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This paper is a draft submission to

Inequality—Measurement, trends, impacts, and policies

5–6 September 2014 Helsinki, Finland

On the Dynamics of Multidimensional Chronic Poverty

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Abstract

We propose a Shapley decomposition of a chronic multidimensional chronic poverty measure. This decomposition helps to find the drivers of the change of chronic poverty and proves to be a valuable tool in the focalization of public policy programs. We present an empirical application of the changes of chronic poverty during the period 2004-2012 using the Permanent Household Survey. The methodology presented can be easily adjusted for the study of other inter-temporal subjects, such as chronic unemployment, chronic health deprivation, and similar measures.

1 Introduction

Poverty eradication is a long-term project that many developing countries are engaged. In order to deepen our understanding of why poverty occurs, and significantly improve the effectiveness of poverty reduction strategies, attention has been paid to its determinants and evolution over time. It is well recognized in the literature that measures of living standards at one point in time may provide limited information regarding its evolution across time and persistence (Aliber, 2003; McKay and Lawson, 2003; Hoy et al., 2012; Hoy and Zheng, 2011). Hulme and Shepperd (2003) points out that waste of precious resources are wasted if not distinguished between chronically poor and episodically poor. Chronically poor are those most likely to remain in poverty in the absence of effective assistance and it is characterized in terms of policy discussions as the type of poverty that does not easily resolve itself. Persistence conditions of poverty have a long lasting effect, since there is evidence that those households in chronic poverty pose a higher risk of inheriting the same living standards to the next generation, therefore perpetuating poverty (Hulme and Shepperd, 2003).

Recognizing dynamics poverty is relevant yet underpinning its determinants is a complex task. Chronic poverty has mostly considered monetary dimension of poverty, partially because are indicators that can fluctuate the most in

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the short time (Baulch and Hoddinott, 2000; McKay and Lawson 2003). Yet, there is evidence that chronic poverty is more incisive in other dimensions of poverty different than income. As pointed out by Hulme (2003), "the chronic poor are likely to be neglected in such an era given the multiple factors that constrain their prospects", hence the need to move efforts to measure poverty dynamics beyond mere income and consumption to multidimensional concepts and definitions of poverty. Recent advances in the conceptualization and measurement of multidimensional chronic poverty offer the possibility to analyze the determinants that can affect poverty overtime (Apablaza and Yalonetzky, 2012; Alkire et al., 2013). On such array of information, is important to disaggregate the poor in order to refine the understanding of the causes of multidimensional chronic poverty and create the knowledge that is needed to design effective policy interventions.

We propose a method to analyze the factors that are driving the change of multidimensional chronic poverty. In order to do that, we build on Alkire et al., (2013) to apply Shapley (1953) decomposition approach to isolate the marginal contributions of each well-being source in the analysis. Following Ravallion and Huppi (1991) decomposition of poverty changes, we use two factors in the analysis: (1) changes due to within group chronic poverty effect associated with changes in the headcount of chronically poor and (2) changes due to demographic or between group effects characterized by the average measure of the intensity of chronic poverty over time. Since there is no natural order of elimination of factors to isolate its marginal contribution to overall chronic poverty, we average these impacts overall possible sequence of eliminations. Thus, in order to assess the marginal contribution of a given factor to overall chronic poverty we apply the before and after concept to the set of all possible combinations of factors and take the average of its contributions.

The determinants of changes in poverty have been while established in the literature. A widely used decomposition analysis in applied studies is the change in poverty in terms of growth and inequality components (some important contributions, among others, are Datt and Ravallion, 1992; Ravallion and Chen, 1997 and Tsui, 1996). These decompositions allow us to understand the interrelation between growth, inequality and poverty, in particular, how increasing trends in inequality may offset the benefits of economic growth. Other dynamic decomposition, look for a series of determinants in some important demographic and sectoral characteristics of the households. Ravallion and Huppi (1991) follow a similar decomposition, but instead focus on quantify the changes in aggregate poverty, in terms of factors relating to sectors in the economy and according to distributional parameters. Despite being widely used, these decompositions pose some limitations in the interpretation of contributing factors since they are not always interpreted in an intuitively way and they are path-dependent to the initial income in the analysis (Shorrocks, 2013). These limitations become more relevant as we try to identify relevant contributions in a multi-variate and dynamic setting. The Shapley method as suggested by Shorrocks (2013) overcomes these limitations by generating a path-independent and exact additive decomposition of changes in poverty into factors. A similar study to ours is Roche

(2012) that used Shapley decomposition to changes in multidimensional poverty in order to assess overall progress of child poverty reduction in Bangladesh.

Nevertheless the changes in poverty analyzed so far, refers to one point in time. Chronic poverty, as mentioned above, is a specific conceptualization of poverty that focuses on its multidimensionality and considers its monotonicity and time persistence as suggested by Foster (2009). The framework here proposed allows us to focus on the permanent and not in the episodically components of poverty. In the long, term, the effect of the episodically components average out, while the effect of the permanent ones persists. This allow us to elucidate the driving forces of some well-being sources that make a strong resistance in the standard of living of the chronically poor and could potentially help to design better anti-poverty policy strategies.

