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DOCUMENTO DE TRABAJO 2021-36

Marzo de 2021

Citar como:
Gallardo, Mauricio, María Emma Santos, Pablo Villatoro y Vicky Pizarro (2021). Measuring vulnerability to multidimensional poverty in Latin America. *Documento de trabajo RedNIE, 2021-36.*

Measuring vulnerability to multidimensional poverty in Latin America

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Abstract

Latin America is not the poorest region in the developing world. It is, however, a region with high inequality, precarious institutional frameworks and high exposition to covariate and idiosyncratic shocks. In this paper, with a sample of more than seven million observations, we perform estimates of vulnerability to multidimensional poverty for 17 Latin American countries at three points in time: 2005/6, 2012 and 2017. We use a multidimensional Bayesian network classifier model to estimate the conditional probability of being multidimensionally poor. We then use these probabilities and the standard downside semi-deviation as the risk parameter to identify the vulnerable households. Our findings suggest that, despite significant reductions over the study period, in 2017, approximately 200 million people – about the size of the population of Brazil – continued living at high risk of becoming poor or remaining multidimensionally poor. We also observe that vulnerability to poverty is reduced at a much slower rate than poverty itself, revealing that poverty reduction accomplishments can actually be quite fragile. Additionally, we perform a decomposition between *poverty-induced* and *risk-induced* vulnerability and find that as poverty decreases, risk-induced vulnerability becomes relatively more important than poverty-induced vulnerability. However, it is the poor-vulnerable group that still constitutes the core vulnerability group.

Keywords: poverty, vulnerability, Bayesian networks, Latin America
JEL: I32, C55, D81, O54, O57

1. Introduction

Latin America constitutes a region particularly relevant for the analysis of vulnerability to multidimensional poverty (VMP), especially with a cross-country comparable methodology. While the region is certainly not the poorest in the developing world, its high levels of inequality, covariate risk exposure and precarious institutional frameworks make it presumably highly vulnerable, with a significant fraction of its population at sustained risk of impoverishment when faced with different kinds of shocks.

This paper estimates VMP for the first time in a cross-country comparable way covering most of the countries in the region. We employ a methodology that integrates the most prevalent form of measuring multidimensional poverty in the region as well as worldwide, the Alkire-Foster (2011) methodology, with a methodology recently being used in data science, the multidimensional Bayesian network classifier (MBC), allowing risk estimates in a relatively easy form that respects the multidimensionality nature of the problem.

Although the concept of vulnerability to poverty was initially coined unidimensionally as the risk exposure of low-income households to monetary poverty, it has recently been extended to the multidimensional space. This trend is influenced by the wide recognition of the multidimensional nature of poverty and, therefore, the need for poverty measurement to include non-monetary dimensions of well-being, allowing a more precise approach to the complexity of this phenomenon.

This consensus has been reflected in the emergence of several methods for measuring multidimensional poverty (e.g., Alkire & Foster, 2011; Bourguignon & Chakravarty, 2003; Chakravarty & Silber, 2008; Mukherjee, 2001; Tsui, 2002). The first United Nations (UN) Sustainable Development Goals (SDGs) (UN, 2015) about reducing, by at least half, the proportion of people living in poverty in all its dimensions confirms this view at the international policy level. Today, many countries in the world compute a Multidimensional Poverty Index (MPI) on a regular basis as part of their official policies to monitor poverty. The Global Multidimensional Poverty Index (Global MPI), developed in 2010 by the Oxford Poverty and Human Development Initiative (OPHI) in collaboration with the United Nations Development Programme (UNDP) (Alkire & Santos, 2010, 2014) using the Alkire and Foster (AF) (2011) methodology, offers estimates of global acute poverty in the developing world, understood as the experience of several simultaneous deprivations in basic dimensions of well-being.

To date, several VMP measures have been proposed. Calvo (2008)introduced a multidimensional counterpart to the unidimensional Calvo and Dercon's (2005, 2007) vulnerability measure, which builds upon the family of multidimensional poverty indexes proposed by Bourguignon and Chakravarty (2003). Abraham and Kavi (2008) suggested another VMP measure based on the fuzzy poverty membership function of Cerioli and Zani (1990). Also, the Global MPI reports elaborated by OPHI (OPHI, 2020; UNDP, 2010), have presented, in addition to the poverty figure, the proportion of people who are vulnerable to multidimensional poverty, defining this group as those with a deprivation score below the minimum required to be multidimensionally poor (33.33%) but above 20%, which places them in a situation close to acute poverty.

