and rural counterparts.

Table 3.A in the appendix shows the overlap association between severe income poverty and multidimensional poverty, while Table 4.A shows the overlap between multidimensional poverty and adjusted income poverty (adjusted by raising provincial monetary poverty lines to match their levels with the multidimensional poverty headcount in each province).[29] From this exercise, we see that that the poverty overlap also depends on the level of poverty identified by both methods, as they capture different households as well as different sets of occupants within the households. Changing either the monetary or the multidimensional poverty line, would yield a different explanation of the socioeconomic characteristics of the household on the poverty overlap at the province level.

4.2 Poverty overlap at the household level

Given the poverty headcounts in Chile over the past 25 years, the overlap R^0 measure corresponds to the proportion of income-poor households that are simultaneously multidimensionally poor. This definition allows us to investigate the probability that an income-poor household is simultaneously multidimensionally poor. We do this by means of a logit probability model for the 1992, 2000, 2009 and 2017 cohorts (see Table 6.A in the appendix). Besides household characteristics and composition, the logit model controls for communal fixed effects, the type and depth of the household non-eligibility and the income level of the household. Table 8 shows the marginal effects at the mean characteristics.

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28 Only these three factors can account for the large decline in the poverty overlap. The unsaturated model (i.e. the model with these three variables) has an adjusted R^2 of 0.56. See Figures 3.A and 4.A in the appendix for the evolution of the population share living in rural areas and the shares of the population living in households of different sizes.

29 Additionally, Table 5.A in the appendix shows the effect of the explanatory variables on the overlap measure after adjusting the province multidimensional poverty headcounts (by decreasing the poverty cutoff k) to match the observed province income-poverty headcounts.

Table 7. Two-way fixed-effect regression of poverty overlap on education and demographic variables at the province level

Explanatory variable / model	Overlap R^0 measure: Income poverty and multidimensional poverty									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Education of head of household (years)	-0.102***								-0.0179*	-0.0244**
	(0.00431)								(0.0108)	(0.0121)
One-person household		-5.389***							0.869	0.848
		(0.379)							(0.534)	(0.534)
Proportion of adults in the household			-2.152***						-0.432	-0.479
			(0.0923)						(0.425)	(0.427)
Household size				0.245***					0.109***	0.113***
				(0.0101)					(0.0351)	(0.0352)
Single-female-headed household					-1.716***				0.120	0.133
					(0.0928)				(0.171)	(0.171)
Rural household						0.847**			0.251***	0.247***
						(0.0948)			(0.0750)	(0.0750)
Depth of non-eligibility (%)							-1.215*		-0.311	-0.253
							(0.698)		(0.825)	(0.826)
HH without children aged 5 or below (%)							0.196*		-0.0192	-0.00797
							(0.113)		(0.140)	(0.140)
HH without children aged 6–18 (%)							1.105***		0.0181	-0.00631
							(0.244)		(0.292)	(0.292)
HH without elderly people (%)							0.419***		0.214	0.191
							(0.154)		(0.175)	(0.176)
HH without women aged 21+ (%)							-2.049***		-1.199**	-1.185**
							(0.562)		(0.556)	(0.555)
Log of per capita household income								-0.159***		0.0408
								(0.00708)		(0.0344)
Constant	1.510***	0.822***	2.113***	−0.472**	0.947***	0.435**	1.897***	2.494***	1.672**	1.281
	(0.0378)	(0.0149)	(0.0641)	(0.0454)	(0.0182)	(0.0214)	(0.729)	(0.0836)	(0.800)	(0.865)
Time dummies	-	-	-	-	-	-	-	-	Yes	-
Observations	516									
Number of provinces	43									
R-squared	0.543	0.300	0.535	0.552	0.420	0.145	0.558	0.516	0.655	0.656

Note: Robust standard errors in parentheses. ***p<0.01, **p<0.05, *p<0.1.
Source: Own elaboration based on CASEN household survey.

