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Chronic Multidimensional Poverty or Multidimensional Chronic Deprivation

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In the wake of the renewed interest in multidimensional poverty measurement, a natural question arising is how and whether indices of multidimensional poverty can be adapted to produce measures that quantify both the joint incidence of multiple deprivations and their degree of persistence, i.e. their chronicity. In this paper we seek to build one bridge between these two literatures (on multidimensionality and on poverty dynamics) by proposing indices that are sensitive, simultaneously, to: 1) the number of poverty dimensions in which people are deprived; and 2) the duration of their poverty experience. We propose two families of measures: one that captures multidimensional chronic deprivations (i.e. the joint existence of several dimension-specific chronic poverty experiences), and one that quantifies chronic multidimensional poverty (i.e. the persistence over several periods of contemporaneous multiple deprivations). Each set of chronic-poverty indices is accompanied by indices that capture transient poverty experiences. We illustrate the indices' usefulness with an empirical application to Chile.

Keywords: **multidimensional poverty dynamics, chronic poverty, chronic deprivation, Chile, panel data.**

1. Introduction

The multidimensionality of poverty is well established (Sen, 2001). However there is an ongoing, lively debate regarding how to account for poverty's different facets and dimensions, especially for quantification purposes. One route chosen in the literature is the computation of composite indices that are sensitive to the joint distribution of deprivations in the population. In particular, indices that follow the counting approach for poverty identification, whereby a person is deemed multidimensinally poor if his/her weighted sum of deprivations (in specific dimensions of wellbeing, individually) crosses a certain cut-off value. Recently, one family of such indices, the Alkire-Foster (Alkire and Foster, 2010), gained notoriety when some of its statistics were computed for 104 countries, and published in the 2010 UNDP Human Development Report.

In the wake of the renewed interest in these measures, a natural question arising is how and whether these indices of multidimensional poverty can be adapted to produce measures that quantify both the joint incidence of multiple deprivations and their degree of persistence, i.e. their chronicity. The literature on poverty dynamics is vast by now, especially in terms of statistical techniques developed to measure poverty transitions, chronic versus transient poverty, expected vulnerability; even for testing poverty traps (e.g. see Dercon and Shapiro, 2007, for a review). Yet all this literature treats poverty as unidimensional, implicitly or explicitly, and focuses on monetary metrics of wellbeing.

In this paper we seek to build one bridge between these two literatures (on multidimensionality and on dynamics) by proposing indices that are sensitive, simultaneously, to: 1) the number of poverty dimensions in which people are deprived; and 2) the duration of their poverty experience. Each set of chronic-poverty indices is accompanied by indices that capture transient poverty experiences. We illustrate their usefulness with an empirical application to Chile, a middle-income country which has a panel dataset spanning 1996 through 2006.

As mentioned, the literature on poverty dynamics is very rich by now, and has at least three basic strands. First, literature that computes and models transition probabilities into and out of poverty (e.g. Baulch, B. and J. Hoddinott, 2000; Jenkins (2000); Cappellari and Jenkins (2004); Petesch (2007)). Second, literature that provides measures of chronic versus transient poverty (e.g. Bossert et al. (2010); Foster (2009); Foster and Santos (2009); Hoy et al. (2010)). Third, literature that tests for poverty traps. All these strands focus on poverty dynamics over one relevant dimension of well-being (e.g. income or consumption), but research on poverty dynamics over several dimensions of well-being, considered jointly at the same time, is in its early stages.

Recently, Apablaza and Yalonetzky (2010) developed a decomposition of some statistics of the Alkire-Foster family that link changes in these statistics across time with the transition probabilities into and out of multidimensional poverty. In that sense, such contribution proposes a bridge between the transition strand of the poverty dynamic literature and the Alkire-Foster framework from within the multidimensional poverty literature.

In this paper we seek to lay a similar bridge, but now between the Alkire-Foster framework and the strand of the poverty dynamics literature that deals with chronic and transient measures of poverty. This sub-literature in itself is rich, offering several classes of chronic poverty measures. In this paper, we choose the class of chronic poverty measures characterized by Foster (2009) as our starting point, acknowledging that future research should also explore more sophisticated measures. However, the Foster (2009) has two appealing traits for the purpose of this paper, which is to offer a first set of multidimensional chronic measures: 1) It is parsimonious and easy to understand; 2) It is based on the same axiomatic foundations as the Alkire-Foster family.

Our proposal consists of two families of measures. The first family captures a notion of *multidimensional chronic deprivations*, i.e. the multiple incidences of experiences of chronic poverty over specific dimensions of wellbeing. In this approach, chronic poverty is computed first for each dimension separately, using the Foster (2009) family in our proposal; and then an assessment of whether an individual experiences these chronic deprivations over several dimensions is conducted in a second stage, using measures from the Alkire-Foster family.

The second family proposed in this paper captures a notion of *chronic multidimensional poverty*, i.e. the persistence of contemporaneous multiple deprivations over several time periods. In this approach, multidimensional poverty is computed first for each time period separately, using the Alkire-Foster family; and then, in a second stage, an assessment of whether an individual experiences this multidimensional poverty over several tie periods is conducted using the Foster (2009) family. For both notions, we also propose measures of transient poverty.

An empirical section computes the headcount ratios of the two families in Chile using a CASEN panel datasets with observations for 1996, 2001 and 2006. The analysis is complemented with an assessment of multidimensional poverty transitions and with an estimation of an ordinal logit model that links the likelihood of being chronically multidimensionally poor, and of being multidimensionally chronically deprived, respectively, with a set of socioeconomic covariates.

The rest of the paper is organized as follows. Section 2 presents the methodological proposal. Section 3 contains the first part empirical application to Chile. Section 4 discussed the ordinal logit model, and the paper ends with some concluding remarks.

2. From unidimensional static poverty to longitudinal multidimensional poverty: A proposal

In this section we present our proposals for the measurement of longitudinal multidimensional poverty building from the Foster-Greer-Thorbecke (FGT) family of unidimensional static measures all the way up.

Let an individual i have a certain level of achievement, x_{id} , in a single dimension/variable d and z_d defines the poverty line for that dimension (usually using a food basket). Individual i is considered poor in dimension d if his achievement x_{id} is lower than the deprivation, or poverty, line z_d.

The FGT family of measures proposed by Foster, Greer, and Thorbecke (1984), one of the most popular families based on an axiomatic approach, defines the following individual poverty function, measured by powers of the normalized gap:

$$g_{id}^{\alpha}(x_{id}) = \begin{cases} \left[1 - \frac{x_{id}}{z_d}\right]^{\alpha} & \text{if } x_{id} < z_d \\ 0, & \text{otherwise} \end{cases} \tag{1}$$

Then the social poverty function from the FGT family is:

$$FTG_{\propto} = \frac{1}{n}\sum_{i=1}^{n} g_i^{\alpha}(x_{id}), \tag{2}$$

Where n is the number of people. Alkire and Foster (2010) proposed a measure of multidimensional poverty based on a combination of the FGT functional form and the counting approach to the identification of the multidimensionally poor (Atkinson, 2003). Alkire and Foster (2010) identify the poor in two stages: first, for each individual, deprivations in each and every dimension are detected by comparing x_i^d against z^d; then a weighted sum of deprivations is computed and compared against a deprivation-count threshold. If the weighted sum is higher than the threshold then the person is deemed multidimensionally poor.

The latter means that, in the multidimensional case, an individual i has the following vector of achievements $X_i = (x_{i1}, x_{i2}, \dots, x_{iD})$ in D different dimension,[1] and $Z = (z_1, \dots, z_D)$ defines the vector of poverty lines for each dimension, which is common for all individuals. As before, individual i is poor in dimension d if $x_{id} < z_d$. Then, the weighted sum of the deprivations, c_i, for individual i is:

$$c_i = \sum_{d=1}^{D} w_d \; I(x_{id} < z_d) \tag{3}$$

Where D is the total number of dimensions, w_d the weight of dimension d, such that $w_d > 0 \wedge \sum_{d=1}^{D} w_d = D$. I is the indicator function, which is equal to 1 if the statement in parenthesis is true; otherwise it is equal to 0. Subsequently, in the second stage, the individual is identified as multidimensionally poor if $c_i \geq k$, where k is the deprivation-count threshold (or, multidimensional threshold). Otherwise the individual is not considered multidimensionally poor.

[1] We also define, for the whole society, $X = (X_1, X_2, \dots, X_n)$.

When $k = \min w_d$, only one deprivation is required to be considered poor. This is the union approach. The other extreme, when $k = D$, yields the intersection approach, in which only individuals with deprivations in all dimensions are considered multidimensinally poor.

The most basic statistic that can be computed in this framework is the multidimensional headcount ratio:

$$H(X; w_d, Z, k) = \frac{1}{n}\sum_{i=1}^{n} I(c_i \geq k) \tag{4}$$

H measures the percentage of the population that is multidimensionally poor. The Alkire-Foster family is the following:

$$M_a(X; w_d, Z, k) = \frac{1}{nD}\sum_{i=1}^{n} I(c_i \geq k) \sum_{d=1}^{D} w_d g_i^{\alpha}\left(x_i^d\right) \tag{5}$$

The Alkire-Foster family depends on a single parameter, α, whose value determines whether the measures are sensitive not just to the prevalence of poverty, but also to its breadth (number of deprived dimensions) and its intensity (magnitude of the dimension-specific poverty gaps). For instance, a notorious member of the family is the adjusted headcount ratio, M_0, which is only sensitive to prevalence and breadth:[2]

$$M_0(X; w_d, Z, k) = H(X; w_d, Z, k)A(X; w_d, Z, k) \tag{6}$$

Where A is the average normalized (and weighted) number of deprivations suffered by the multidimensionally poor :

$$A(X; w_d, Z, k) = \frac{1}{nHD}\sum_{i=1}^{n} I(c_i \geq k)c_i \tag{7}$$

M_0 quantifies the weighted average number of deprivations (as a proportion of the maximum number of possible deprivations) across the population, but censoring the deprivations of those deemed to be non-poor multidimensionally. As mentioned, it is sensitive both to the prevalence of poverty (through H) and to its breadth (through A). [3]

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[2] The adjusted headcount ratio is the statistic used in the calculation of the MPI in the most recent Human Development Reports (e.g. see Alkire and Santos 2010).

[3] For an overview of the axioms satisfied by the Alkire-Foster family the reader is referred to Alkire and Foster (2010).

2.1. Introducing time

For panel datasets the information consists of matrices X_t for different t periods in time. We add the subscript t to the previous statistics to denote poverty situations in specific periods. For instance, now x_{tid} denotes the attainment of individual i in dimension d in period t. Likewise, we have c_{it} , H_t, etc.

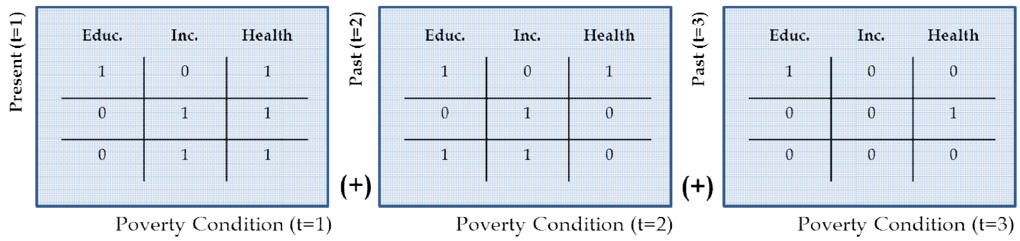
Now, the traditional, unidimensional poverty dynamics literature introduced the concepts of chronic and transient poverty, where the former denotes a status of persistent poverty, while the latter relates to occasional spells of deprivation. In the multidimensional context, the concepts of chronicity and transiency can be understood in two ways, which give rise to the notions of multidimensional chronic deprivations, and chronic multidimensional poverty.