An empirical section estimates the Shapley decomposition of chronic multidimensional are applied to panel data from Argenina's Encuesta Permanente de Hogares carried out by Insituturo Nacional de Estadísticas y Censos (INDEC), covering 32,772 households during four waves of October 2004, May 2004, October 2012 and May 2012. We found that chronic multidimensional poverty decreased from 2.7% in 2004 to 0.84% in 2012. The vast majority of this change was driven by a change in the incidence of poverty rather than in the intensity of poverty, which maintained its level relatively the same. Furthermore, the households with children but without elderly accounted for 77% of the total change in chronic multidimensional poverty. In regard to the importance of the indicators, the change in income poverty was the main driver of the improvement in chronic multidimensional poverty, whereas the variables of unemployment and availability of proper shelter were the indicators that worsen the most. ... The methodology proposed allows us to systematically assess a vast array of information on chronic poverty defined in several dimensions. Considering all dimensions and time variations, we found that changes in chronic poverty are sometimes small in relation to changes in income poverty; nevertheless it is possible to disentangle and quantify impacts of various causal factors that play a role in the gestation of chronic poverty.

The structure of this paper is as follows. The chronic multidimensional framework used in the analysis is supplied in section 2. In Section 3, we define our decomposition analysis using the Shapley rule to analyze the determinants of the dynamics of poverty over time. Section 4, contains the application the case of Argentina. Section 5 concludes.

2 Multidimensional chronic Poverty

This section lays down the conceptualization of multidimensional chronic poverty. Before introducing the definitions, an explanation of our notation is in order. We suppose a population of size n, person i possesses an m-row vector of attributes in time t, $x_i^t \in R_+^m$ where R_+^m is the non-negative orthant of the Euclidean m-space R^m. The vector $x_{i.}^t$ is the row of a $n \times m$ matrix $x^t \in M^n$ is the set of all $n \times m$ matrices in time t , whose entries are non-negative reals. The x_{ij}^t denotes the quantity of attribute j possessed by person i in time t. Therefore, $x_{\cdot j}$, is the column jth column of X^t, gives a distribution of attribute j among n persons in time t. The median of each of the attribute in time t is denoted by μ_j^t. With regard to the identification problem in time t, a threshold for each dimension is determined to represent the minimum level of basic needs and $z_d \in Z$ be a vector of thresholds for different dimensions, where Z is a non-empty subset of R^m_{++}.

In what follows is convenient to re-express the original matrix of achievements in time t, x^t, in terms of deprivations. To this end, from the original matrix of attributes we can generate an associated matrix of deprivations. For a given x^t, let $g^t(0)$ denote a matrix of deprivations associated with x^t, whose typical element of the matrix is $g^t_{ij}(0) = 1$ if $x^t_{ij} < z_j$, while $g^t_{ij}(0) = 0$ if $x^t_{ij} \geq z_j$. The matrix $g^t(0)$ is the size $n \times d$, and elements are either zero or one, zero when individual is non-poor and 1 when individual is poor. We now, generate a matrix of normalized poverty gaps or shortfalls than allow us to evaluate different aspects of poverty. Let g^1 be the matrix of normalized gaps of size $n \times d$, where a typical element of the matrix is defined by $g^t_{ij}(1) = g^0_{ij}(z_j - x_{ij})/z_j$. The poverty gap measures the deepness of poverty by weightening for the difference between the attribute and its poverty line. We can generalize the associated matrix to analyze different aspects of poverty, for this purpose, we can define and associated matrix $g^t_{ij}(\alpha)$, whose typical entry is $g^t_{ij}(\alpha) = (1 - \frac{x_{ij}}{z})^\alpha$, where $\alpha \geq 0$.

The measurement of the multidimensional chronic poverty can be divided into an identification step and an aggregation step. We follow Alkire et al. (2009) two stage process to identify the multidimensional chronic poverty. The procedure consist on a series of transformations of the original matrix, x^t, in relation to its dimensions and time. The aggregation step takes the set of multidimensional chronically poor as given and combines information in both, the number of deprivations and their level across periods -information on poverty depth and distribution can be incorporated also. The resulting functional relationship, M^c, is called an index, or measure of multidimensional chronic poverty.

2.0.1 The identification of the multidimensional chronically poor

The identification of the multidimensionally poor is well recognized in the literature (Tsui (2002), Bourguingnon and Chakravarty (2003), Duclos et. al (2006)). A natural starting point is to consider poor all those deprived in at least one dimension, the so called union approach. However, we might consider more demanding criteria and consider one individual poor if she is deprived in all dimensions, defined as the intersection approach. Alkire and Foster (2011) generalize these two positions by defining an intermediate cutoff, k, which is the number of dimensions someone is required to be considered poor. The identification cutoffs ranges from $k = 1$, corresponding to the union approach, to $k = d$, corresponding to the intersection approach. This approach also allows to assign different positive weights to the attributes according to its importance, for that, we define a vector of attributes weights, $w = [w_1, w_2, ..., w_d]$ where

$\sum_{j=1}^{d} w_j = d$.