We find that income-poor households are less likely to be multidimensionally poor if they have a higher stock of education, if they consist of a single person, and if they have higher income levels. However, the correlation between the household income and the poverty overlap is unimportant. For instance, doubling the income level of a household is associated with a reduction in the probability of its occupants being multidimensionally poor of 4.99%, 8.78%, 3.17%, and 4.25% in 1992, 2000, 2009, and 2017, respectively.[30] On the other hand, rural and larger households are more likely to also be multidimensionally poor. An income-poor household located in a rural location is about 15 to 20% more likely to be multidimensionally poor than an income-poor household in an urban area with the same income level.[31]

Our results show a reduction in the rural bias since the early 2000s which is significant at the 1% level between 2000 and 2017. This positive trend can be explained by better-functioning and export-oriented agriculture, as well as the introduction of public policies devoted to improving the quality of life in areas that lag behind (see IFAD, 2016).[32] Finally, the non-eligibility of households across indicators does affect the probability of income-poor households of being simultaneously multidimensionally poor.

Table 8. Marginal effects (at means) after complex survey logit estimation

Variable / Year	Overlap at the household level – $\delta y / \delta x$			
	1992	2000	2009	2017
Avg. years of education of adults in the HH	-0.0799***	-0.0800***	-0.0777***	-0.0662***
	(0.00440)	(0.00570)	(0.00441)	(0.00413)
One-person household	-0.276***	-0.212**	-0.208***	-0.0785*
	(0.0772)	(0.0866)	(0.0477)	(0.0457)
HH head is elderly	0.0188	-0.0419	-0.0264	-0.0697*
	(0.0430)	(0.0456)	(0.0426)	(0.0396)
HH head is female	0.0458**	0.111***	0.0431**	-0.00144
	(0.0198)	(0.0237)	(0.0211)	(0.0225)
Household size	0.0779***	0.0879***	0.105***	0.0835***
	(0.00762)	(0.00869)	(0.0101)	(0.0100)
Rural household	0.188***	0.237***	0.211***	0.156***
	(0.0195)	(0.0162)	(0.0227)	(0.0245)
Number of indicators in which the HH is non-eligible	0.0183	0.00170	-0.0544***	-0.0418***
	(0.0117)	(0.0140)	(0.0121)	(0.0138)
HH without children aged 5 or below	0.137***	0.0823***	0.0427*	0.0773***
	(0.0169)	(0.0226)	(0.0233)	(0.0250)
HH without children aged 5–18	-0.0669	-0.0935**	-0.237***	-0.206***
	(0.0412)	(0.0410)	(0.0406)	(0.0387)
HH without elderly people	0.0936**	0.163***	0.0803*	0.175***
	(0.0379)	(0.0405)	(0.0438)	(0.0432)

30 As the income variable is expressed in natural logarithms, the probability changes at the mean characteristics were calculated by multiplying the reported marginal effect by 100 and dividing it by 171.8282.

31 Access to markets, public services, and improved education can account for a large part of this gap. For instance, Jensen et al. (2012) show that a child living in a rural area in Chile is more likely to work than her urban counterparts (probably a manifestation of reduced job opportunities in rural areas).

32 IFAD (2016) provides a comprehensive socioeconomic characterization of rural areas since the 1990s in Latin America.

HH without women aged 21+	-0.0348	-0.153***	-0.0904	0.0339
	(0.0426)	(0.0440)	(0.0615)	0.0447
Municipality controls	Yes	Yes	Yes	Yes
Observations (households)	35,939	64,925	70,748	70,666
Pop size	13,330,843	14,959,739	16,375,919	17,737,520
Sub population observations	10,655	13,429	9,934	5,719
Sub population size	4,258,759	2,993,033	2,474,368	1,472,235
F	17.90	13.99	27.36	10.40
Prob > F	0.0000	0.0000	0.0000	0.0000

Note: Robust standard errors in parentheses. ***p<0.01, **p<0.05, *p<0.1.
Source: Own elaboration based on CASEN household survey.

5. Conclusion

In this paper, we have focused on the consequences of using different approaches to define and measure poverty. We have explored at different levels of aggregation the degree of association between the utilitarian approach and the capability approach (implemented using the standard monetary FGT measure and the Alkire-Foster method, respectively) in the identification of the poor. We have empirically addressed the issue of non-eligibility of households across indicators of the MPI, aiming to understand the factors behind the poverty overlap divergence in Chile during the past 25 years. To the best of our knowledge, this is the longest trend comparison of identification outcomes brought about by such different approaches.