Multidimensional chronic deprivation is the joint, simultaneous incidence of chronic deprivation over two, or more, dimensions of wellbeing. Thus, at the individual level, it requires establishing, first, the presence, or not, of a minimum level of poverty persistence over each and every dimension of wellbeing; and then aggregating these chronic statuses in order to determine whether the individual is chronically poor over multiple dimensions. In this proposal, we operationalize this notion by, firstly, computing chronic poverty for each dimension using the family of chronic poverty measures of Foster (2009); and, then, aggregating the dimension-specific poverty conditions using the Alkire-Foster family.

Alternatively, chronic multidimensional poverty measures the incidence of persistent multidimensional poverty. Thus, at the individual level, it requires establishing, first, the presence, or not, of multidimensional poverty in every time period; and, then, ascertaining whether its persistent incidence along time warrants a chronic status. In this proposal we operationalize this notion also by using the families of Foster (2009) and Alkire and Foster (2010); but in reverse order of identification.

The following example illustrates the main differences between the two approaches. In Figure 1, the three deprivation matrices reflect the poverty experience of three individuals (each row in a matrix) in three different dimensions (each column) over three years (one matrix per year). Each matrix grid has the value of the dimension-specific deprivation status, $I(x_{tid} < z_d)$.

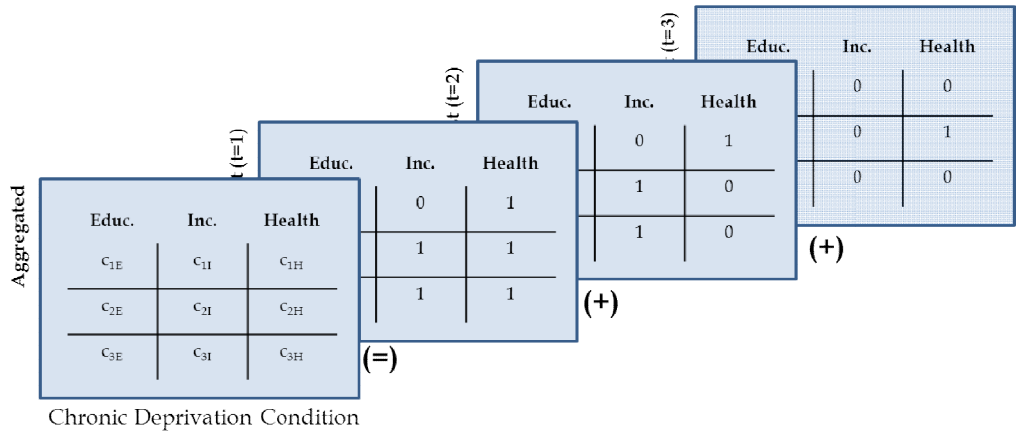
Figure 1: Deprivation Matrices of Chronic Multidimensional Poverty



In the case of chronic multidimensional poverty, the poverty condition of each individual, is defined in each period and then these results are aggregated across time. is the multidimensional deprivation-count cut-off. So, chronically, multidimensionally poor individuals can be identified according to the number of periods experiencing multidimensional poverty.

On the other hand, the multidimensional chronic deprivation, aggregates the deprivation matrices of each period in a new cumulative matrix whose grids contain the weighted sum of deprivation in each dimension for each individual , where now we use a new set of time-specific weights, . Figure 2 shows the composition of the cumulative matrix.

Figure 2: Deprivation Matrices of Multidimensional Chronic Deprivation



Finally the new cumulative matrix is treated as a cross-sectional deprivation matrix. Multidimensional chronic deprivation ensues if =1, where is a chronic-poverty threshold, as in Foster (2009).

2.2. New measures of multidimensional chronic deprivations and chronic multidimensional poverty

Combining the functional forms proposed by Foster (2009) and Alkire and Foster (2010) we propose, in this section, two new families of measures: one of multidimensional chronic deprivation, and another one of chronic multidimensional poverty.

The family of Chronic Multidimensional Poverty is:

$$M_\alpha^{cm}(X_1, \dots, X_T; k_D, k_T, w_d, w_t, Z) =$$

$$\frac{1}{n}\sum_{i=1}^{n}\left[I\left(\sum_{t=1}^{T} w_t * I(c_{it} \geq k_D) \geq k_T\right) * A_i^\alpha\right] \tag{8}$$

And the family of Multidimensional Chronic Deprivation is:

$$M_\alpha^{mc}(X_1, \dots, X_T; k_D, k_T, w_d, w_t, Z) =$$

$$\frac{1}{n}\sum_{i=1}^{n}\left[I\left(\sum_{d=1}^{D} w_d * I(c_{id} \geq k_T) \geq k_D\right) * A_i^\alpha\right] \tag{9}$$

A_i^α is the intertemporal average deprivation *per individual* which is equivalent in both cases to:

$$A_i^\alpha = \frac{1}{DT}\sum_{t=1}^{T}\sum_{d=1}^{D} w_t w_d \, g_{tid}^\alpha(x_{tid}), \tag{10}$$

Where now the powered normalized gaps have a time subscript. Additionally, the average deprivation of the society can be defined as the mean of the average individual deprivations (A_i^α) among the poor.

$$AD^\alpha = \frac{1}{p}\sum_{i=1}^{p} A_i^\alpha \tag{11}$$

Where p is the total number of poor people under each measure.

Just like in the simpler case of static multidimensional poverty, we can also define the following two headcount ratios for the cases of chronic multidimensional poverty and multidimensional chronic deprivation:

$$H^{cm} = \frac{1}{n}\sum_{i=1}^{n}\left[I\left(\sum_{t=1}^{T} w_t * I(c_{it} \geq k_D) \geq k_T\right)\right] \tag{12}$$

$$H^{mc} = \frac{1}{n}\sum_{i=1}^{n}\left[I\left(\left(\sum_{d=1}^{D} w_d * I(c_{id} \geq k_T)\right) \geq k_D\right)\right] \tag{13}$$

In terms of properties, since both measures are averages across populations, they are decomposable by any subgroup. Furthermore, since operations are commutative, both measures after identification can be aggregated indistinctively by dimension or across time allowing the decomposition by indicator just like with the Alkire and Foster family. Hence, we can define the following contribution by dimension:

$$Contribution_d = \frac{w_d}{nDT} * \sum_{i=1}^{n}\sum_{t=1}^{T} w_t * g_{tid}^{\alpha}(x_{tid}) \Big/ M, \tag{14}$$

Where M can either be M_{α}^{cm} or M_{α}^{mc}. In relation to the fulfilment of other properties, the two measures inherit the duration-related properties of the family characterized by Foster (2009), while it inherits the multidimensionality-related properties of the Alkire-Foster family.

Concerning poverty identification approaches, it is worth noting the following interesting cases. Firstly, a double union approach can be defined, whereby the deprivation-count cut-off is set to the minimum weight, i.e. $k_D = \min\{w_d\}$ and the temporal cut-off is also set to the minimum (time) weight, i.e. $k_T = \min\{w_t\}$. Secondly, a double intersection approach can be defined whereby the same two cut-offs are set to their maximum value, i.e. $k_D = 1 \wedge k_T = 1$. In both extreme identification cases, the two poverty measures are equivalent:

$$\begin{aligned} M^{cm}(k_D = \min\{w_d\}, k_T = \min\{w_t\}) \\ = M^{mc}(k_D = \min\{w_d\}, k_T = \min\{w_t\}) \end{aligned} \tag{15}$$

$$M^{cm}(k_D = D, k_T = T) = M^{mc}(k_D = D, k_T = T) \tag{16}$$

Finally, we the same framework we also propose two measures of *transient* poverty. Firstly, multidimensional transient deprivation (M^{mt}) captures the poverty of people who experience occasional deprivations on several dimensions of wellbeing, but who are not, otherwise, chronically deprived on any of these. Secondly, transient multidimensional poverty (M^{tm}) is based on the identification of people who are multidimensionally poor at least in one year, but not chronically. Respectively the two measures of transiency are:

$$\begin{gathered} M_{\alpha}^{mt}(X_1, \dots, X_T; k_D, k_T, w_d, w_t, Z) = \\ \frac{1}{n}\sum_{i=1}^{n}\left[I\left(\sum_{d=1}^{D} w_d * [I(c_{id} \geq \min\{w_T\}) - I(c_{id} \geq k_T)] \geq k_D\right)\right] * A_i^{\alpha} \end{gathered} \tag{17}$$

$$M_{\alpha}^{tm}(X_1, \dots, X_T; k_D, k_T, w_d, w_t, Z) =$$

$$\frac{1}{n}\sum_{i=1}^{n}\left[I\left(\sum_{t=1}^{T} w_t * \; [I(c_{it} \geq \min\{k_D\}) - I(c_{it} \geq k_D)] \geq k_T\right)\right] * A_i^{\alpha} \tag{18}$$

3. Longitudinal multidimensional poverty: The case of Chile

Since a pioneer work measuring long-term poverty transitions in rural areas (Scott, 2000), the literature on poverty dynamics in Chile is abundant, although it focuses on (unidimensionalized) income measures (see, for instance, Castro, 2011; Neilson et al. 2008; Hoces de la Guardia et al., 2011; Celhay et al., 2010; Nunez and Miranda, 2011). Literature on longitudinal multidimensional analysis is still at an early stage.

In this section, we study multidimensional poverty dynamics in Chile with a panel database with three time data points spanning 1996-2006. The period is characterized by three identifiable GDP and income growth experiences. Firstly, in 1996, Chile was undergoing one of the most successful decades in terms of growth and income poverty reduction of its history (Contreras, 2003; Contreras et al., 2001). By 2001, the impact of the Asian crises in employment and growth were evident (Corbo and Schmidt-Hebbel, 2010); and by 2006, with lower growth rates, a more robust set of public policies was implemented (Galasso, 2011; Glick and Menon, 2009).

The main purposes of this section are: firstly, to understand the cross-sectional patterns of multidimensional poverty in the three years; then, secondly, to delve deeper into the dynamics by looking at the multidimensional poverty transition rates; and, then, finally to compute the two indices combining chronicity and multidimensionality of poverty. Since we consider ordinal indicators of wellbeing, the multidimensional poverty measures are restricted to cases where $\alpha = 0$. An ordered logit model is estimated to study the correlates of multidimensional and chronic poverty status. The results are also compared to those for chronic income poverty in Chile.

3.1. Data

The Panel CASEN (National Survey of Economic Characterization) follows households in four regions (covering 60% of the national population) during three waves: 1996, 2001 and 2006. The survey was not conceived originally as a panel survey; however, in 2001, the Chilean Government and the Centre of Micro data (University of Chile) selected and polled a representative subsample of 5,209 households based on the cross-sectional survey of 1996.

	1996	2001	2006
Individuals	20,942	18,857	14,578
Households	5,209	4,648	3,769
Urban	89%	89%	88%
Males	48%	49%	50%
III Region	3%	3%	3%
VII Region	10%	10%	10%
VIII Region	21%	20%	20%
Stgo. (CAPITAL)	66%	67%	67%

The survey is considered one of the longest panel surveys for a developing country with longitudinal and cross-sectional representativity (Dercon and Shapiro, 2007). Since in its design the evolution of the poor has a key role, the survey tends to overestimate the level of income poverty with respect to national levels by approximately 5%. The selection of weights was designed to correct partially the problems of attrition detected in young individuals (20-29 years) and older ones (over 60s) in large households and those living in rented dwellings[4] (Bendezu et al., 2007).