Another VMP measure was introduced by Feeny and McDonald (2016) in the context of vulnerability as expected poverty (e.g., Chaudhuri et al. 2002; Christiaensen & Subbarao, 2005), according to which the vulnerable are those who have a high probability of remaining poor whenever they are already poor, or becoming poor if they are non-poor. More recently, Gallardo (2020) proposed another VMP measure as an extension of the mean-risk unidimensional vulnerability approach previously introduced in Gallardo (2013). In this paper, we apply a VMP measure that is conceptually close but more parsimonious and general than the latter. We implement the MBC approach developed in Gallardo and Bekios (2021).

The approach follows two main steps, as in poverty measurement. For the identification of the multidimensionally poor, it uses an MBC model to estimate the conditional probabilities of being multidimensionally poor, which, alongside its standard downside semi-deviation, is used as the risk parameter to identify the vulnerable households. Then, for the aggregation step, a Foster–Greer–Thorbecke design (Foster et al., 1984) is applied.

Our reference indicator of effective poverty is the Multidimensional Poverty Index for Latin America (MPI-LA) designed by Santos and Villatoro (2018) under the AF methodology. As supported by Sen's capability approach (Sen, 1979, 2009), this MPI combines monetary and non-monetary indicators, including information on functionings in as much as household survey data in Latin America permits. However, because the identification of the vulnerable in this methodology is not performed counting dimension-vulnerabilities as in Gallardo (2020), but rather using the estimated probability of being multidimensionally poor with the MBC, this approach can also be used in combination with other multidimensional poverty measurement methodologies, and not only the AF one.

The contribution of this paper to the literature on poverty is twofold. First, we increase the knowledge on the VMP's measurement methodology, offering wide new empirical evidence of applicability of the MBC estimator introduced in Gallardo and Bekios (2021) with a sample of more than 7.1 million observations for 17 Latin American countries at three points in time: 2005/6, 2012 and 2017. Second, we present an analysis of the trends and characteristics of VMP in Latin American and Caribbean regions over the past 15 years which illuminates possible policy actions.

The remainder of the paper is as follows. Section 2 presents the context of the risk exposure faced by people in Latin America and the Caribbean region. Section 3 describes the measurement methodology and data. Section 4 presents the main measurement results and main findings. Finally, Section 5 offers a brief discussion and concluding remarks.

2. Latin America: A region exposed to covariate and idiosyncratic shocks

Latin America and the Caribbean (LAC) is a profoundly unequal region (Gasparini & Lustig, 2011), with societies where economic inequalities are intertwined with gender inequalities, racism, territorial segregation and huge differences in the quality of children's education and in people's access to health services as well as a culture of unequal treatment towards people in all areas of living according to their social origin (ECLAC, 2019).[1] At the same time, countries in the region are systematically exposed to covariate shocks affecting the whole country or broad regions within a country, such as macroeconomic crises, natural disasters and pandemics, as well as idiosyncratic ones affecting a particular household, such as a health event or a job loss. The rooted inequalities imply that shocks, either covariate or idiosyncratic, affect households very differently, depending on their socioeconomic position. Moreover, inequality favours the emergence of sociopolitical instability, crime and violence, and it is thus a conditioning factor for the occurrence of certain shocks.

In fact, LAC region registers high rates of crime and violence. Around 2016, the intentional homicide rate in 18 LAC countries was the highest in the world (21.5 deaths per 100.000 individuals per year), much above the observed rates in Africa, Oceania, Asia and Europe (8.4, 4.3, 2.7 and

[1] These rooted inequalities are, amongst other things, related to the social and political institutions introduced by Spanish and Portuguese colonisation (see: Acemoglu et al., 2005a, 2005b; Bértola, 2011; Robinson, 2006).

1.8, respectively).[2] In 2016, the homicide rates were extremely high in El Salvador (82.8), Honduras (56.5) and Venezuela (56.3) (UNODC database). During the same year, 36% of the Latin American population aged 18 and over declared that either they or a family member had been the victim of a crime in the previous 12 months; the highest victimisation rates were observed in Venezuela (48%), Mexico (46%) and the Dominican Republic (41%).[3] Latin America has also been affected by civil conflicts. Colombia still has not yet completely recovered from the effects of 50 years of domestic conflict: it has been estimated that over 7.2 million people remained internally displaced during 2016 in Colombia – higher than any other country in the world (IOM, 2017). Crime, violence and social conflict are experienced by households primarily as idiosyncratic shocks, when directly affected by a particular event, but the pervasive presence of such a phenomenon also affects behaviour and long-term household decisions, from household location to educational decisions, which may place the household at a higher vulnerability level.[4]