We find that the poverty overlap between multidimensional poverty and income poverty, and between multidimensional poverty and severe income poverty, have declined over the past 25 years at a rate of about 1.5% and 1.75% respectively per year. While the overlap decline was almost non-existent during the 1990s, a decade of rapid economic growth, it was remarkably pronounced during the period 2000–17, a period which was characterized by low economic growth and the introduction and deepening of social policies. The decline in the level of association between the two poverty measures is robust in alternative overlap definitions, but it is still affected by the non-eligibility of households across some MPI indicators.

Two sets of estimates were produced to investigate the correlation between socioeconomic characteristics, household composition, and location, and the observed poverty association measure. The first set of estimates was based on a province-level panel fixed-effect model, and the second was obtained using different cross-sections to study the association of the poverty measures at the household level by means of a logit model. We have shown that in both estimates, the household non-eligibility across indicators of the HMPI is a relevant empirical issue, as it has the potential to bias the true poverty overlap figures.

The strong empirical result of this research is that household education is inversely correlated with the level of the association between the two poverty measures, while a rural location and household size are associated in the opposite direction.

The key conclusion of this study is that the poverty overlap decline is a real process, in which the misidentification of the poor is not randomly distributed across the population. Therefore, an understanding of this divergence is crucial, as poverty alleviation initiatives are partially based on poverty statistics. The fact that household education, household size, and a rural location are behind the observed divergence in Chile over the past 25 years, raises the question of how general this process is. On the basis of our results, we hypothesize that this could be happening in all developing countries undergoing demographic transition, urbanization, and progress in education.

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Appendix

Table 1.A. The association of the two different official poverty identification methods, Chile, 1992–2017

Year	Multidimensional and income poverty		Multidimensional and severe income poverty	
	Overlap R^0	Cramer's V	Overlap R^0	Cramer's V
1992	0.711	0.226	0.788	0.150
1994	0.719	0.287	0.808	0.184
1996	0.707	0.239	0.807	0.156
1998	0.734	0.260	0.805	0.156
2000	0.699	0.249	0.796	0.168
2003	0.659	0.222	0.772	0.153
2006	0.639	0.179	0.701	0.104
2009	0.578	0.167	0.602	0.088
2011	0.525	0.144	0.575	0.078
2013	0.512	0.165	0.578	0.117
2015	0.501	0.152	0.542	0.097
2017	0.489	0.118	0.506	0.065

Source: Own calculations based on CASEN household surveys.

Table 2.A. Annualized relative rate of change in overlap R^0 measure between severe income-poverty and multidimensionally poor households, Chile, 1992–2017

Aggregation level	Whole period 1992–2017	Washington consensus period 1992–2000	Period of slowing growth and the introduction of social policies 2000–09	Period of slow growth and more comprehensive social policies 2009–17
Country level	-1.76	0.13	-3.06	-2.15
		Geographic location		
Urban areas	-2.09	0.09	-3.17	-3.01
Rural areas	-1.17	0.01	-1.92	-1.50
Region I	-0.26	4.41	-6.32	2.25
Region II	-0.76	-3.60	2.46	-1.42
Region III	-0.20	1.07	-3.53	2.40
Region IV	-1.13	0.18	-3.32	0.07
Region V	-1.36	1.92	-2.59	-3.19
Region VI	-2.24	-0.13	-5.27	-0.85
Region VII	-2.27	-0.30	-3.72	-2.60
Region VIII	-3.20	-0.55	-2.45	-6.58
Region IX	-0.70	0.52	-2.24	-0.17
Region X	-2.36	-0.35	-2.77	-3.86
Region XI	-3.04	-0.94	-10.03	3.23
Region XII	1.94	3.69	-8.18	12.75
Region XIII (metropolitan)	-1.37	0.30	-3.23	-0.90
		Household type		
HH head is not elderly	-1.90	0.16	-3.36	-2.28
HH head is elderly	-1.32	0.23	-2.70	-1.31
One-person HH	-1.33	3.45	-8.26	2.12
Two-person HH	-2.27	1.96	-7.14	-0.78
HH consists of 3 or more people	-1.53	0.08	-2.56	-1.96
		Average education amongst adult household members		
Less than 8 years	-0.81	0.03	-1.40	-0.98
8 years of more	-1.55	0.68	-3.30	-1.76

Source: Own elaboration based on CASEN household survey.