The amplitude of the survey, including subsections for education, employment, income, health and dwelling, allows the construction of multidimensional indicators with the same structure as the one proposed in our previous section, with two restrictions. However, there are changes in the questionnaire that forbids analysis in some dimensions. More conceptually, the questions are meant to elicit information on the levels of resources or functionings attained, rather than capabilities.

3.2. Multidimensional Poverty

Several choices of wellbeing dimensions, and respective indicators, have been made in the literature. Asselin (2009) presents a summary of those most common used. Since our application has a time component, our choices have been constrained by the need to guarantee longitudinal comparability. The set of dimensions and indicators are presented in Table 1:

Table 1: Dimensions and Indicators Panel Survey

Dimension	Indicator	Deprivation Cut-off
Housing	Shelter (Walls[5]/ Floor[6] / Roof[7])	At least two deprived indicators
	Overcrowding	More than 3 individuals per room

[4] Other variables included are the marital status (single), schooling (high), and higher deciles of autonomous income.

[5] Deprived Walls: adobe, wall without interior protection, mud, thatch, artisanal construction, rubbish, cardboard, tin and rubber.

[6] Deprived Floor: earth.

[7] Deprived Roof: clinkstone, straw, bulrush, rubbish, cane.

	Tenancy	Illegal settlement
Education	Illiteracy	At least one member over 17 illiterate
	Enrolment	At least one member between 6 and 16 not enrolled
	Schooling	No member older than 17 with more than 8 years of education
Living standards	Toilet	Box over black well, irrigation ditch or no system
Employment	Unemployment	All member over 17 in unemployment or with temporal works
	Security	Art least one member over 17 has not signed contract
	Pension System	No social security system
Income/Nutrition	Basic Basket	Earnings lower than those required to buy at least one basic basket accounting for rural and urban areas.

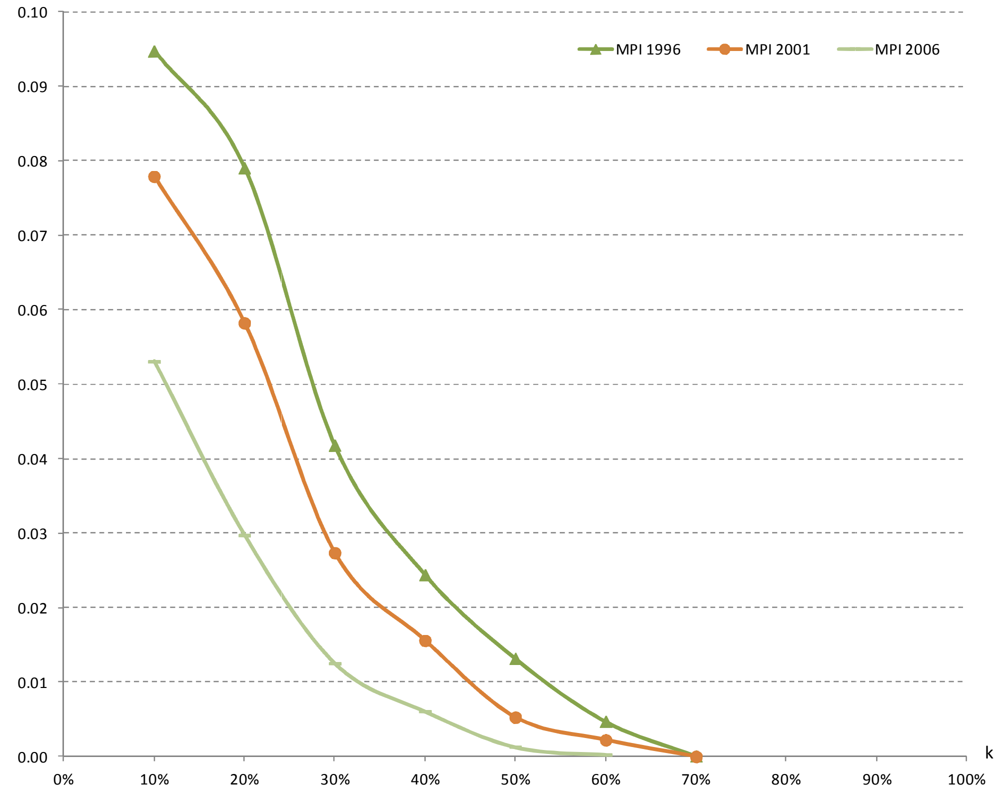
Several checks were implemented to compare the robustness of the measure mainly based on the ranking sensitivity of changes in the dimensions, indicators, weights and poverty cut-offs. Only the exclusion of the income factor (nutrition) seems to affect the confidence of the results implying that this indicator is able to capture information that is not revealed by the other components. Despite the reduction of indicators in the category of living standards its exclusion does not affect the general trend. Indicators with low incidence were conserved to increase the comparability between these results and those found in the previous section. For instance, enrolment and schooling have incidences lower than 1%; however, since these are associated with social (and legal) rights are included.

3.2.1. General results

Figure 3 shows cross-sectional results of the adjusted headcount ratio (M_0). There is a reduction in levels of multidimensional poverty among the individuals in the sample for every level of the multidimensional cut-off (k). Detailed results support this conclusion with one exception; there is an increase in the intensity of poverty between 1996 and 2001 for individuals with more than 70% of their (weighted) indicators deprived (for detailed information see Table 12: Multidimensional Poverty, Headcount ratio and Average deprivation (Panel Survey)).

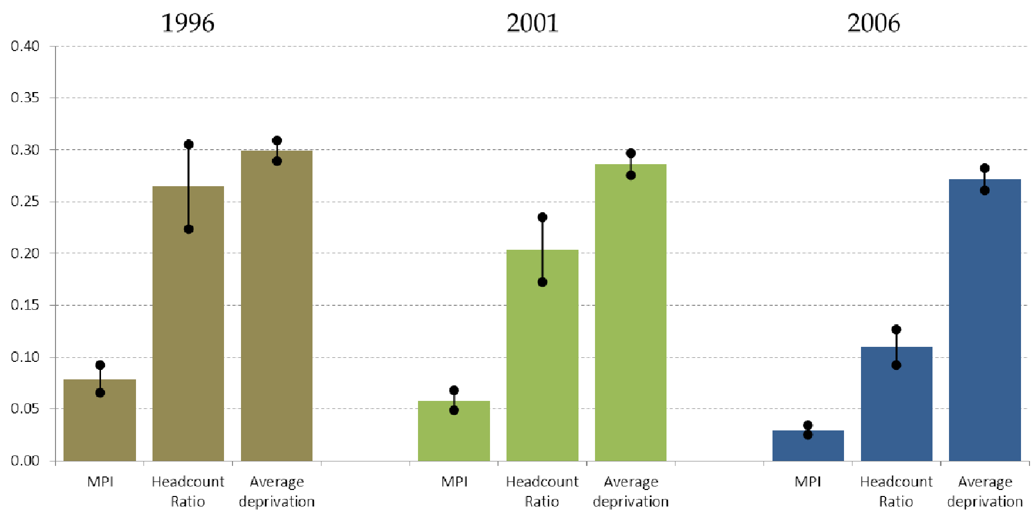
With a poverty cut-off of 20%, M_0 drops from 0.08 in 1996 to 0.06 in 2001, and, then, to 0.03 in 2006. This phenomenon is explained mainly by the reduction in the headcount ratio. The percentage of poor people in 1996 was 26% (22.9% by the income measure), it fell to 20% after 5 years and finally reached 11% in 2006 when income poverty affected 12.7% of the population. Clearly there is a faster reduction in multidimensional poverty, which is distributed in both periods. The average deprivation seems to fall in the periods analysed.

Figure 3: Multidimensional Poverty index under different cut-offs

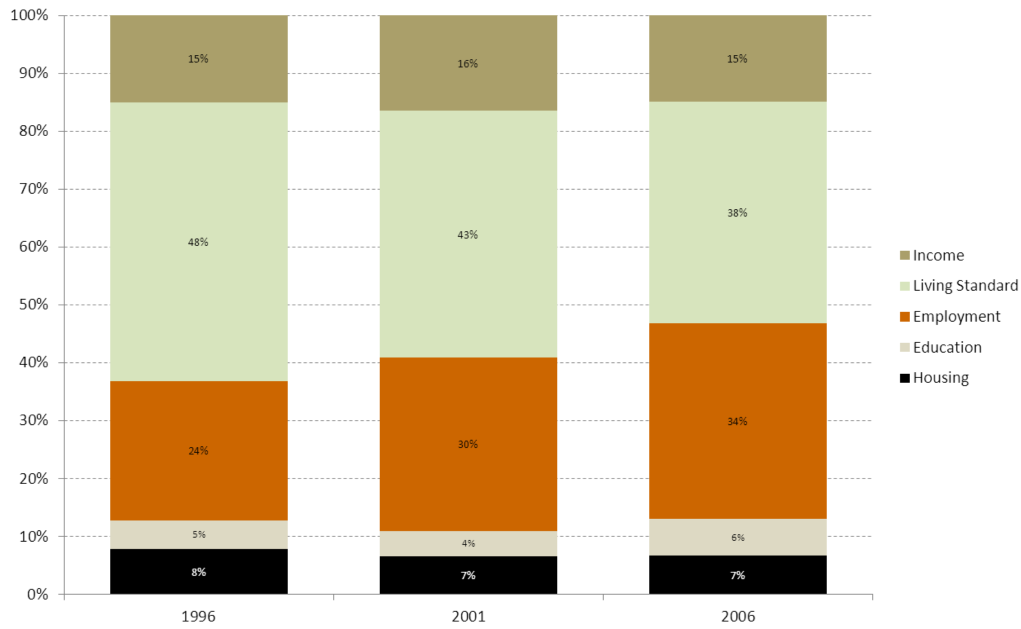


Nevertheless the confidence intervals show that all measures in 2001 are not significantly different from those in 1996, and are significantly different in 2006 compared to 2001. Only is not significantly different between the periods but it is in the long run (comparing 1996 and 2006).

Figure 4: Multidimensional Poverty Indicators 1996-2001-2006 K=20%



In terms of decomposition, living standards, and its subcomponent, quality of toilet, is the dimension that contributes most to multidimensional poverty in all years; however, its relative importance is smaller in each period. The second component in terms of importance is employment; in this case, its relevance is increasing. All the indicators inside this dimension are higher in each period, led by the increase in unemployment. Finally, income, education and housing do not show significant changes between periods[8].



Cross-sectional results clearly establish that multidimensional poverty is lower in 2006 compared with 1996. In general, differences are not conclusive in the first period (1996-2001) but become significant in the second period. Finally, employment and living standards are the key variables explaining multidimensional poverty in all three years.