The most significant covariate and recurrent shocks in the region are macroeconomic crises, both caused by external shocks or by the mismanagement of fiscal and monetary policies during the past. From 1977 to 1986, there were 81 GDP per capita annual drops in 18 LAC countries. This number decreased to 52 from 1987 to 1996, 37 from 1997 to 2006 and 29 from 2007 to 2016. However, after 1977–1986, the mean intensity of the crisis events remained almost the same: from 1987 to 1996, the mean decline of GDP per capita in the crisis episodes was 3.3%, while from 2007 to 2016, this number was 3.4%.[5]

An important economic downturn occurred from 2008 to 2009, driven by the financial collapse that originated in the real estate sector of the United States. In 2009, 15 out of 18 LAC countries saw losses in their outputs, with Argentina, Mexico, Venezuela, Nicaragua and Honduras being the most

[2] Authors' calculations based on United Nations Office on Drugs and Crime (UNODC) database. https://dataunodc.un.org/crime

[3] Source: ECLAC database, https://cepalstat-prod.cepal.org/cepalstat/tabulador/ConsultaIntegrada.asp?idIndicador=1842&idioma=e. The regional value is a simple (unweighted) mean.

[4] The region also experiences significant intraregional migration; this rose by 11% in South America from 2010 to 2015. Over the last several years, millions of migrants have arrived in countries which do not always have the capacity to provide minimum conditions for the well-being og this population. Some transit and destination countries have increased border enforcement and control (IOM, 2017).

[5] Authors' calculation based on World Bank Database.

affected (GDP per capita annual drops of 6.9%, 6.7%, 4.6%, 4.6% and 4.5%, respectively).[6]

In recent years, Venezuela, Argentina, Brazil and Ecuador have been beaten down by further losses in the GDP per capita for different reasons. Venezuela has been experiencing a sustained and severe stagflation process since 2014. Argentina experienced recessions (about 3% GDP fall) in 2014, 2016 and 2018 in combination with high inflation levels, whereas Brazil experienced reductions in its GDP per capita in 2014 (a drop of 0.4%), 2015 and 2016 (about a 4% fall each year). It seems that LAC countries have achieved a higher resiliency level to external economic downturns, an outcome usually attributed to the more effective macroeconomic policies that several countries have implemented (Báez et al., 2017). However, the region remains vulnerable to external economic shocks, amongst other things, because of its dependency on prices of their primary goods exports. In fact, the commercial and political tensions between China and the USA have increased the uncertainty levels in the region.

Natural disasters are another significant covariate kind of shock that affects the LAC population. Their frequency has increased in the last decades (Holt, 2014; SELA, 2017) as an outcome of both climate change and the increase in human settlements in risk areas (Báez et al., 2017; Banco Mundial, 2013). It is expected that the intensity of extreme weather events in LAC countries will increase in the coming years (Magrin et al., 2014). There are different types of natural disasters to which distinct countries of the region are exposed. For instance, storms and cyclones start in the eastern Atlantic, but hurricanes can make landfall in Central America. At the same time, the dry corridor, which includes parts of Costa Rica, El Salvador, Guatemala, Honduras, Nicaragua and Panama, usually experiences severe droughts (Báez et al., 2017). In recent years, densely populated areas of south-east Brazil have been affected by prolonged droughts, which have resulted in water scarcity in Sao Paulo. Droughts have also affected Andean areas in Bolivia and Peru. In contrast, other countries such as Argentina, experience recurrent floods, with persistent detrimental effects on human development (Gonzalez, Santos and London, 2020).

Moreover, the risk of geological disasters is higher in the Andean zone and Central American countries situated within the Pacific Ocean area known as the 'Ring of Fire'. This is a string of volcanic sites and seismic activity, which

[6] Data from World Bank Database and ECLAC statistics database for Venezuela's figures.

accounts for more than 75% of the world's dormant and active volcanoes and around 90% of the world's earthquakes. Western South American countries experience around a quarter of all earthquakes of magnitude 8.0 or higher in the world (Báez et al., 2017). Table A1 in the Appendix lists the natural disasters that affected more than 5% of the national populations of Latin American countries from 2001 to 2017.