Table 3.A. Two-way fixed-effect regression of poverty overlap on education and demographic variables at the province level

Explanatory variable / model	Overlap R^0 measure: Severe income poverty and multidimensional poverty									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Education of head of household (years)	-0.116***								0.00573	-0.00212
	(0.00752)								(0.0195)	(0.0219)
One-person household		-6.332***							0.670	0.646
		(0.588)							(0.962)	(0.963)
Proportion of adults in the household			-2.600***						-1.276*	-1.332*
			(0.155)						(0.766)	(0.770)
Household size				0.287***					0.119*	0.124*
				(0.0175)					(0.0632)	(0.0636)
Single-female-headed household					-2.219***				-0.488	-0.472
					(0.144)				(0.308)	(0.308)
Rural						0.951**			0.287**	0.283**
						(0.142)			(0.135)	(0.135)
Depth of non-eligibility							-2.524**		-0.307	-0.237
							(1.198)		(1.487)	(1.490)
HH without children aged 5 or below							0.0891		-0.160	-0.146
							(0.193)		(0.252)	(0.253)
HH without children aged 5–18							1.094***		-0.229	-0.258
							(0.418)		(0.526)	(0.527)
HH without elderly people							0.313		0.573*	0.545*
							(0.264)		(0.315)	(0.317)
HH without women aged 21+							-3.481***		-2.177**	-2.161**
							(0.964)		(1.002)	(1.002)
Log of per capita household income								-0.187***		0.0490
								(0.0120)		(0.0621)
Constant	1.688***	0.910***	2.477***	-0.607***	1.096***	0.465**	3.763***	2.883***	3.260**	2.792*
	(0.0659)	(0.0232)	(0.108)	(0.0786)	(0.0282)	(0.0321)	(1.250)	(0.141)	(1.442)	(1.560)
Time dummies	-	-	-	-	-	-	-	-	Yes	-
Observations	516									
Number of provinces	43									
R-squared	0.336	0.197	0.372	0.362	0.335	0.087	0.381	0.342	0.466	0.467

Note: Robust standard errors in parentheses. ***p<0.01, **p<0.05, *p<0.1.
Source: Own elaboration based on CASEN household survey.

Table 4.A. Two-way fixed-effect regression of poverty overlap on education and demographic variables at the province level

Explanatory variable / model	Overlap R^0 measure: Adjusted income poverty and multidimensional poverty									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Education of head of household (years)	-0.00801								-0.00185	-0.0190
	(0.00605)								(0.0173)	(0.0193)
One-person household		-0.451							0.787	0.734
		(0.431)							(0.853)	(0.851)
Proportion of adults in the household			-0.231*						-0.111	-0.234
			(0.128)						(0.679)	(0.680)
Household size				0.0238*					-0.0453	-0.0348
				(0.0144)					(0.0561)	(0.0561)
Single-female-headed household					-0.132				0.124	0.159
					(0.116)				(0.273)	(0.272)
Rural household						0.234**			0.0513*	0.0427*
						(0.0384)			(0.120)	(0.120)
Depth of non-eligibility							-0.124		-0.203	-0.0493
							(0.994)		(1.318)	(1.316)
HH without children aged 5 or below							0.188		0.403*	0.432*
							(0.160)		(0.224)	(0.224)
HH without children aged 5–18							-0.0543		-0.0256	-0.0898
							(0.347)		(0.466)	(0.466)
HH without elderly people							0.0583		0.175	0.114
							(0.219)		(0.279)	(0.280)
HH without women aged 21+							0.683		0.860	0.895
							(0.800)		(0.888)	(0.885)
Log of per capita household income								-0.00968		0.107*
								(0.00968)		(0.0549)
Constant	0.652***	0.599***	0.742***	0.476***	0.607***	0.531**	-0.0905	0.696***	-0.145	-1.169
	(0.0531)	(0.0170)	(0.0892)	(0.0644)	(0.0227)	(0.0107)	(1.037)	(0.114)	(1.278)	(1.378)
Time dummies	-	-	-	-	-	-	-	-	Yes	-
Observations						516				
Number of provinces						43				
R-squared	0.004	0.002	0.007	0.006	0.003	0.025	0.012	0.002	0.027	0.035