3.2.2. Multidimensional poverty transitions

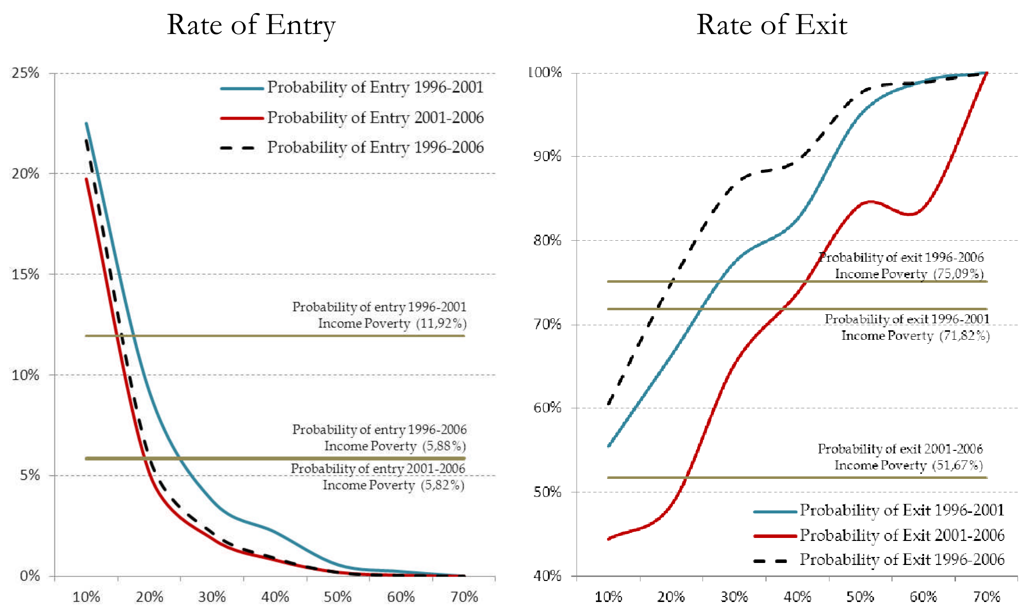
The ex post conditional probability of poverty entry reflects the chances of a non-poor individual in the first period becoming poor in the following period. In general, a higher poverty cut-off should imply a lower probability of entry, since the requirements to be considered poor are increasing. In the left panel of Figure 5, this pattern in can be appreciated in all periods. Additionally, the probability of entry in the first five years is higher than in the second and in the entire period is mainly influenced by the negative economic situation.

Conversely, the probability of exit is the number of individuals who are able to leave poverty between the two periods over the total number of poor individuals in the first period. The right panel of Figure 5 shows that a higher level of poverty cut-off implies a greater probability of exit since it is more likely to leave

[8] Details of censored headcounts and raw headcounts can be found in the annexes.

poverty with an extremely high poverty line[9]. In terms of within-year changes, the probability of exit is significantly lower during the first period, increasing during the second, and reaching its peak when 10 years are considered.

Figure 5: Rate of poverty entry and exit with different cut-offs[10]



Specifically, when probabilities of entry and exit are compared under – , the probabilities of entry and exit are significantly different between the first and the second period. The rate of entry into poverty is higher and the rate of exit is lower in the first period explaining the reduced improvement in the aggregated indicators, mainly the headcount ratio.

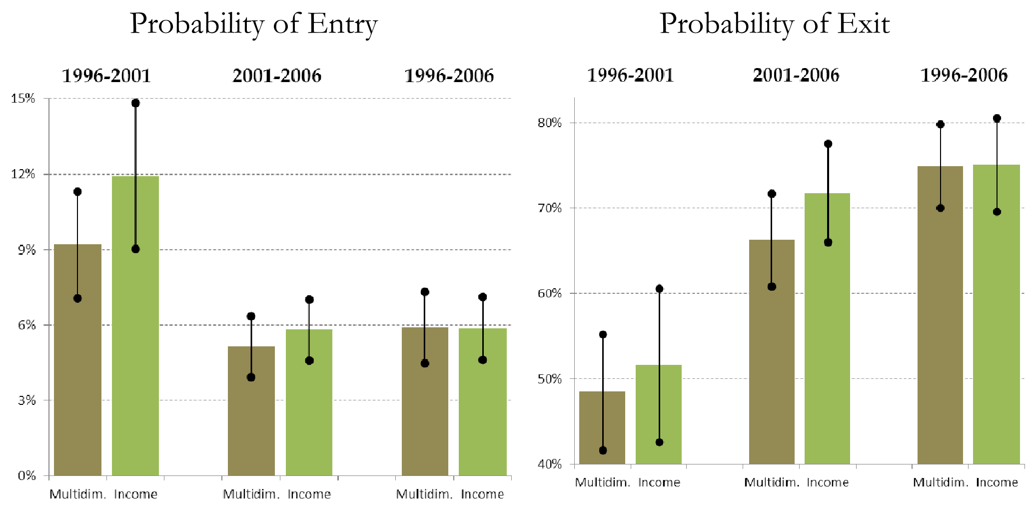
In the case of the rate of entry, the second period seems to be more similar to the long-run patterns of change (1996-2006); moreover, there are no significant differences among these changes. An analogous situation could be appreciated in the case of the probabilities of exit. However, despite the lack of significant differences, a higher average for the last period and the long run can be observed.

Finally, non-significant differences between the conditional probabilities of poverty entry and exit by the multidimensional and income approach were detected, but it should be recognized that the means are lower for the multidimensional indicators. This phenomenon explains partially the more stable longitudinal results in the case of the multidimensional approach which will be explored in the next section.

[9] The negative movement of probabilities between the cut-off of 50% to 60% is based on the reduction of poor individuals in the initial period in both levels. The number of poor individuals in 1996 with a cut-off of 50% was 312 individuals and with 60% only 72.

[10] For more details see table 20 in the annexes.

Figure 6: Probability of entry and exit in different periods (k=20%)



As before, under a poverty cut-off of – , more than 50% of the individuals who were poor in 1996 are still poor in 2001 (45% in the case of income) and, conversely, only 9.2% of those who were non-poor in 1996 became poor after 5 years (11% for income). Consequently, poverty in 2001 could be explained as 66.8% for those individuals who remain in poverty and 33.2% for new poor.

Table 2: Matrix of Transitions Multidimensional Poverty 1996-2001 (–=20%)

	2001		
1996	**Poor**	**Non-Poor**	**Total**
Poor	1,289	1,214	2,503
% row	51.5%	48.5%	100.0%
% column	66.8%	16.1%	26.5%
Non-Poor	640	6,319	6,958
% row	9.2%	90.8%	100.0%
% column	33.2%	83.9%	73.5%
Total	1,929	7,532	9,461
% row	20.4%	79.6%	100.0%
% column	100.0%	100.0%	

Between 2001 and 2006, 650 individuals remain in poverty. That implies that 66.31% of the individuals who were poor in 2001 are not in 2006. The additional individuals (388) are those who fall into poverty from non-poverty (5.15%). Table 3 also presents final results for the entire period showing the poverty condition in each period. For instance, from those who were poor in 1996 and 2001 62.21% had left poverty by 2006. On the other hand, 13.4% of the poor in

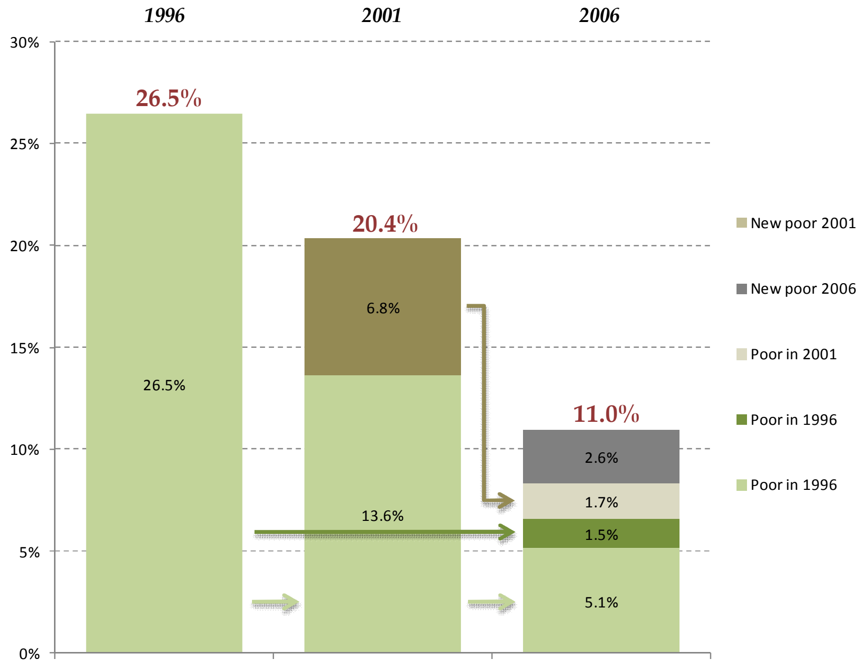
2006 are individuals who were poor in 1996 but had temporarily left poverty in 2001 and 23.9% had never being poor before.

Table 3: Transition Matrix 1996-2006 ($\frac{k}{D}$=20%)

	2006		
1996-2001	**Poor**	**Non-Poor**	
Always Poor (1996-2001)	487	802	1,289
% row	37.79%	62.21%	100%
% column	46.96%	9.52%	13.63%
Poor 1996 Non-Poor 2001	139	1,075	1,214
% row	11.46%	88.54%	100%
% column	13.4%	12.76%	12.83%
Non-Poor 1996 Poor 2001	163	477	640
% row	25.43%	74.57%	100%
% column	15.68%	5.66%	6.76%
Never poor (1996-2001)	249	6,070	6,319
% row	3.93%	96.07%	100%
% Column	23.96%	72.06%	66.79%
Total	1,037.53	8,423.47	9,461
% row	10.97%	89.03%	100%
% column	100%	100%	100%

Figure 7 summarizes the information provided in the previous table showing the temporal composition of poverty. The figure implies that, in 2001, 13.6% of the poor population was poor already in 1996. The remaining 6.8% are new poor in 2001. In 2006, 5.1% of the population was poor in both the previous periods; 1.5% was poor only in 1996; 1.7 only in 2001; and 2.6%, are new poor. Consequently, using the standard denomination of longitudinal income studies, in 2006, 5.1% of the population is in chronic poverty and 5.9% is in transient poverty. In a similar trend, income chronic poverty reached 4.2% and transient 6.3% showing an akin pattern but with stronger differences in the last case.

Figure 7: Temporal composition of Poverty



Additionally, conditional probabilities per indicator can be obtained (and required for further decompositions). In this case, the probability of entry into deprivation and poverty at the same time are considered. For instance, in the first period the probability of being dimensionally poor and deprived in security at work is 8.3%, being the highest among the indicators. This means that for those non-poor or non-deprived in 1996 the chances of being deprived and poor are 8.3%. For all periods, the higher probabilities of entry are clearly related to the employment dimension showing implicitly its short run dependency.

On the other hand, during the first years, the highest probabilities of exit are concentrated in the educational and housing dimension with an average of 85%. Between 2001 and 2006, the higher probability of exit is in the housing dimension (85% on average) and secondly in the income dimension (83% on average). Finally, in the long run the probability of exit is based on the educational dimension with an average of 93%. These results start to provide some insight into trends in the short and long run changes, even providing details and differences for both sub-periods.

Table 4: Rates of entry into and exit from Deprivation and Poverty (k/D =20%)

	1996-2001		2001-2006		1996-2006	
	Pr. Entry	**P. Exit**	**Pr. Entry**	**P. Exit**	**Pr. Entry**	**P. Exit**
Housing	0.5%	84.0%	0.1%	87.4%	0.1%	92.6%
Overcrowding	3.2%	79.3%	1.6%	77.9%	2.0%	91.3%
Settlement	0.5%	92.0%	0.2%	89.5%	0.2%	80.9%

Illiteracy	1.6%	65.0%	1.7%	73.4%	2.0%	86.5%
Attendance	0.4%	98.3%	0.2%	98.3%	0.2%	97.4%
Schooling	0.0%	90.6%	0.0%	63.9%	0.0%	95.5%
Unemployment	5.9%	90.8%	2.6%	83.1%	3.2%	91.8%
Contract	6.8%	83.8%	3.4%	84.2%	4.0%	92.6%
Security	8.3%	64.2%	4.6%	73.9%	5.4%	82.3%
Toilet	2.5%	45.3%	1.8%	66.8%	1.8%	77.8%
Income	3.5%	74.6%	1.4%	82.6%	1.7%	89.4%

3.2.3 Longitudinal Multidimensional Poverty: The case of Chile

This section extends the longitudinal multidimensional poverty analyses by estimating measures based on the two notions of multidimensional chronic deprivation and chronic multidimensional poverty. We focus on the two respective headcount ratios, since these constitute the main difference between the two sets of indices (see equations 8 and 9).