We proceed to define those multidimensionally poor, for that, we need to count the number of deprivations suffered by person i in time t, denoted as c_i^t. Then, the deprivation counts in time t is a n-dimensional vector given by, $c^t = g^t(0)w$, where a typical element of the vector is given by, $c_i^t = \sum_{j=1}^{d} w_j g_{ij}^t(0)$. Using the deprivation count vector in time, c^t, we now identify the multidimensionally poor through an identification vector in time t, $I^t(k)$, such that a typical element is given by $\rho_i^t(k) = I(c_i^t < k)$. This identification vector elements take the value of 1 if $c_i^t < k$, or the value of 0, if otherwise.

The second stage proceeds to identify multidimensional poverty across time. For that purpose, we use the duration cut-off τ that specifies the minimum fraction of time that must be spent in poverty in order for a person to be considered chronically poor. In each period t, $t = 1, 2, ...T$, households poverty status is determined by the identification vector $I^t(k)$, previously defined, thus we define a $n \times T$ matrix in which each of the t column vectors is the identification vector $I^t(k)$. With that information, we now proceed to define the chronic counting vector $c = I(k)1_T$, where I_T is a T-dimensional column vector of ones. The chronic counting vector is a n-dimensional vector, whose a typical element is given by $c_i = \sum_{t=1}^{T} \rho_i^k(k)$. Finally we identify the chronically poor by as an n-dimensional vector $\rho^c(k, \tau)$, in which a typical element, $\rho_i(k, \tau)$, is given by: $\rho_i(k, \tau) = I(c_i > \tau)$. As before, the identification vector elements takes value of 1 when $c_i > \tau$ and 0, otherwise.

2.0.2 Multidimensional chronic poverty and aggregation

Following Alkire and Foster (2011) the aggregation step takes the identification function $\rho^c(k, \tau)$ and its associated matrix of achievements x, the attributes' cutoff vector, z, the weights of the attributes, w, the number of dimensions cutoff, k and the duration period cutoff τ. The resulting functional relationship $M : x \times R_{++}^d \rightarrow R$ is an index called a multidimensional chronic poverty index.

The multidimensional headcount is the simplest version of a multidimensional index. It is straight forward to calculate the fraction of the population deprived in k or more dimensions and during at least τ fraction of time. Formally, this can be expressed as:

$$H_c(x; z, k, \tau) = \frac{1}{n} \sum_{i=1}^{n} \rho_i(k; \tau) = \frac{q}{n} \quad (1)$$

that is, the number of the poor identified using the dual cutoff approach and the duration approach (q) over the total population (n). The headcount has some important shortcomings. One limitation is that the multidimensional account is not sensitive to the number of deprivations and the number of periods that multidimensionally poor experience. That is, the index violates dimensional monotonicity (Alkire and Foster ,2011) and time monotonicity (Alkire et al., 2011). Given k value, if an individual is identified as poor and becomes deprived in an additional dimension or for another period of time, the multidimensional headcount does not change. Another important shortcoming of the multidimensional headcount is that it ignores all information about the extent of poverty. On this sense, a multidimensional poverty measure should show that poverty becomes more severe at increasing rate as successive decrements of achievements and longer periods of poverty are considered.

In order to overcome the limitations of the multidimensional headcount measure we need to include more information on the number of deprived dimensions and the number of periods of poverty experienced by the poor. Alkire et al. (2011) proposed the dimension and time adjusted FGT measure, or M_c^{α}, family of measures, defined as:

$$M_c^{\alpha}(x;z,w,k,\tau)=\frac{1}{ndT}\sum_{i=1}^{n}\rho_i(k;\tau)\sum_{t=1}^{T}\sum_{j=1}^{d}w_j g_{ij}^{t}(\alpha)=H_c A_c \qquad (2)$$

where H_c is as in equation (1) and $A_c=\frac{1}{qdT}\sum_{i=1}^{N}\rho_i(k;\tau)\sum_{t=1}^{T}\sum_{j=1}^{d}w_j g_{ij}^{t}(\alpha)$. The partial index A_c represents the average deprivation share across the chronic poor. It is important to notice that the simple product of the two partial indices H_c and A_c generates a weightening system in (2) that is affected this time by the frequency, the number of deprived dimensions and the period of time in deprivation. When $\alpha=0$ is the adjusted headcount ratio, this time the multidimensional poverty measure clearly satisfy dimensional and time monotonicity. When $\alpha=1$, the measure is the adjusted chronic poverty gap which is the sum of the normalized chronic poverty gaps of the poor. If the deprivation of a poor person deepens in any dimension or duration, then the index will rise. When $\alpha=2$, we obtain the squared poverty gaps, in this case the index provides information on the average severity of deprivations in dimensions and time people experience.