Note: Robust standard errors in parentheses. ***p<0.01, **p<0.05, *p<0.1.
Source: Own elaboration based on CASEN household survey.

Table 5.A. Two-way fixed-effect regression of poverty overlap on education and demographic variables at the province level

Explanatory variable / model	Overlap R^0 measure: Income poverty and adjusted multidimensional poverty									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Education of head of household (years)	-0.00296								0.0243	0.0171
	(0.00617)								(0.0175)	(0.0197)
One-person household		-0.125							1.074	1.052
		(0.439)							(0.866)	(0.866)
Proportion of adults in the household			-0.155						-0.0837	-0.135
			(0.131)						(0.689)	(0.692)
Household size				0.0163					0.00691	0.0113
				(0.0147)					(0.0569)	(0.0572)
Single-female-headed household					-0.0790				0.136	0.151
					(0.118)				(0.277)	(0.277)
Rural household						0.0835			0.0309	0.0273
						(0.0529)			(0.122)	(0.122)
Depth of non-eligibility							-0.124		0.734	0.798
							(0.994)		(1.337)	(1.340)
HH without children aged 5 or below							0.188		0.125	0.137
							(0.160)		(0.227)	(0.228)
HH without children aged 5–18							-0.0543		0.281	0.254
							(0.347)		(0.473)	(0.474)
HH without elderly people							0.0583		0.254	0.229
							(0.219)		(0.283)	(0.285)
HH without women aged 21+							0.683		0.403	0.418
							(0.800)		(0.901)	(0.901)
Log of per capita household income								-0.00968		0.0446
								(0.00968)		(0.0559)
Constant	0.374***	0.352***	0.455***	0.275***	0.363***	0.330**	-0.0905	0.696***	-0.776	-1.203
	(0.0541)	(0.0173)	(0.0910)	(0.0657)	(0.0231)	(0.0153)	(1.037)	(0.114)	(1.297)	(1.403)
Time dummies	-	-	-	-	-	-	-	-	Yes	-
Observations	516									
Number of provinces	43									
R-squared	0.000	0.000	0.003	0.003	0.001	0.002	0.012	0.002	0.033	0.034

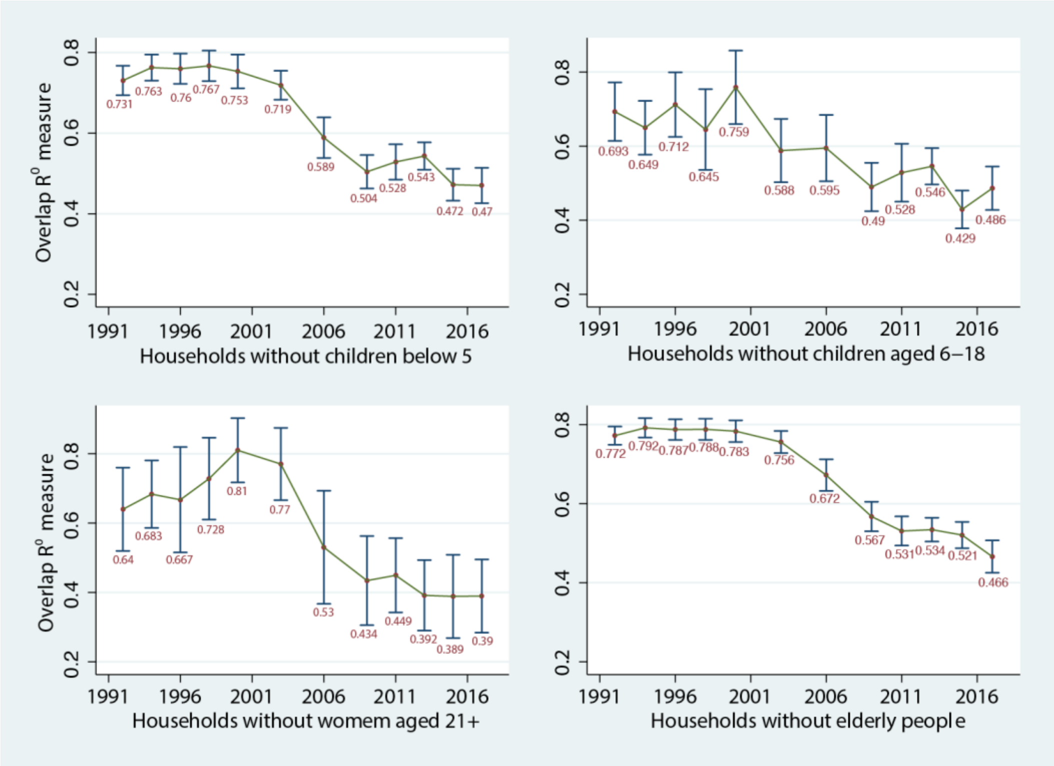
Note: Robust standard errors in parentheses. ***p<0.01, **p<0.05, *p<0.1. Source: Own elaboration based on CASEN household survey.