Table 5 presents headcount ratio results for the two measures of chronicity. On the left side, results for chronic multidimensional poverty and on the right side results for multidimensional chronic deprivation. In each case the first column represents the percentage of people considered never poor, so, the sum between those and the second column individuals, at least once poor ($\frac{k_T}{T} = 1/3$) should add up to the total population. For the double union approach the headcount is equal to 0.8973, whereas for the double intersection approach it is 0%.[11]

Table 5: Headcount Ratio Multidimensional Chronic Poverty

	Chronic Multidimensional Poverty				**Multidimensional Chronic Deprivation**			
$\boldsymbol{\frac{k_D}{D}}$	**Never Poor**	$\boldsymbol{\frac{k_T}{T} = \frac{1}{3}}$	$\boldsymbol{\frac{k_T}{T} = \frac{2}{3}}$	$\boldsymbol{\frac{k_T}{T} = 1}$	**Never Poor**	$\boldsymbol{\frac{k_T}{T} = \frac{1}{3}}$	$\boldsymbol{\frac{k_T}{T} = \frac{2}{3}}$	$\boldsymbol{\frac{k_T}{T} = 1}$
10%	39%	61%	30%	11%	22.2%	77.8%	24.0%	6.2%
20%	64%	36%	17%	5%	42.8%	57.2%	14.2%	4.0%
30%	85%	15%	5%	1%	64.2%	35.8%	4.3%	0.4%
40%	92%	8%	2%	0%	72.4%	27.6%	1.6%	0.0%
50%	97%	3%	0%	0%	82.2%	17.8%	0.5%	0.0%
60%	99%	1%	0%	0%	85.5%	14.5%	0.2%	0.0%
70%	100%	0%	0%	0%	91.9%	8.1%	0.0%	0.0%
80%	100%	0%	0%	0%	94.2%	5.8%	0.0%	0.0%
90%	100%	0%	0%	0%	97.0%	3.0%	0.0%	0.0%
100%	100%	0%	0%	0%	97.9%	2.1%	0.0%	0.0%

[11] See equation 16.

As expected, the percentage of chronically poor individuals falls in both cases when the cut-offs (poverty and time) are increased. Additionally, there is dominance among the never poor population, but this becomes unclear when population in poverty under different cut-offs are analysed.

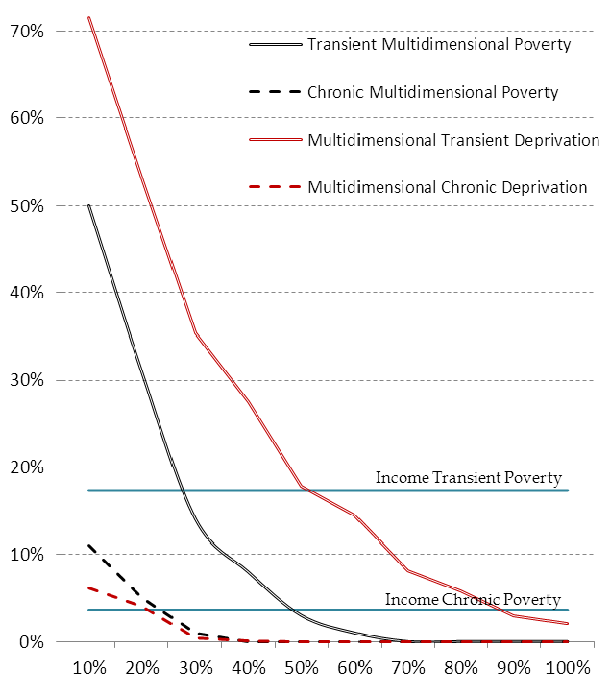
The population not classified as poor in the first measure is always higher than the second regardless of the poverty line. As mentioned before, increasing the multidimensional cut-off in the Alkire and Foster family increases the requirements to be considered poor; and, in turn, the probability of being non-poor. For the first measure, the probability of being poor in at least one period with a poverty cut-off higher than 70% is 0 and, hence, all individuals are non-poor under those parameters. However, interestingly, there are still poor individuals according to the second measure. This implies, for instance when $\frac{k_D}{D}$ =100% and $\frac{k_T}{T}$ =1/3, 2.1% of the population have had all dimensions deprived but not at the same time.

When a low time cut-off is considered, the multidimensional chronic deprivation is always higher than the chronic multidimensional poverty. This phenomenon is explained by the low probability of accumulating an important number of deprivations in only one year necessary for the first measure. The second measure relaxes the simultaneity condition increasing the probability of being considered poor at any poverty cut-off.

For those most chronically poor individuals, ($\frac{k_T}{T} = 1$) the situation seems to be more ambiguous. Figure 8 presents the information of the headcount ratio for transient and chronic poverty for both measures, as was presented in equations (13) and (14). Dark lines represent the first aggregation methodology (by dimension, then across years) and the red lines the second aggregation strategy (across years and then by dimension). The multidimensional transient deprivation is always higher than the transient multidimensional poverty mainly because, as was described before, the measure relaxes the requirements of deprivation across years.

For chronic poverty (dashed lines) the transient multidimensional poverty dominates the chronic deprivation at a low level of ($\frac{k_D}{D}$ ≤30%). As the cross-sectional results have shown before, low multidimensional poverty lines increase the likelihood of being poor in each period. Differences might be explained by changes in the dimensions in which the individuals are deprived. If chronically poor individuals are always deprived in the same dimensions the results of both measures should be identical.

Figure 8: Transient and Chronic Poverty



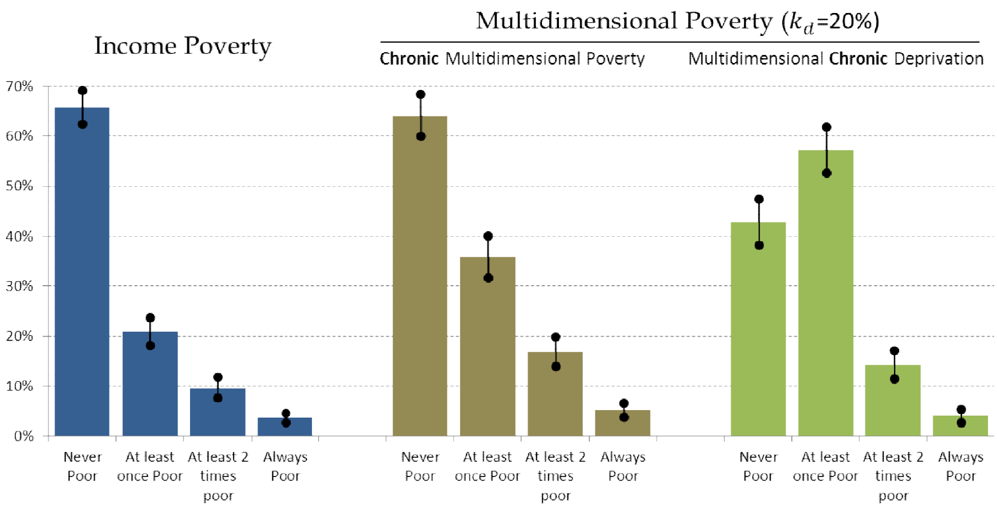
As before, chronic multidimensional poverty seems to have behaviour more similar to the income measures than multidimensional chronic deprivation. Figure 9 presents more details of this comparison. The first set of bars shows the results for income poverty using the national poverty line in the following order: never poor population, population at least once poor (—), population at least twice in poverty (—); and, those who are always poor (—). The second and third set of bars present information for chronic multidimensional poverty and multidimensional chronic deprivation respectively using a poverty cut off of 20% (—=20%).

Implicitly, measures are dependent on different ex post probabilities. The chronic multidimensional poverty is based in the probability of remaining poor or non-poor (as an inverse of the probability of poverty entry and exit). Results across years of the probability of remaining as non-poor are constant across all periods and not significantly different from income poverty results. However, the probability of stay poor falls when the first period (1996-2001) is compared with the second one or the entire range (detail can be found in Figure 12).

The multidimensional chronic deprivation depends on the probability of remaining deprived or not in a specific dimension. These probabilities will affect the number of periods of deprivation and consequently the chances of being chronically deprived. Results (Table 16 in the annexes) suggest that the chances of remaining as non-deprived are for all cases more than 95%, except for the employment variables during the first period. However, the probabilities of remaining deprived are distributed in a longer range from 2% to 55% showing patterns consistent with the economic context (especially for its impact on employment). Additionally, the dimension toilet keeps the higher level of probability of remaining as deprived, impacting directly on the aggregated poverty indicator.

Distribution of the first two measures seems to be similar at least for those who are never poor and always poor; indeed, results are not statistically different for these subgroups[12]. The multidimensional measures are not significantly different for poorer subgroups (—). The correlation between the income measure and the chronic multidimensional poverty reaches 0.49; with the multidimensional chronic deprivation 0.44; and, between the multidimensional measures 0.85, all of them significant at the 5% level.

Figure 9: Longitudinal Poverty Statistics



Finally, these results confirm previous insights for the population who were at least once poor. The population who are not poor in the first measure are considered poor in the second measure due to its lower temporal restrictions of simultaneity.

Table 6 confirms that the higher number of poor people measured by the multidimensional chronic deprivation is explained by individuals who are at least once poor (2,020) under the chronic multidimensional poverty measure. At the other extreme, only 383 individuals are chronically poor using both methodologies. The rest are still poor but not with enough dimensions simultaneously.

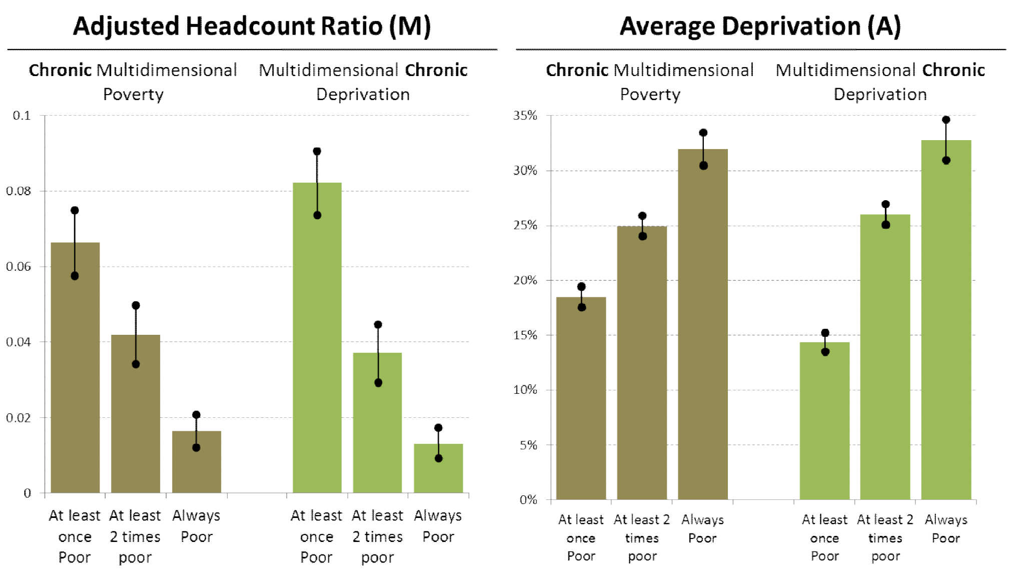
12 See Table 15: Headcount Ratio by Poverty condition for detail in confidence intervals.