Finally, the COVID-19 pandemic has also shown that the LAC region is highly vulnerable to epidemiological shocks (World Bank, 2020). The overcrowded conditions in many households in Latin America, the large proportion of informality in employment and small businesses in the region, the frequent presence of older adults in large families, the problems with drinking water supply that persist in some localities, the precarious health systems and the higher fiscal constraints to finance policy responses, along with the weakness of the political institutions in some countries to take effective and timely decisions, have provoked greater health and economic damage to the population from the pandemic shock in comparison with other regions of the world.

3. Methodology

We now introduce the VMP measurement procedure proposed in Gallardo and Bekios (2021) which is employed in this paper. This methodology is based on an MBC, which is used to estimate the probabilities of being multidimensionally poor as well as the probabilities of being deprived in each welfare dimension. Then, the downside mean semi-deviation is used as the risk parameter. This approach assumes a mean-risk behaviour framework (Gallardo, 2013, 2020) considering that economic agents act under the usual consumer theory principles of local non-satiety and risk aversion. In this section, we present the MBC model that we use in our estimation strategy; then, we introduce the VMP measurement. Next, we introduce the measures for assessing the MBC predictive performance, followed by a description of the MPI-LA reference indicator; we conclude the section describing the feature variables of the model and data sources.

3.1. A multidimensional Bayesian network classifier

Let us define a population on N individuals $i = 1, 2, 3, ..., N$. For each individual in this population, there is a Bernulli random variable y_i^w which is equal to one if that person i is classified as multidimensionally non-poor. Conversely, y_i^w is equal to zero in the event that person i is identified as multidimensionally poor. The two possible realisations of y_i^w depend in turn on the values taken by the random vector $\mathrm{y}_i = (y_{i1}, ..., y_{iM})$ which is composed of M random variables, all of which are also Bernulli distributed. Each random variable y_{im} is equal to one in the event of successful welfare achievement for person i in the dimension m, and is equal to zero in the event of deprivation in this welfare dimension. In addition, the random variables in vector $\mathrm{y_i}$ depend on person i's household characteristics, which can be understood as proximate determinants of poverty in each dimension m. We define these household characteristics through the random vector $\mathrm{x_i} = (x_{i1}, ..., x_{iH})$. Each entry x_{ih} in this vector is a categorical variable which can have more than two possible outcomes. That is, for each person i, we have a system of $1 + M + H$ discrete random variables. To model the uncertainty regarding multidimensional poverty in this population, we are interested in estimating the following joint probability mass function:

$$P\left(y_i^w, \mathrm{y}_i, \mathrm{x}_i\right) = P\left(y_i^w; y_{i1}, ..., y_{iM}; x_{i1}, ..., x_{iH}\right), i = 1, 2, 3, ...N \qquad (1)$$

To solve this problem, as in Gallardo and Bekios (2021), we follow a supervised statistical learning strategy through an MBC. This kind of model has been developed in the recent machine learning and artificial intelligence research literature (Bielza et al., 2011; Van der Gaag & De Waal, 2006; see Gil-Belgue et al., 2020 for a review). However, our aim is not to classify ex-post the multidimensional poor people in a population given a set of observed data for which there are already well-established measurement methodologies (e.g. Alkire & Foster, 2011; Bourguignon & Chakravarty, 2003; Tsui, 2002, amongst others). Rather, our aim here is to model the uncertainty present in the conditional probability that every individual has to be multidimensionally poor and deprived in each welfare dimension. We then use such information to measure VMP, as we will explain in the next subsection.

An MBC (Bielza et al., 2011) is a type of Bayesian network with a restricted topology that deals with a complex classification problem that includes multiple *class variables*, which in our framework are y_i^w and $y_{i1}, ..., y_{iM}$. The solution to the multidimensional classification problem consists of assigning a classifier vector $\mathrm{c}_i = (y_i^w = c_i^w; y_{i1} = c_{i1}, ..., y_{iM} = c_{iM})$ to each instance i, which in this case are individuals, given the outcome of a vector of *feature variables*, which in our framework are the proximate determinants of poverty included in the array $\mathrm{x_i} = (x_{i1}, ..., x_{iH})$.[7]

[7]To be more precise, since our model is a two-level MBC as will be seen later (Figure 1), then, the vector of class variables $\mathrm{y_i}$ also acts in this case as a vector of feature variables