3 The Shapley decomposition of chronic poverty

In order to disaggregate the effect of some household characteristics have in chronic poverty, we follow Roche (2013) two stage disaggregation procedure. On the first stage, it is important to disaggregate how household's characteristics determines chronic poverty. For that purpose, we partitioned the population into m subgroups of households differentiated by characteristics l. Let θ_l be subgroup l's population share, i.e. the number of households in subgroup l, divided by the total number or households. In order to identify the subgroups contributions to poverty changes over time. If θ_l^t and M_c^t represent the population share and chronic poverty level of subgroup $l\in m$, at time t ($t=1,2$) then equation (2) yields

$$\Delta M_c=\sum_{l\in 1}^{m}\left[\theta_l^2 M_{cl}^2-\theta_l^1 M_{cl}^1\right]=\sum_{l\in 1}^{m}\left[\theta_l^2 H_{cl}^2 A_{cl}^2-\theta_l^1 H_{cl}^1 A_{cl}^1\right] \qquad (3)$$

The formula (3) represents the overall change in chronic poverty, ΔM_c, in terms of changes in chronic poverty within groups, $\Delta M_{cl}=M_{cl}^2-M_{cl}^1$, $l\in m$ and the population shifts between groups $\Delta\theta_l = \theta_l^2 - \theta_l^1$, $l \in m$. The second side of the equality re-expresses changes of chronic poverty in terms of its incidence and intensity components. Using the first part of the equality we apply the Shapley decomposition proposed by Shorrocks (1999) to changes in decomposable poverty indices, for that we obtain:

$$\Delta M_c = \sum_{l=1}^{m} \frac{\theta_l^2 + \theta_l^1}{2} \left(M_{cl}^2 - M_{cl}^1\right) + \sum_{l=1}^{m} \frac{M_l^2 + M_l^1}{2} \left(\theta_l^2 - \theta_l^1\right) \tag{4}$$

the first term in (4) represents the Shapley contribution associated with the changes in chronic poverty within population subgroups l and the second term represents the Shapley contribution to demographic shift factors.

The second stage involves a decomposition of changes in chronic poverty in terms of its incidence and intensity components. For this, we use the second part of equality in formula (3) for subpopulation $l \in m$ and apply the Shapley decomposition again, it follows that,

$$\Delta M_{cl} = \frac{A_{cl}^2 - A_{cl}^1}{2} \left(H_{cl}^2 - H_{cl}^1\right) + \frac{H_{cl}^2 - H_{cl}^1}{2} \left(A_{cl}^2 - A_{cl}^1\right) \tag{5}$$

where the first component is the Shapley contribution associated with the incidence of chronic poverty and the second component is the Shapley contribution associates with the intensity of chronic poverty. Combining (4) and (5) we obtain the overall decomposition of changes in poverty:

$$\begin{aligned} \Delta M_c \quad = \quad & \sum_{l=1}^{m} \left(\frac{M_l^2 + M_l^1}{2}\right) \left(\theta_l^2 - \theta_l^1\right) + \sum_{l=1}^{m} \left(\frac{\theta_l^2 + \theta_l^1}{2}\right) \left(\frac{A_{cl}^2 - A_{cl}^1}{2}\right) \left(H_{cl}^2 - H_{cl}^1\right) \\ & + \sum_{l=1}^{m} \left(\frac{\theta_l^2 + \theta_l^1}{2}\right) \left(\frac{H_{cl}^2 - H_{cl}^1}{2}\right) \sum_{j=1}^{d} \frac{w_j}{d} \left[\frac{CH_{jcl}^2}{H_l^2} - \frac{CH_{jcl}^1}{H_l^1}\right]. \end{aligned} \tag{6}$$

The first term in the equation refers to the population shift effect that show how changes in the distributions of the population across subgroups contributed to the change in aggregate multidimensional chronic poverty, ΔM_c. The second and the third term, accounts for changes in multidimensional chronic poverty within subgroups, which is further decomposed in terms of the incidence and intensity effect.

4 Application to chronic multidimensional poverty in Argentina

In this section we study the presence of chronic multidimensional poverty in Argentina and we present its Shapley decomposition for the period of 2004 to 2012. We use the rotating panel Permanent Household Survey (EPH for its initials in Spanish) which uses the sampling format 2-2-2, that is, the survey follows a household for two consecutive periods, retrieves those households for the following two, and finally resamples them in the subsequent two. With this format, the survey allows us to follow a household during four points in time in a span of one year and a half. We use this data for illustration purposes since the EPH database presents a wide range of variables that allow us to construct a multidimensional poverty measure. Moreover, given that the questionnaire didn´t change since 2003, it allows us to keep track of the development of the chosen variables for a long span of time.

In this section we will first discuss the selection of the well-being indicators, followed by a cross-section description of the deprivation indicators at a point in time. Subsequently, we report various measures of chronic multidimensional poverty for different dimensional and time cutoffs. Finally, we study the relative importance of each variable at a certain period, and we use the Shapley decomposition to point out which indicators are driving the change in chronic poverty.

Following Alkire et al (2013), we used three dimensions: education, housing and employment/income. We followed their selection of variables because they also considered a chronic multidimensional measure, and because they applied their research for the case of Chile, a country that has similar characteristics to Argentina. In Table 1 we see a description of the indicators used and their corresponding cut-offs. For the estimation of chronic multidimensional poverty all our indicators will be equally weighted, wj = 1/9.This could be changed in order to give more importance to certain subjects.

For the education dimension we use the indicators of educational achievement, school attendance and illiteracy. In regard to the indicators related to housing, we used a measure of overcrowding, a measure of shelter deprivation and a dummy variable for the availability of a toilet in the household. Finally, when considering the income/employment measures we used the indicators of income poverty, unemployment and quality of employment. We report the raw headcounts of each variable for 2003 and 2012, and their respective change in percentage points. All variables improved with the exception of educational achievement and unemployment. The most striking change is that of the income poverty, which drops 40 percentage points.