Table 6: Matrix of Individuals in Multidimensional Poverty (— =20%)

		Multidimensional Chronic Deprivation				
		Never Poor	**Once**	**Twice**	**Always**	**Total**
Chronic Multidimensional Poverty	**Never Poor**	4,050	0	0	0	**4,050**
	Once	2,020	1,781	253	10	**4,064**
	Twice	0	20	851	94	**965**
	Always	0	0	0	383	**383**
	Total	**6,070**	**1,800**	**1,104**	**487**	**9,461**

The differences in headcount ratios across subgroups are implicitly compensated by the average deprivation. The additional individuals considered in the multidimensional chronic deprivation (2,020) have a low average deprivation reducing the average of the first subgroup. Figure 10 shows these differences.

Figure 10: Adjusted Headcount Ratio and Average Deprivation (k=20%)



For all subgroups, there are no significant differences between the results of the adjusted headcount ratio (M) for both measures. Results are significantly different only for the average deprivation of the population who are poor in at least one period.

Using analogous properties as those proposed by Alkire and Foster, both longitudinal measures of poverty can be decomposed by dimension and population subgroups. For instance, Figure 11 presents decomposition by area and dimension for population in chronic poverty (—=1/3 and —=20%).

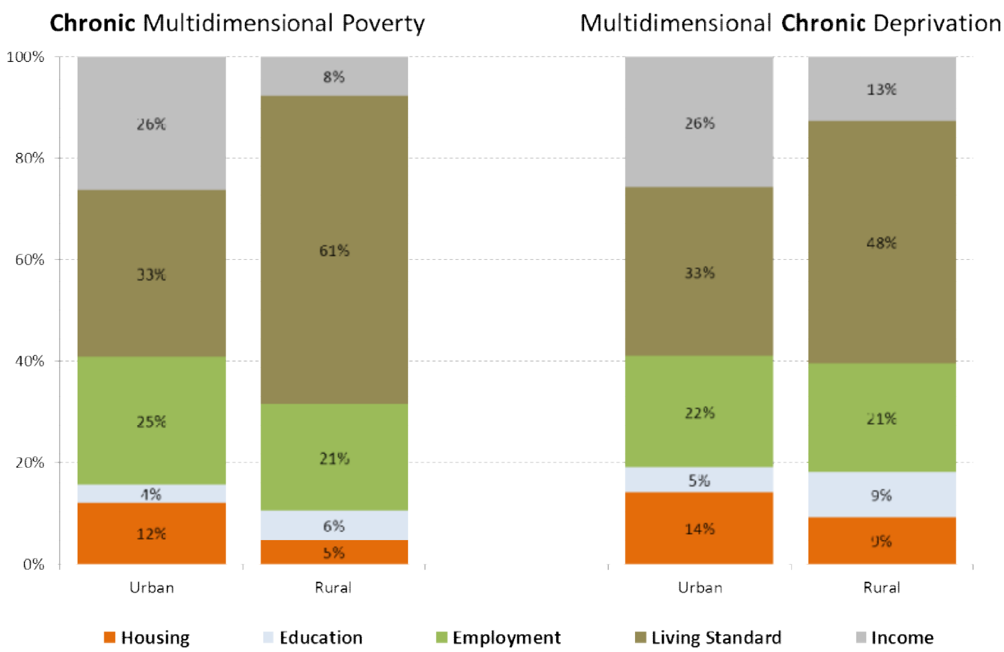
In general, the dimensional contribution explains the relevance of each dimension to the total level of multidimensional poverty, in this case, to the two proposed measures for longitudinal poverty. It evaluates the contribution of each dimension according to the censor headcount of each dimension. Consequently, it shows how much of the total poverty is explained by those individuals who are chronically poor (in each case) and deprived at the same time.

In the graphs there are small differences in the contribution of each dimension between the two measures. Only for rural cases, the contribution of living standards is significantly higher for the first measure. Oppositely, in the multidimensional chronic deprivation education and housing show a higher contribution.

Additionally, different patterns can be observed between geographical areas. In rural areas, living standards are clearly the most important contributor to multidimensional poverty. Despite this dimension also being relevant in urban areas, its relative importance is lower since it is better distributed with income and employment. Additionally, the contribution of income as a proxy of nutrition is significantly lower in rural areas mainly due to access to self-consumption.

Figure 11: Decomposition of Chronic Poverty by Dimension and Area

(—=1/3 and —=20%)



When different levels of chronic poverty are decomposed by dimension, it is clear that for low levels of — (at least once poor) the contribution is mainly distributed between income and living standards. However, when — increases the relevance of living standards grows at the expense of employment, as can be observed in Figure 13 in the annexes.

4. Determinants of Chronic Poverty: The case of Chile

In this section, two types of multidimensional chronic poverty will be presented and compared. The first one conceives the concept of chronicity by aggregating the number of periods in multidimensional poverty of each individual (multidimensional chronic poverty by poverty condition). On the other hand, the second strategy defines chronicity at the level of dimension and, then, it aggregates these results (multidimensional chronic poverty by dimensional deprivation).

A set of independent variables will be tested based on previous literature on income poverty and the data availability. Variables with a high correlation among them and with the multidimensional poverty statics are excluded[13].

Table 7: Set of Independent Variables

Household Structure	Household Composition	Labour Market
Female Household Head	Age Household Head	Firm 5-50 Employees
Married Household Head	Number of Children 0-5	Firm 50+ Employees
Percentage of Females	Number of Children 6-10	Entrepreneur House. Head
Individual with Deficiency	Number of Children 10-15	Agricultural Activities
	Almost retired (60-65)	
	Elderly >65	

Human Capital	Intergenerational	Other
Schooling Household Head	Parent Entrepreneur	Monetary Subsidies[14]
Experience Last Employment	Schooling Father	Social Capital[15]
Training		

Geographic Characteristics	Shocks
Urban Household	Health Problem[16]
Santiago	

As one of the expected outcomes of this section is to compare results and, to a second extent, to obtain a suitable model to predict the multidimensional poverty condition, the inclusion or exclusion of variables will be relaxed bringing the indicators of goodness of fit, in some cases, out of the recommended ranges. Additionally, since data is coming from a complex survey, standard measures will not be calculated. In survey data individual observations are no longer

[13] For instance, there is an almost perfect correlation between female as household head and the chances of being a widow or separated. On the other hand, a period in unemployment and second house ownership were highly correlated with the multidimensional index.

[14] Pensions, family allowances and other direct transferences.

[15] Access to help in case of economic or health problem.

[16] Have any member of the Household experienced an extended health problem.

independent; consequently, any likelihood index does not take into account the clustered and weighted properties of the data (Chambers and Skinner, 2003; Lee and Forthofer, 2005). Instead, count and variability measures will be calculated.

Using the results of chronic poverty, the population has been subdivided into four different groups: Never poor individuals ($m = 0$); only once poor ($m = 1$); twice poor ($m = 2$), and, always poor ($m = 3$). Using this structure, an ordinal logit model will be estimated to determine the influence of a set of initial variables (x') in the level of chronic poverty among the individuals. The significance of the differences between the coefficients of the multidimensional measures will be estimated.

The following table presents the results of the ordered logit model (in brackets the t-value). In this section the main analyses will be based on the significance and the sign of the coefficients. For more details about the relevance of each independent variable over the different outcomes see marginal results in the annexes. Results were compared with a generalized ordered logit model - that relaxes the parallel lines assumption - without substantial differences. Additionally, a second model was tested defining a selectivity process (for thos individual who are never poor) before the calculation of the determinants of chronic poverty levels. Finally, coefficients were compared using Wald tests.

Table 8: Ordered Logit Model for Longitudinal Poverty

	Chronic Multidimensional poverty	**Multidimensional Chronic Deprivation**	**Income Poverty**
Female Household Head	0.267	0.211	0.674***
	(1.15)	(0.93)	(3.45)
Married House. Head	-0.152	-0.200	0.609**
	(-0.80)	(-1.12)	(2.92)
Individual w/Deficiency	0.570***	0.535**	0.228
	(3.54)	(3.02)	(1.40)
Percentage of Female	-0.670*	-0.422	0.434
	(-2.33)	(-1.52)	(1.50)
Age Household Head	-0.0195**	-0.0116	-0.0266***
	(-3.25)	(-1.83)	(-4.47)
Children 0-5	0.371***	0.388**	0.876***
	(3.51)	(3.22)	(6.81)
Children 6-10	-0.0507	-0.0127	0.495***
	(-0.48)	(-0.12)	(4.54)
Children 11-15 years	0.180	0.0800	0.715***
	(1.49)	(0.66)	(5.77)
Almost retired (55+)	-0.363*	-0.268	-0.248
	(-2.31)	(-1.54)	(-1.32)
Elderly >65	-0.542**	-0.563*	-0.251
	(-2.61)	(-2.09)	(-1.44)
Firm 5-50 Employees	-0.167	0.0424	-0.580***

	(-1.16)	(0.27)	(-3.35)
Firm 50+ Employees	-0.335	-0.163	-0.517**
	(-1.61)	(-0.86)	(-2.87)
Entrepr. House. Head	-0.124	0.0900	-0.00144
	(-0.62)	(0.48)	(-0.01)
Agricultural Activities	0.434*	0.413	0.472*
	(2.11)	(1.72)	(2.28)
Schooling House. Head	-0.00905	-0.00669*	-0.00896**
	(-1.91)	(-2.09)	(-2.64)
Experience	-0.00482	-0.00893	-0.0206*
	(-0.56)	(-1.11)	(-1.97)
Training	-1.027***	-0.696**	-1.294***
	(-4.62)	(-2.79)	(-4.69)
Social Capital	0.542**	0.240	0.0749
	(2.92)	(1.36)	(0.49)
Parent Entrepreneur	0.109	-0.0334	0.0161
	(0.83)	(-0.26)	(0.12)
Schooling Father	-0.0655**	-0.0444	-0.0647**
	(-3.11)	(-1.86)	(-3.18)
Urban Household	-2.169***	-2.465***	0.502**
	(-11.60)	(-10.30)	(2.66)
Santiago	-0.673***	-0.423**	-1.105***
	(-4.65)	(-2.73)	(-8.27)
Health Problem	-0.186	-0.109	-0.158
	(-1.01)	(-0.72)	(-1.03)
Subsidies	0.0524**	0.0326	0.0527**
	(3.14)	(1.66)	(2.88)
Cut 1	-2.894***	-3.796***	0.124
	(-7.22)	(-9.45)	(0.31)
Cut 2	-1.437***	-1.040**	1.745***
	(-3.89)	(-2.71)	(4.34)
Cut 3	0.343	0.802*	3.403***
	(1.00)	(2.27)	(7.33)
Lacy pseudo R2	**0.28**	**0.21**	**0.26**
McKelvey and Zavoina	**0.50**	**0.50**	**0.50**
Observations	**9461**	**9461**	**9461**

t statistics in parentheses- * $p<0.05$, ** $p<0.01$, *** $p<0.001$

First, since the data has a stratified survey structure, fewer tests of goodness of fit were performed. Two measures of goodness of fit, based on the explained variability of the model, were constructed and implemented for the survey data. The McKelvey and Zavoina pseudo R^2 is considered as the categorical estimator that most closely approximates the R^2 from linear regression models (Long and Freese, 2006). However, its outcomes fail in two aspects: it still rests on the latent continuous variable approach and, in this case, it is not informative to compare the regressions. A second measure of goodness of fit was estimated based on the proportion of variation in the observed response (not in the latent continuous variable) that is accounted for by a regression model (Lacy, 2006). In this case, the set of predefined indicators is more suitable to predict results for the first multidimensional model (Chronic Multidimensional Poverty), then for income chronic poverty and finally with the multidimensional chronic deprivation. Finally, using the counting R^2 the same conclusion is reached[17]. The predicted results for the first model predict correctly 67.37% of the cases; the third model 64.4%; and, the second one, only 55% of the cases.