Table 6.A. Logit estimation for the overlap at the household level

Variable/Year	Overlap at the household level			
	1992	2000	2009	2017
Education of adults in the HH (avg. years)	-0.353***	-0.333***	-0.312***	-0.276***
	(0.0174)	(0.0223)	(0.0181)	(0.0186)
One-person household	-1.135***	-0.861**	-0.910***	-0.340
	(0.327)	(0.363)	(0.241)	(0.207)
HH head is elderly	0.0836	-0.173	-0.106	-0.295*
	(0.193)	(0.187)	(0.172)	(0.170)
HH head is female	0.207**	0.480***	0.173**	-0.00602
	(0.0917)	(0.106)	(0.0848)	(0.0939)
Household size	0.344***	0.366***	0.421***	0.348***
	(0.0343)	(0.0363)	(0.0404)	(0.0414)
Rural household	0.945***	1.131***	0.866***	0.633***
	(0.116)	(0.0934)	(0.0993)	(0.0993)
Number of indicators in which the HH is non-	0.0806	0.00710	-0.218***	-0.174***
	(0.0518)	(0.0582)	(0.0484)	(0.0572)
HH without children aged 5 or below	0.612***	0.346***	0.171*	0.319***
	(0.0761)	(0.0960)	(0.0935)	(0.103)
HH without children aged 5–18	-0.305	-0.401**	-0.968***	-0.854***
	(0.196)	(0.184)	(0.175)	(0.161)
HH without elderly people	0.430**	0.714***	0.322*	0.723***
	(0.182)	(0.192)	(0.176)	(0.179)
HH without women aged	-0.157	-0.705***	-0.363	0.143
	(0.197)	(0.232)	(0.249)	(0.239)
Municipality controls	Yes	Yes	Yes	Yes
Observations	35,939	64,925	70,748	68,187
Pop size	13,359,601	14,959,739	16,375,919	17,056,174
Subpopulation	10,762	13,429	9,934	5,637
Subpopulation size	4,287,517	2,993,033	2,474,368	1,455,790
F	16.67	13.99	27.36	10.40
Prob > F	0.0000	0.0000	0.0000	0.0000