Table 1. % in deprivation		
	2004	**2012**
Educ Aciev	8.55%	8.87%
School Attendance	7.81%	6.56%
Illiteracy	4.23%	2.79%
Overcrowding	31.35%	27.15%
Shelter	12.66%	9.33%
Toilet	10.06%	5.55%
Income	45.81%	4.97%
Unemployement	10.97%	12.48%
Quality of employment	43.29%	37.82%
n	32772	38812

Two of the great advantages of the Alkire and Foster (2011) methodology are their dimension and subgroup decomposability. This attributes allow studying the relative importance and development of each dimension, and furthermore to do it by different groups. We will distinguish four different types of households, which we will classify depending on the presence of children or elderly in the household. Specifically, the groups are: households with children and elderly (HH1), households with children but no elderly (HH2), households with elderly but no children (HH3), and households without children or elderly (HH4)[1]

Before describing in more detail the household dynamics by group, we discuss the results of the entire population. In Table 2 we show the results of chronic poverty Mc(x,z,t=4;k) as defined in equation 2, with t=4 and for different dimensional cut-offs. If we follow the union approach for the dimensional cut-offs, we see that, in 2004, 63.73% of the population were chronically poor in at least one dimension. That percentage decreased to 51.79% in 2012. Since in both years the intensity of poverty was low, around 7% and 5.5% for the respective years, the censored matrix is as low as 4.49% and 2.87% when we consider the union approach, and 1.09% and 0.22% when we consider the intersection approach.

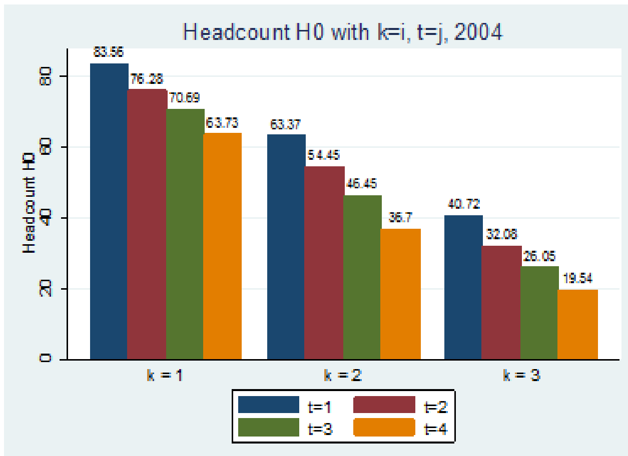
Table #. Headcount ratio by poverty cutoff (t=4)

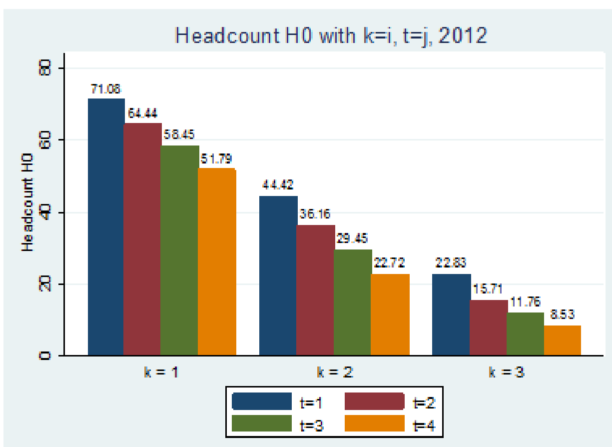
	pov cut-off, k = 1		pov cut-off, k = 2		pov cut-off, k = 3		pov cut-off, k = 4	
	2004	2012	2004	2012	2004	2012	2004	2012
H	63.73%	51.79%	36.70%	22.72%	19.54%	8.53%	8.26%	1.67%
A	7.04%	5.54%	9.13%	7.80%	11.08%	9.88%	13.23%	13.28%
M	4.49%	2.87%	3.35%	1.77%	2.17%	0.84%	1.09%	0.22%

A more complete image can be perceived when we vary both the dimensional

[1] We define a household with children if at least one individual in it has at most 12 years old. Similarly, a household with elderly will have at least one individual with at least 65 years old.

and the time cut-offs. In the Figures 1 and 2 we show the different headcounts (not censored) for each combination of t=j and k=i,for j=1,2,3,4 and i=1,2,3, that is Hc (x,z; k,t) as defined in equation 1.