As expected, the variables related to the structure have a positive impact on the ordered log-odds of being in a worse longitudinal poverty condition. However, these results are not transversal across models, for instance Female Household Head and Married Household Head only affect income poverty. The presence of a handicapped individual is positively related to the multidimensional indicators and the percentage of females only with chronic multidimensional poverty. Despite, the high correlation between the partnership status and the head of the household's gender, to include both it helps us to define different intra-household situations. For instance, the probabilities of being longitudinally poorer are higher for households with a married male as household head compared with another led by a non-married female as presented in Table 9.

Table 9: Conditional probabilities according to head of the household and partnership status

	Chronic Multidimensional Poverty		**Multidimensional Chronic Deprivation**		**Chronic Income Poverty**	
	Before	After	Before	After	Before	After
Pr(y=0|x)	54.8%	44.3%	29.2%	21.5%	54.2%	52.6%
Pr(y=1|x)	29.1%*	33.0%*	57.5%*	59.7%*	31.5%	32.3%
Pr(y=2|x)	13.0%	17.9%	11.0%	15.3%	11.3%	11.9%
Pr(y=3|x)	3.1%	4.7%	2.4%	3.6%	3.1%	3.3%

* Significant change at the 5%

The first and second columns of each measure present the conditional probability of being in a specific category before the proposed shock and after assuming that all other variables remain constant (and equal to the population average). So, an individual living in a household with a married male head has a 54.8%, 29.2% and 54.2% probability of being never poor according to the respective measures and models. The same individual, but living in a household headed by a non-married female, has a lower probability of being never poor. In this case the probability of being poor once is significantly different before and after, but only for the multidimensional models. This first conclusion cannot be interpreted as an ideal

[17] Since observations are concentrated only in one subgroup for chronic multidimensional poverty and chronic income poverty its results for the Adjusted Count R^2 are biased. The indicator is 14%, 47% and 22% for model 1, 2 and 3, respectively.

household structure, but as a mechanism for targeting those in more vulnerable households.

The age of the household head seems to have a negative impact on the log-odds of being poor for more periods but is insignificant only for the second model. The presence of children between 0 and 5 years has the same effect as the independent variable, but in this case the values are significant for all measures. For older children, the impact is only in the income model (positive). In the case of multidimensional measures, the relationship is negative between 6-10 years and positive between 11-15 years. This could be explained by the relevance and coverage of enrolment of children in the first group and the higher probability of dropping out in the second period. Finally, the presence of elderly (almost retired and over 65 years old), which seems to reduce the log-odds of being poorer, is significant only in the multidimensional models.

The following group of independent variables are related to the labour market and human capital. In general they are significant for the income model but only in one case with the multidimensional model, despite these included an employment dimension and even an income indicator. To be in a bigger firm, the schooling of the household head or his/her experience reduce the probability of being income chronically poor and participating in agricultural activities has the opposite effect. Additionally, the social capital (or access to monetary or any other kind of help) only affects chronic multidimensional poverty. Interestingly, only training (during the last period) has a significant negative impact increasing the log-odds of being poor for more periods in all measures.

Table 10: Conditional Probabilities According to Training

	Chronic Multidimensional Poverty		**Multidimensional Chronic Deprivation**		**Chronic Income Poverty**	
	Before	After	Before	After	Before	After
Pr(y=0|x)	49.3%*	73.1%*	25.6%*	40.8%*	52.7%*	80.2%*
Pr(y=1|x)	31.4%*	19.0%*	58.8%*	50.7%*	32.2%*	15.1%*
Pr(y=2|x)	15.4%*	6.5%*	12.8%*	7.0%*	11.8%*	3.7%*
Pr(y=3|x)	3.9%*	1.4%*	2.8%*	1.4%*	3.3%*	0.9%*

* Significant change at the 5% level

In this case, the initial condition is an individual without any training in the last year compared with the same mean individual that had training (second column). Unambiguously, training reduces the probability of being longitudinally poor using all models (and measures) and at any level (all results are statistically different at the 5% level). Interestingly, the impact is higher for chronic multidimensional poverty and chronic income poverty. It seems to suggest that training reduces income and multidimensional poverty in each year but not the vulnerability to being deprived in new dimensions.

From the intergenerational variables, only the schooling level of the parents seems to affect negatively the probability of being poorer but is significant only in the first and third model. Intergenerational transmissions reduces the probability to be chronically poor in all models but it is not relevant to reduce those dimensions that are constantly deprived (model 2).The employment condition of the parents on the other hand seems to be insignificant.

Finally, as expected, the urban condition and the geographic location (in the national capital) tend to reduce the log-odds of being chronically poor in the multidimensional measures. This is mainly explained by easier access to basic services like education and health. However, results are positive for the income measure. This might be explained by the economic context, basically in the first period of the analyses where urban areas were characterized by high levels of unemployment, especially in 2001.

As before, the conditional probabilities show first an individual living in a rural area and, then, the same average individual living in urban areas ceteris paribus. In the multidimensional measures, there is a higher probability of never being poor in an urban area and, in general, while individuals are more likely to be longitudinally poor (except for the second model when one period is analysed). As described before, the third model shows a different pattern increasing for all levels of poverty in urban areas compared with rural ones.

Table 11: Conditional Probabilities According to Training

	Chronic Multidimensional Poverty		**Multidimensional Chronic Deprivation**		**Chronic Income Poverty**	
	Before	After	Before	After	Before	After
Pr(y=0|x)	16.6%*	63.5%*	5.0%*	38.3%*	66.5%*	54.6%*
Pr(y=1|x)	29.4%*	24.7%*	40.4%*	52.4%*	24.4%*	31.3%*
Pr(y=2|x)	37.5%*	9.6%*	38.6%*	7.7%*	7.2%*	11.1%*
Pr(y=3|x)	16.5%*	2.2%*	16.0%*	1.6%*	1.9%*	3.0%*

* Significant change at the 5% level

In general, estimated models for chronic multidimensional poverty and multidimensional chronic deprivations show similar patterns according to the Wald tests. Furthermore, only in 1 case (percentage of females) were coefficients significant between the two methodologies. These results are consistent with those obtained in the selection model; however, in that model more differences were perceived in the selection process. Finally, health shocks seem to be insignificant in all models, and subsidies (only in 1996) seem to affect the first model and the last one, but surprisingly not multidimensional chronic deprivation. This tends to confirm that this measure captures information that is not explained by the other measures.

To sum up, there are small differences between the two models of longitudinal multidimensional poverty mainly based on the lower requirement for k_t=1/3 in the case of the Multidimensional poverty requirement. The joint results for higher levels of k_t generate relevant information to identify those individuals who are poor during several periods but not necessarily with similar deprivations across years.

The chronic multidimensional poverty captures information of those individuals who are constantly in poverty condition regardless of the dimensions in which they are deprived. In the margin, this measure reflects those household close to the deprivation cut-offs that are vulnerable to any shock. An alternative interpretation is to consider household that are doing a trade-off between dimensions interchanging deprivation across dimensions. For instance, a poor household deprived in living standards (toilet) could improve that condition but worsening another one like employment. This not only reflects a condition of vulnerability but also, using the vocabulary of the integrated method of poverty measure, shows a structural kind of poverty that despite the household efforts is not able to leave the poverty.

On the other hand multidimensional chronic deprivation captures information of those individuals who are constantly deprived in the same dimension across years. Different to the previous definition, identify those households with achievements extremely distant from the poverty line. In this case, individuals despite their efforts are not able to solve an specific problem. Alternatively, it could reflex a lower valuation of that chronically deprived dimension.

Interestingly, cross results for transitional poverty are also relevant since they provide information about individuals who are not considered poor in cross-sectional measure and with intermittent and different deprivations across years. The methodology redefines standard considerations for vulnerability. In other words, it reflects those individuals who are alleviating one deprivation; but, at the same time, are entering a second one.

The econometric models show, once again, the similarities among the measures but highlight the higher correspondence of chronic multidimensional poverty and chronic income poverty. In general, the high relevance of employment variables was established in the multidimensional income poverty model. Despite our multidimensional specifications including an employment dimension and even an income indicator, these results were not always significant.

5. Concluding remarks

With this paper's contribution we have sought to provide a first example of the different ways in which bridges can be laid between two rich literatures that have not yet been intertwined: the literature on multidimensional poverty measurement and the literature on (unidimensional) poverty dynamics. Our focus has been on linking the subliterature of chronic poverty and counting poverty measures.

More narrowly, the two sets of measures proposed in this paper seek to connect the class of chronic poverty measures characterized by Foster (2009) with the Alkire-Foster family (Alkire and Foster, 2010). Since both measures are based on a common heritage of axioms, which in turn draws from the FGT family, we believe that our proposal constitutes the logical next generation in this tradition of poverty measurement.

The measures we have proposed inherit the properties of the two classes they mimic. Since other contributions, especially in the chronic poverty literature, have made substantial progress in the proposal of measures that satisfy a richer set of axioms, we think that future research should explore alternative multidimensional chronic poverty measures that combine alternative measurement frameworks, among those used for capturing multidimensionality, i.e. the presence of joint deprivations, and for capturing chronicity. For instance, it may be worth exploring a combination of the Alkire-Foster framework with the chronic poverty measures of Bossert et al. (2010). Many other possibilities could be considered. Investigating, and understanding, the differences in the theoretical (i.e. property fulfilment) and empirical behaviour between these different proposals of multidimensional chronic poverty measures, holds the promise of a stimulating, and fruitful, research agenda.

6. Annexes

Table 12: Multidimensional Poverty, Headcount ratio and Average deprivation (Panel Survey)

	1996			2001			2006		
k	**A**	**H**	**M**	**A**	**H**	**M**	**A**	**H**	**M**
10%	0.25	0.38	0.09	0.22	0.35	0.08	0.19	0.28	0.05
20%	0.30	0.26	0.08	0.29	0.20	0.06	0.27	0.11	0.03
30%	0.41	0.10	0.04	0.40	0.07	0.03	0.38	0.03	0.01
40%	0.49	0.05	0.02	0.46	0.03	0.02	0.44	0.01	0.01
50%	0.56	0.02	0.01	0.57	0.01	0.01	0.55	0.00	0.00
60%	0.62	0.01	0.00	0.64	0.00	0.00	0.60	0.00	0.00
70%	0.73	0.00	0.00	0.73	0.00	0.00	.	0.00	

Table 13: Raw Headcount and Censored Headcount (k=20%)

		Raw Headcount			Censored Headcount k=20%		
		1996	**2001**	**2006**	**1996**	**2001**	**2006**
Housing	Housing	2%	1%	0%	2%	1%	0%
	Overcrow.	10%	7%	4%	7%	5%	3%
	Settlement	0%	1%	0%	0%	1%	0%
Education	Illiteracy	8%	7%	10%	5%	3%	3%
	Attendance	1%	1%	1%	1%	0%	0%
	Schooling	0%	0%	0%	0%	0%	0%
Employment	Unemploy.	10%	16%	14%	5%	6%	3%
	Contract	19%	20%	19%	8%	8%	4%
	Security	40%	40%	39%	15%	12%	7%
Liv. Standard	Toilet	19%	12%	6%	19%	12%	6%
Income	Income	6%	5%	2%	6%	5%	2%