A Bayesian network, in turn (Koller & Friedman, 2009; Pearl, 1988), is a pair $B = (G, \Theta)$, where G is a directed acyclic graph conformed by a set of nodes (vertices) that represent random variables, and a set of arcs (arrows) that represent direct probabilistic dependencies amongst such random variables, whereas Θ is a set of parameters that draw the conditional probabilities of each random variable. In the terminology of Bayesian networks, the conditioning variables are called the 'ancestors' or 'parents'.[8] Formally, given a set of discrete random variables $\{z_1, z_2, ..., z_k\}$, the pair $B = (G, \Theta)$ represents the joint probability distribution structured as follows:

$$P_B\left(z_1, z_2, ..., z_k\right) = \prod_{i=1}^{k} P\left(z_i \left| \mathrm{pa}\left(z_i\right)\right.\right) \tag{2}$$

where $\mathrm{pa}\left(z_i\right)$ is the set of parents of the random variable z_i. In the specific topology of unidimensional Bayesian network classifier models (Bielza & Larrañaga, 2014; Friedman et al., 1997), the class variable is drawn as the parent of the feature variables. In the same way, the class variables in the MBC's models are also drawn as ancestors of the feature variables.

Our MBC graph is reproduced in Figure 1.[9] Each node represents a random variable of our reference set $\{y_i^w; y_{i1}, ..., y_{iM}; x_{i1}, ..., x_{iH}\}$, and each directed arc represents the direction of a conditional dependence between two random variables. In this topology, we have a 'super-class' variable y_i^w, which is taken as the super-parent of all the class-dimensional variables $y_{i1}, ..., y_{iM}$. In turn, the class-dimensional variables are the parents of the feature variables $x_{i1}, ..., x_{iH}$.

It is worth noting that the dependence relationships appear in this graph in inverse order according to our intuition regarding the causal mechanism. That is, an economist or a development scholar would expect the conditional relationship: $\mathrm{x}_i \rightarrow \mathrm{y}_i \rightarrow y_i^w$, instead of $y_i^w \rightarrow \mathrm{y}_i \rightarrow \mathrm{x}_i$. This is because a Bayesian network classifier operates learning from the likelihood of the

to predict the probabilities of a 'super-class' variable: y_i^w.

[8]That is, given two random variables z_1 and z_2, we say that z_1 is the parent of z_2 whenever the dependency relationship established in the topology of the directed acyclic graph G is of type $z_1 \rightarrow z_2$, which means that the probability of the random variable z_2 is conditional to the outcome of the random variable z_1: $P\left(z_2 \left| z_1\right.\right)$.

[9]This Bayesian network has the same structure as the network of model 3 proposed in Gallardo and Bekios (2021). The only difference is that, in this case, there is not a vector of the community characteristics due to the lack of such data for most countries in our sample. Instead, a categorical geographic unit variable was incorporated as specified according to the availability of data in each country.

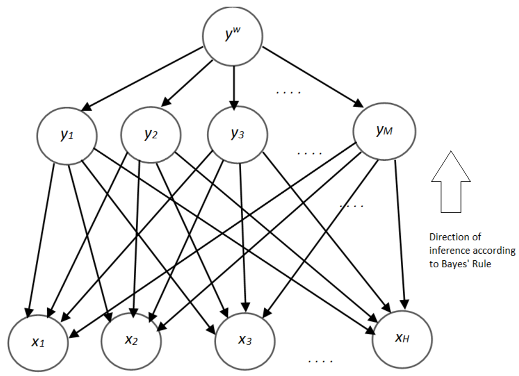

Figure 1: *Multidimensional Bayesian network classifier of multidimensional poor people.*

data in such an inverse order, getting information from the class conditional probability, i.e. from the conditional probability of each attribute given the class categories (Friedman et al., 1997). Then, in reverse, the Bayes rule is applied to compute the probability of the class categories given the evidence provided by the attributes, and consequently the class variables are finally predicted with the maximum posterior probabilities of: $P\left(y_i^w \,|\mathrm{y}_i\right)$ and $P\left(y_{ij} \,|\mathrm{x}_i\right), \forall i, \forall j$.