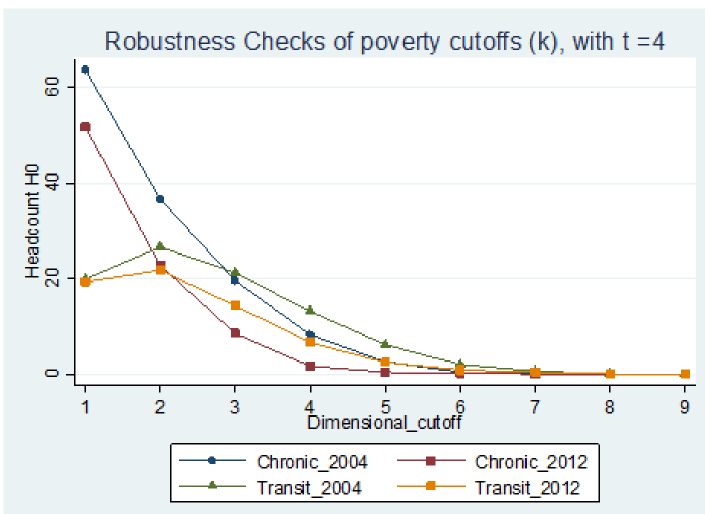


In Figure 1 we see that, when considering the union approach, 83.56% of the population in 2004 is poor in at least one dimension and at least at one point in time during the span of one year and a half. That same percentage decreases to 71.08% for 2012. On the other extreme, when considering the intersection approach for the time cut-off and taking the dimensional cut-off of k=3, we see percentages of 19.54% and 8.53% for 2004 and 2012. Notice that if we fix the dimensional cut-off, the headcount does not decrease rapidly. For example, in 2012 when we have k=1, 71.08% of the population are poor with t=1, 64.44% when t=2, 58.45% when t=3 and 51.79% when t=4. Each of those changes is around six percentage points, which are very different from the drops we see when we have the time cut-off fixed and vary the dimensional cut-off. These last drops are around the order of thirty percentage points. This applies both for 2004 and 2012 and for every dimensional cut-off, suggesting that given a dimensional cut-off we can see persistence in chronic poverty.

In Figure 4 we check for the robustness of the measure. We consider both the headcount of chronic and transient poverty for each dimensional cut-off. Notice that a measure of transient poverty can be easily derived from equation (1) if we adjust the identification vector to be pi(k, ■) = I(1 < ci < ■).

There are two important facts to point out from figure 4. The first one is that the curves of 2004 monotonically dominate the curves in 2012, i.e., for each dimensional cut-off, both the chronic and transient poverty were higher in 2004 than in 2012. The second is that when we have low dimensional cut-offs of one to three dimensions, the level of chronic poverty is higher or equal to the level of transient poverty. This last observation highlights the importance of considering both chronic and transient poverty measures since significant shares of the population lie in one of these forms of poverty.

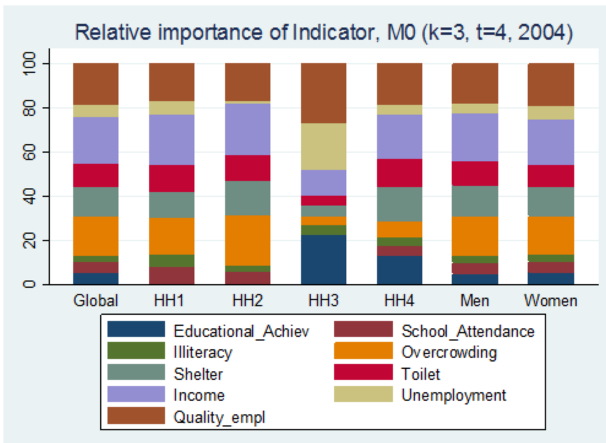
It is important to mention that this counting approach does not take into consideration whether the household was chronically poor in the same indicator or not; the household could change of deprivations from quarter to quarter and it would be counted as chronically poor as long as it presents a greater number of deprivations than the dimensional cut-off chosen. What this measure addresses is the extent to which a household persistently experiences deprivations in the indicators mentioned.



From this time on we will use a dimensional cut-off of k=3, this seems to be a reasonable cut-off as the Figure above shows.

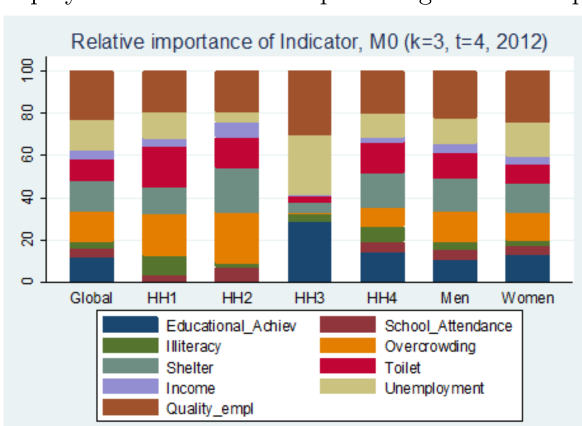
In the following figures we see the relative importance of each indicator for 2004 and 2012. This analysis is done for the entire data set as well as for different groups. For 2004, the most important variables are income, quality of employment, overcrowding and shelter. This pattern does not change within groups, with the only exception that for HH3 (households with children but without elderly), the variables of educational achievement and unemployment matter relatively more, whereas overcrowding matter relatively less.

For 2012 the variables of quality of employment, overcrowding and shelter are still important, the relative relevance of income decreases, and relative importance of the dummy variable for toilet increases. Again, these patterns are homogeneous within groups with the exception of HH3. For the exact percentages see Appendix 2 and 3.



HH1 = households with children and elderly
HH2 = households with children but without elderly
HH3= households without children but with elderly
HH4= households without children and without elderly

If we now take consider the results for 2012 we see that the relative importance of each variable present some variation. In general, the importance of the income variable decreases, and the importance of employment and quality of employment increases. The biggest changes were experienced by the households with only elderly, for whom 87% of the relative importance of each variable are concentrated between educational achievement, unemployment and quality of employment. For the exact percentages see the Appendix_.