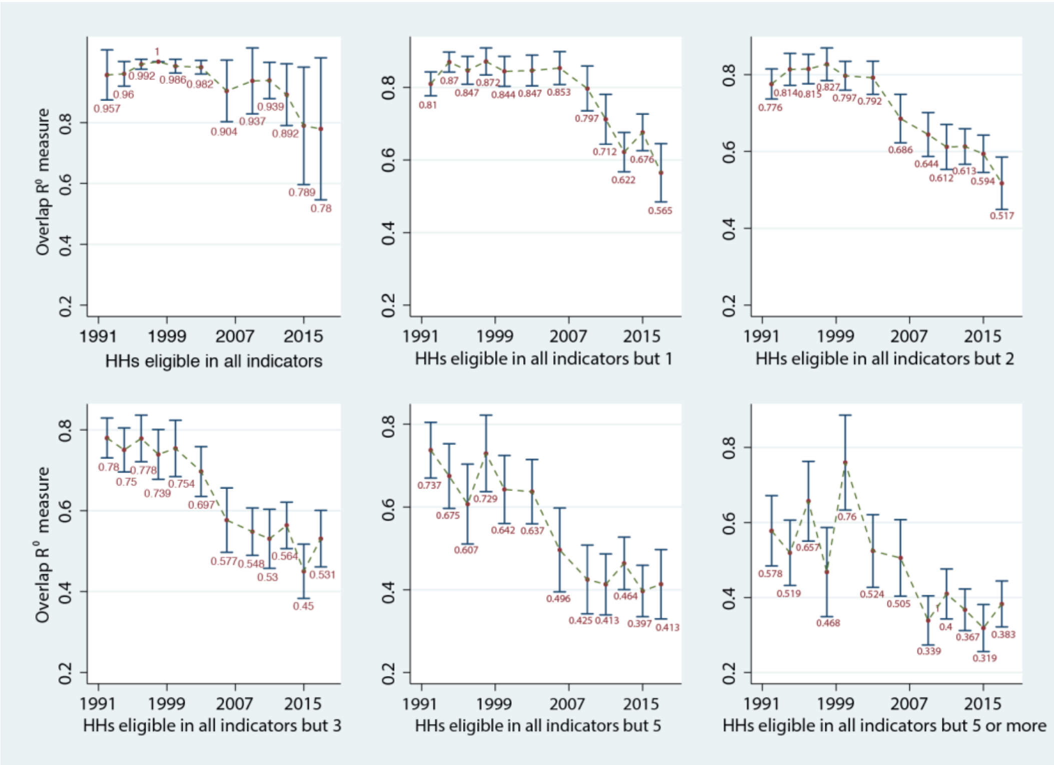
Note: Robust standard errors in parentheses. ***p<0.01, **p<0.05, *p<0.1.
Source: Own elaboration based on CASEN household survey.

Figure 1.A. Multidimensional and severe income-poverty overlap R^0 trends for groups of non-eligible households, Chile, 1992–2017



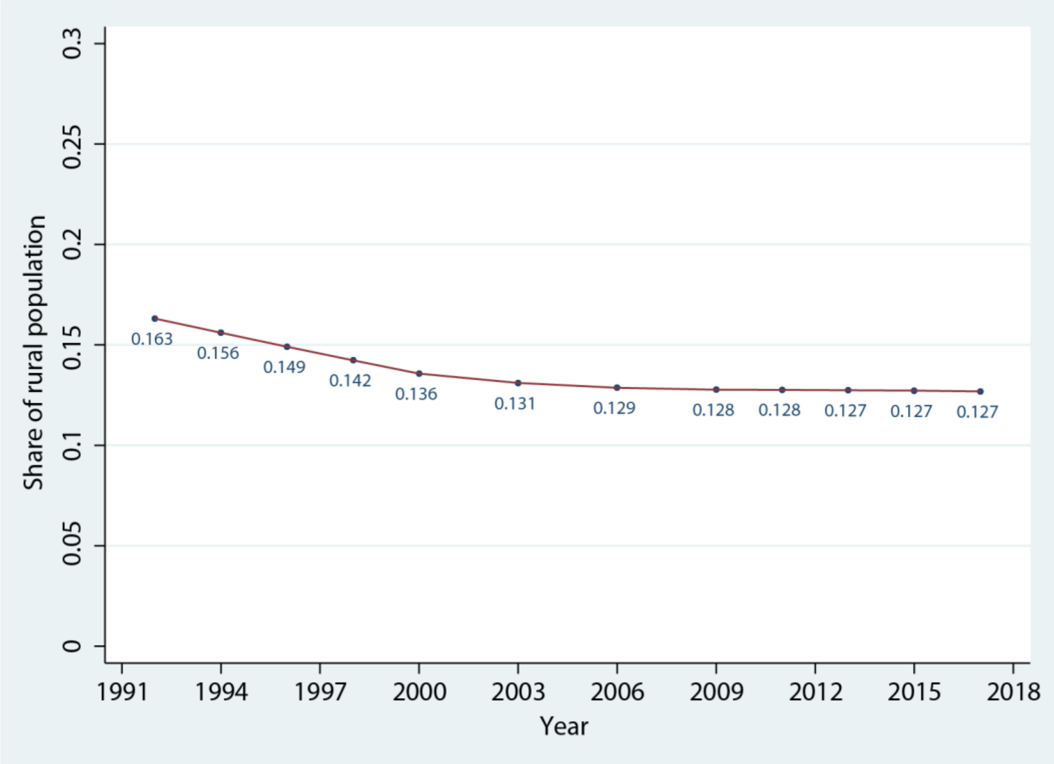
Note: 95% confidence intervals. Source: Own elaboration based on CASEN household surveys.