Table 14: Rates of entry and exit in Multidimensional Poverty

	1996-2001		2001-2006		1996-2006	
k	**Pr. Entry**	**P. Exit**	**Pr. Entry**	**P. Exit**	**Pr. Entry**	**P. Exit**
10%	22.5%	44.4%	19.7%	55.5%	21.6%	60.5%
20%	9.2%	48.5%	5.1%	66.3%	5.9%	75.0%
30%	3.8%	65.2%	1.9%	77.4%	2.2%	86.6%
40%	2.2%	73.8%	0.8%	82.6%	0.9%	89.6%
50%	0.6%	84.3%	0.2%	95.0%	0.2%	97.6%
60%	0.2%	83.9%	0.0%	100.0%	0.0%	98.8%
70%	0.0%	100.0%	0.0%	100.0%	0.0%	100.0%

Table 15: Headcount Ratio by Poverty condition

				Multidimensional Chronic Poverty (k_d=20%)					
	Income Poverty			Chronic Multi. Poverty			Multi. Chronic Deprivation		
	Mean	Conf. Interval		Mean	Conf. Interval		Mean	Conf. Interval	
Never Poor	66%	63%	69%	64%	60%	68%	43%	38%	47%
At least once Poor	21%	18%	24%	36%	32%	40%	57%	53%	62%
At least 2 times poor	10%	8%	12%	17%	14%	20%	14%	11%	17%
Always Poor	4%	3%	5%	5%	4%	7%	4%	3%	5%

Figure 12: Probability of Remaining Non-Poor and Poor for Different Periods (—=20%)

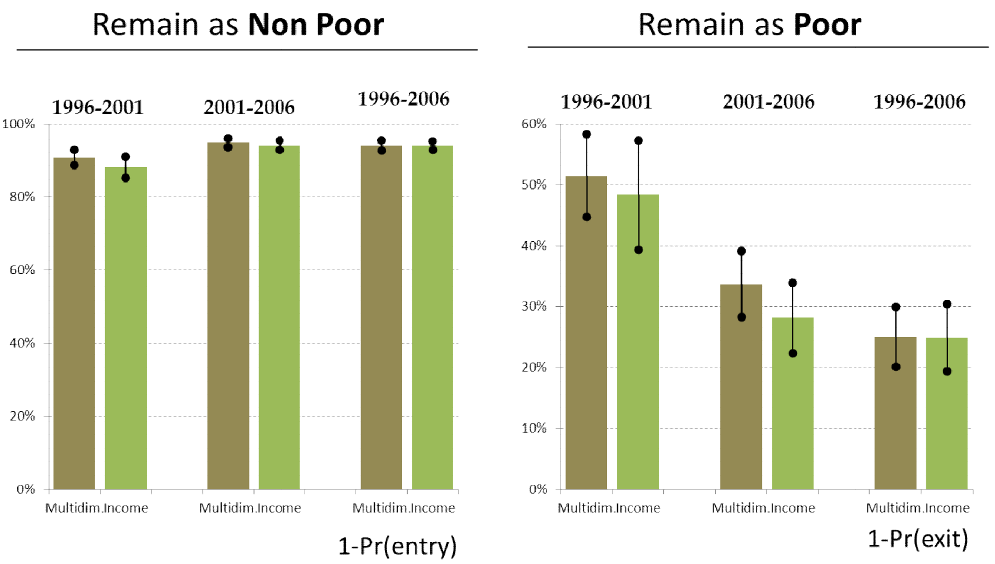


Table 16: Probability of Remaining Deprived and Non-Deprived for Different Periods (—=20%)

	Probability of Remaining Non-Deprived			Probability of Remaining Deprived		
	1996-2001	**2001-2006**	**1996-2006**	**1996-2001**	**2001-2006**	**1996-2006**
Housing	100%	100%	100%	16%	13%	7%
Overcrowding	97%	98%	98%	21%	22%	9%
Settlement	100%	100%	100%	8%	11%	19%
Illiteracy	98%	98%	98%	35%	27%	14%
Attendance	100%	100%	100%	2%	2%	3%
Schooling	100%	100%	100%	9%	36%	5%
Unemployment	94%	97%	97%	9%	17%	8%
Contract	93%	97%	96%	16%	16%	7%
Contract	99%	99%	98%	36%	26%	18%
Toilet	98%	98%	98%	55%	33%	22%
Income	97%	99%	98%	25%	17%	11%

Figure 13: Decomposition by dimension Longitudinal Poverty (=20%)

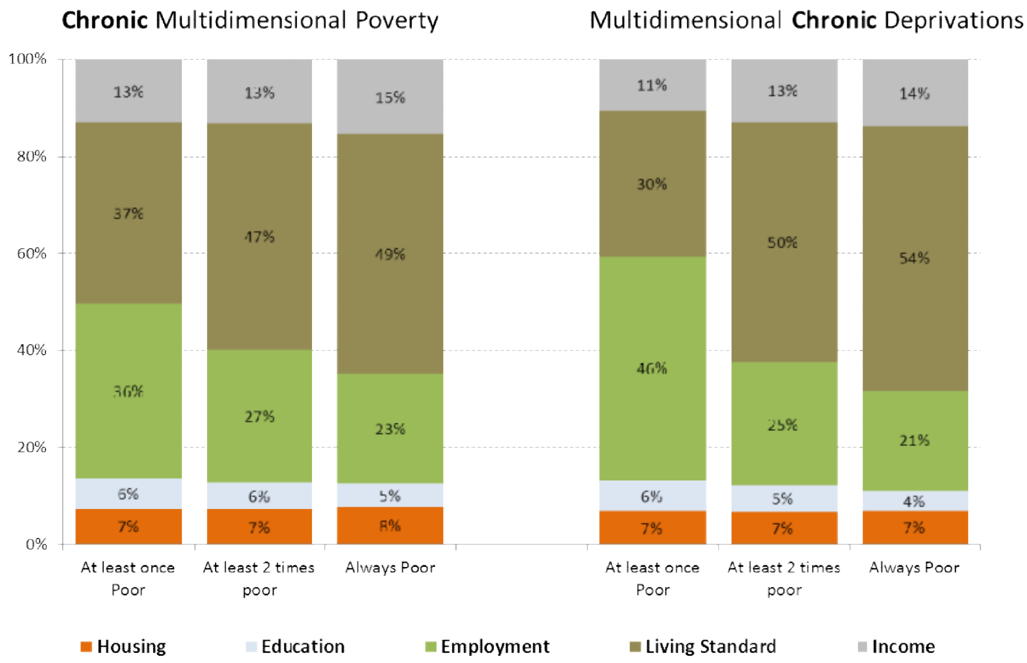


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Table 17: Regressions selection model for Chronic Poverty

	Chronic Multidimensional Poverty		Multidimensional Chronic Deprivation		Income Chronic Poverty	
	Selection	Level	Selection	Level	Selection	Level
Female Household Head	-0.183	0.488*	-0.102	0.545*	-0.704**	0.317
	(-0.77)	(2.15)	(-0.39)	(2.48)	(-3.28)	(0.89)
Married Household Head	0.0215	-0.343	0.0997	-0.530*	-0.775***	-0.307
	(0.10)	(-1.75)	(0.46)	(-2.13)	(-3.41)	(-0.95)
Individual with Deficiency	-0.831***	-0.00906	-0.720**	0.886	-0.386	-0.169
	(-4.29)	(-0.03)	(-3.19)	(1.17)	(-1.84)	(-0.55)
Percentage of Female	0.757*	0.165	0.348	-0.812	-0.374	0.262
	(2.34)	(0.35)	(1.11)	(-1.49)	(-1.23)	(0.68)
Age Household Head	0.0192**	-0.0119	0.00857	-0.0240*	0.0299***	-0.00787
	(2.84)	(-1.45)	(1.17)	(-2.55)	(4.07)	(-0.64)
N. of Children 0-5 years	-0.338**	0.378*	-0.362*	0.762	-0.795***	0.715*
	(-2.74)	(2.42)	(-2.50)	(1.82)	(-5.97)	(2.50)
N. of Children 6-10 years	0.128	0.193	0.0818	0.0726	-0.526***	0.324
	(1.17)	(1.47)	(0.69)	(0.40)	(-3.90)	(1.51)
N. of Children 10-15 years	-0.227	0.0361	-0.122	0.121	-0.736***	0.391
	(-1.56)	(0.26)	(-0.79)	(0.72)	(-5.40)	(1.49)
Almost retired 1996	0.446*	-0.131	0.328	-0.408	0.211	0.0311
	(2.50)	(-0.48)	(1.64)	(-0.87)	(1.04)	(0.10)
Elderly >65 1996	0.701**	-0.0230	0.748*	-0.715	0.0615	-0.925**
	(2.99)	(-0.06)	(2.40)	(-0.82)	(0.23)	(-2.80)
Firm 5-50 Employees	0.155	-0.280	-0.134	-0.179	0.595**	-0.126
	(0.94)	(-1.58)	(-0.70)	(-0.80)	(3.02)	(-0.43)

Firm 50+ Employees	0.340	-0.354	0.0803	-0.507*	0.487*	-0.381
	(1.36)	(-1.45)	(0.36)	(-2.48)	(2.27)	(-1.16)
Agricultural Activities	-0.705**	0.329	-0.606*	1.121	-0.440	0.403
	(-3.12)	(0.94)	(-2.50)	(1.44)	(-1.61)	(1.48)
Schooling Household Head	0.0109*	0.00274	0.00757*	-0.00786	0.00773*	-0.00546
	(2.42)	(0.73)	(2.37)	(-0.92)	(2.20)	(-1.07)
Experience	0.00773	-0.00182	0.0132	-0.0144	0.0231*	-0.00840
	(0.69)	(-0.18)	(1.32)	(-0.71)	(2.06)	(-0.61)
Training	1.117***	-0.134	0.750**	-0.812	1.347***	-0.394
	(4.42)	(-0.35)	(2.75)	(-1.05)	(4.54)	(-0.81)
Social Capital	-0.610**	0.130	-0.160	0.534*	0.0708	0.434
	(-2.90)	(0.49)	(-0.78)	(2.01)	(0.38)	(1.62)
Parent Entrepreneur	0.0692**	-0.0220	0.0395	-0.104*	0.0830***	0.0241
	(2.95)	(-0.77)	(1.48)	(-2.39)	(4.05)	(0.56)
Schooling Father	2.175***	-1.697*	1.789***	-4.053*	-0.458*	0.408
	(10.63)	(-2.47)	(7.32)	(-2.09)	(-2.30)	(1.34)
Urban Household 1996	0.598***	-0.471	0.207	-1.047***	1.068***	-0.815*
	(3.73)	(-1.79)	(1.19)	(-3.52)	(7.35)	(-2.24)
Santiago	-0.0564**	0.0194	-0.0291	0.0742*	-0.0463*	0.0398
	(-2.99)	(0.78)	(-1.25)	(2.17)	(-2.37)	(1.53)
Health Problem	0.227		0.0587		0.160	
	(1.06)		(0.32)		(0.92)	
Constant	-2.786***		-2.779***		-0.197	
	(-6.54)		(-6.30)		(-0.47)	
Mills Ratio		-0.0650		-1.284		0.0853
		(-0.16)		(-0.99)		(0.20)
Constant		-1.691		-5.573		1.549*
		(-1.39)		(-1.43)		(2.38)
Constant		0.342		-3.542		3.449***
		(0.28)		(-0.90)		(4.87)
Observations	**9461**	**4650**	**9461**	**6480**	**9461**	**4540**

t statistics in parentheses- * $p<0.05$, ** $p<0.01$, *** $p<0.001$

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