HH1 = households with children and elderly

HH2 = households with children but without elderly
HH3= households without children but with elderly
HH4= households without children and without elderly

Shapley decomposition In this section we apply the decomposition described in equation 6 in order to study the drivers of the change of chronic multidimensional poverty. This decomposition will allow us to determine whether the change in multidimensional chronic poverty was due to a change in the incidence of poverty or whether it is due to a change in the intensity of it. Furthermore, it will allow us to separate the marginal effect of each group, and the effects of each indicator.

In table 3 we present a set of drivers of the change in chronic poverty at different levels of aggregation. We first recall the analysis of the first section and we observe the aggregate changes. As mentioned before, the overall level of multidimensional chronic poverty Mc[redacted] reduced. When comparing the headcount Hc and the intensity of poverty Ac, we see that the intensity of poverty remain almost the same, reducing 1.2 percentage points, whereas the overall headcount reduced 11.01 percentage points. Nevertheless, this story varies for each household group. Although all groups improved, the third household group experienced a poor improvement relative to the other household groups. That is, households without children but with elderly improved the least.

These changes become clearer when we see the share of poverty by household group. On the one hand, in 2004, households only with elderly represented 16.27% of the population, but represented 19.11% of the poor. For 2012, their share in the population did not change significantly (16.92%), but their share of the poor population almost double to 39.61%.

On the other hand, the group two, which are the households with children only, experienced the biggest improvement. Their headcount reduced 16.53 percentage points and their share of the total poor population decreased from 65.46% to 47.95%. It is still the group that presents the highest incidence of poverty, but improved significantly in the period studied.

Shapley decomposition					
Decomposition variation in Multidimensional Poverty (2004-2012)					
	Hog1	**Hog2**	**Hog3**	**Hog4**	**Total**
Total % contribution	5.49%	77.77%	4.75%	11.98%	100.00%
- Demographic effect	-0.53%	4.39%	-1.00%	-0.79%	2.07%
- Withing group effect	6.03%	73.38%	5.75%	12.77%	97.93%
- Incidence	5.44%	67.67%	3.52%	11.91%	88.54%
- Intensity	0.58%	5.71%	2.24%	0.86%	9.40%
- Educ Aciev	0.00%	0.00%	-1.05%	-0.02%	-1.07%
- School Attendance	0.24%	-0.47%	0.05%	-0.02%	-0.20%
- Illiteracy	-0.11%	0.57%	0.32%	-0.36%	0.42%
- Overcrowding	-0.02%	0.62%	0.86%	-0.17%	1.29%
- Shelter	0.03%	-2.96%	0.28%	0.06%	-2.60%
- Toilet	-0.22%	-0.99%	0.28%	-0.12%	-1.04%
- Income	0.89%	11.96%	3.06%	2.33%	18.23%
- Unemployement	-0.22%	-2.42%	-1.26%	-0.73%	-4.63%
- Quality of employment	-0.01%	-0.59%	-0.31%	-0.10%	-1.01%

HH1 = households with children and elderly
HH2 = households with children but without elderly
HH3= households without children but with elderly
HH4= households without children and without elderly

In the third part of the table we see the results of the Shapley decomposition, which, as mentioned in the introduction, has the virtue of being an exact additive decomposition of changes in poverty. If we first see the overall contribution of each household, again, household two fares better as it contributes 77% of the total change in multidimensional chronic poverty, a percentage much higher than its population share. The rest of the households contributed less than their population shares.

We further decompose the total contribution of each group in their demographic and within group effects. The demographic group effect reflects the changes in poverty due to changes in population shares in each household group, holding the poverty level within a household group constant. The within group effect reflects the changes in poverty that would have occurred if the population shares in each household groups did not change. For households one, three and four, the demographic effect barely decreased the change in poverty, whereas for household two it contributed 4% to the overall change in poverty.

On a second level of disaggregation, following equation 5, we can assess whether the change in the within group effect was due to a change in the incidence of poverty or if it is due to a change in the intensity of poverty. The biggest change is due to the incidence of poverty, which overall accounts for 88.54% of the within group effect. In all household groups the changes in incidence are much higher than the intensity effect with the exception of household three for which the incidence and intensity effects are almost the same. Household three (HH without children but with elderly) present the lowest improvement in incidence, especially when considering their population share of 16%, but they present a higher relative improvement of the intensity of poverty.

Finally, we disaggregate the intensity effect to study the marginal effect of each indicator. The main indicator that is driving the improvement in the intensity effect is income; nevertheless, almost all the other variables actually contributed to an increase in intensity of poverty or did not change it at all. The indicator of unemployment fared worst, followed by a worsening in the shelter conditions. This worsening of the employment condition may be the reason why the households with elderly performed relatively poor.