Figure 2.A. Multidimensional and severe income-poverty overlap R^0 trends by depth of non-eligibility, Chile, 1992–2017



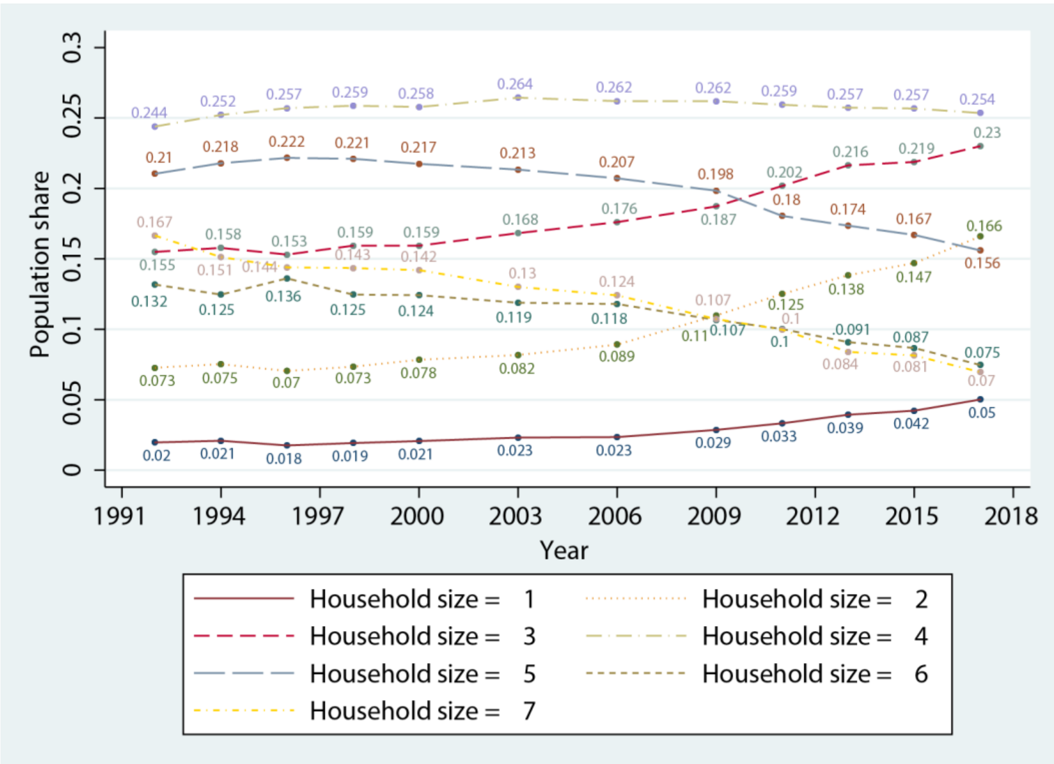
Note: 95% confidence intervals. Source: Own elaboration based on CASEN household surveys.

Figure 3.A. Rural share of the population, Chile, 1992–2017



Source: Own elaboration based on CASEN household surveys.

Figure 4.A. Population share by household size, Chile, 1992–2017



Source: Own elaboration based on CASEN household surveys.