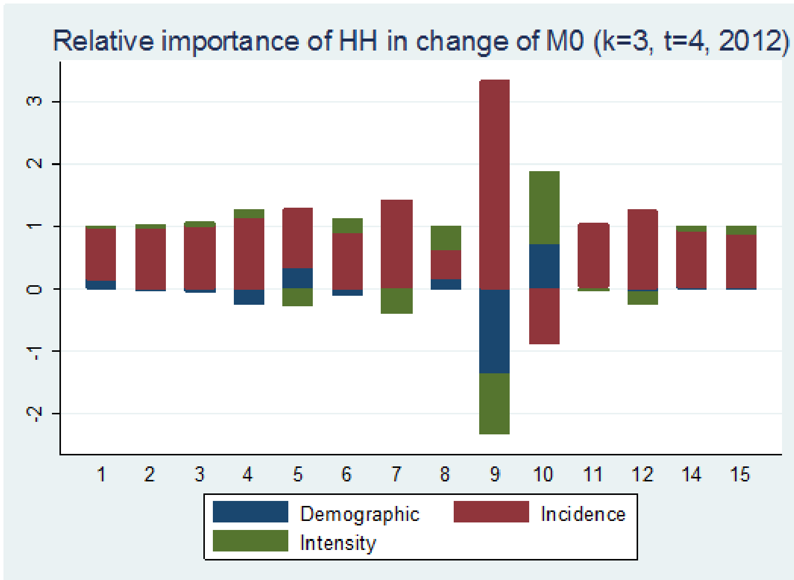
Again, the dominant group is the household group two. This consistent pattern shows the difference in mobility between these household groups, where the households that have children but not elderly are moving upwardly at a faster rate than the rest of the household groups.

In the following figure we consider the relative importance of the demographic effect and within group effect, and we decompose the within group effect in the incidence and intensity effect. As we can see, the incidence effect dominates over the other, and its relative importance is constant around 90% of the total change in multidimensional chronic poverty.

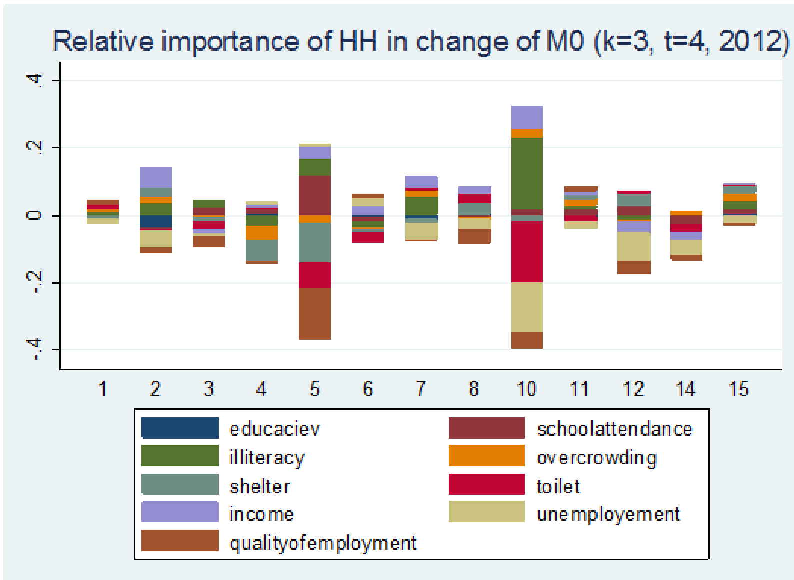
Shapley decomposition over time As commented earlier, the EPH is a rotating panel, which means that it contains superimposed panels through time. This characteristic allows us to derive the Shapley decomposition for different periods, and therefore we can follow how the drivers of chronic multidimensional poverty change over time. At figure 7 we follow the relative importance of each household in the change of chronic poverty. Notice that each bar sums to one; in each period chronic multidimensional poverty decreased with the only exception of period 3 and 13, so at period 3 the fact that HH2 present positive values actually reflects that this group worsened in chronic multidimensional poverty.

What we see in figure 7 is that the relative importance of each household changes differently depending on household type. Households with children but without elderly (HH2) constantly drove the decrease in chronic poverty, but its importance varied through time. This was not the case for households only with children and elderly (HH1) and households with only elderly (HH3), which showed to be the most vulnerable.

This seems to point out that when considering a chronic measure of poverty, the intensity of poverty does not vary greatly. On the other hand, incidence seems to be more volatile, probably suggesting that it is more sensible to shocks in the economy.



In the following figure we consider the relative importance of the demographic effect and within group effect, and we decompose the within group effect in the incidence and intensity effect. As we can see, the incidence effect dominates over the others, and its relative importance is constant around 90% of the total change in multidimensional chronic poverty. This seems to point out that when considering a chronic measure of poverty, the intensity of poverty does not vary greatly, while the intensity seems to be more volatile, probably suggesting that it is more sensible to shocks in the economy.



Finally, we decompose the intensity effect to study the relative importance of each indicator. Notice that the data in the graph represent the relative importance over the change in multidimensional chronic poverty (as presented in Table 3, to see the same graph but presenting the relative importance of each indicator over the change in Incidence see Annex. Also notice that the periods 9 and 13 were not included for illustration purposes. The message of this graph is that the relative importance of each indicator varies greatly across time, and it is not possible to point to a single indicator or a couple of indicators that may be leading the change in chronic multidimensional poverty. This may not be encouraging for public policy purposes but reflects the complexity of the problem of chronic multidimensional poverty. Nevertheless, it is important to remember that we are analyzing the relative importance of each group of a small absolute change. We expect this graph to be much more informing when the absolute change in poverty is greater.

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