At this point, we would like to clarify a reasonable doubt that could arise to the reader. It may look tautological to use the deprivation vector $\mathrm{y_i}$ to estimate the probability of being multidimensionally poor, since the condition of being multidimensionally poor is deterministically defined by a specific number of deprivations: a deprivation score at or greater than k under the AF methodology imply that the person is poor with certainty. However, the key point is that the Bayesian network allows us to model the uncertainty by considering the parameters of interest –i.e. the probabilities of being multidimensionally poor given the deprivations– as unknown random variables uniformly distributed in the interval [0,1]. Notice also that, according to the direction of the arcs in our Bayesian network, we initially get information from the probabilities of being deprived in each dimension separately, *given* the condition of being multidimensionally poor –i.e. in the Bayesian graph the super-class variable is the parent of the dimensional variables– and only *a posteriori* we recover the desired probability doing the inference 'in reverse order' through the Bayes rule. Moreover, the applied algorithm allows the model to simulate the unobservable cases in the data. For example, in those cases in which a person would be unequivocally identified as poor according to her observed deprivations, with the Bayesian method, this person could actually have a non-zero probability of being non-poor, that is, she could have probabilistically a non-zero frequency of non-poverty states of nature, which we do not observe in the data.

Once the posterior probabilities have been estimated, we obtain the conditional expected value of the super-class variable $\mu_i = E(y_i^w|\mathrm{y_i})$, for each individual $i = 1, 2, 3, ...N$. As y_i^w follows a Bernulli distribution, its expected value is equal to the probability of being multidimensionally non-poor. In addition, the MBC in Figure 1 provides the probabilities of being deprived in each welfare dimension for each individual, i.e. the conditional expected values of the class variables $y_{i1}, ..., y_{iM}$. In this way, the MBC method allows for estimating vulnerability in a relatively simple form while simultaneously respecting the multidimensionality of the problem.

To estimate the MBC model presented in Figure 1, we used the *bnlearn* R-package developed by Scutari (2010). We applied the Bayesian parameter estimation method, which is available in this R-package for discrete data networks. The estimation of the MBC was performed separately for each country (17 in total) at three different points in time (circa 2006, circa 2012 and circa 2017).

3.2. The multidimensional vulnerability measurement

The MBC provides us with estimates of the conditional probabilities of being multi-dimensionally poor and deprived in each dimension of well-being for each individual. However, these probabilities only correspond to the expected values of these random variables, which is not sufficient to measure vulnerability. To obtain a measure of vulnerability to poverty, we need to have a measure of the average risk that people face of experiencing deviations in their welfare outcomes below their expected values. We specifically refer to the mean deviations below the expected value and not to the standard deviation (SD), as there is a strongly rooted position in the vulnerability to poverty literature that the risk that matters for such measurement is the downward risk (Calvo & Dercon, 2013; Dutta et al., 2011; Gallardo, 2013; Povel, 2015). In other words, the upward deviations are not relevant for the vulnerability assessment.

Following this idea, in the next step, we introduce the standard downside semi-deviation σ_i^- as the risk parameter. This parameter is a summary measure of downward deviation from the expected value, and it is therefore a relevant parameter for assessing the risk of impoverishment (see Gallardo, 2013, 2018, 2020). The standard downside semi-deviation of our reference random variable y_i^w is defined as follows:

$$\sigma_i^- = \sqrt{E\left\{\min\left[(y_i^w - \mu_i), 0\right]^2\right\}} \tag{3}$$

However, given that y_i^w is a Bernulli random variable, its standard downside semi-deviation is a function of the mean, which takes the following form:

$$\sigma_i^- = \sqrt{p_i^2\left(1 - p_i\right)} \tag{4}$$

where p_i is the probability of being multidimensionally non-poor for person i.

Assuming that the individual preferences satisfy the local non-satiation and risk aversion properties, then, for any two random outcomes and y_i^w, y_j^w, the following preference relation holds (Ogryczak and Ruszczynski, 1999, 2001):

$$y_i^w \succ y_j^w \Leftrightarrow \mu_i \geq \mu_j \wedge \sigma_i^- \leq \sigma_j^- \tag{5}$$

with at least one inequality strict.

To consolidate the mean and risk parameters into a single expression, we introduce a mean risk aversion parameter $\gamma \in [0, 1]$ as was done by Ogryczak and Ruszczynski (1999, 2001). It allows us to define the 'risk adjusted mean' of random variable y_i^w as follows:

$$\mu_i^{ra} = \mu_i - \gamma\sigma_i^- = p_i - \gamma\sqrt{p_i^2\left(1 - p_i\right)} \tag{6}$$

That is, the risk-adjusted mean μ_i^{ra} is just the probability of being multidimensionally non-poor p_i, adjusted by the downside-risk component $\gamma\sigma_i^-$. Hereafter, we will refer to μ_i^{ra} as 'the risk adjusted probability' to being non-poor, and we will use this term and 'the risk adjusted mean' interchangeably.

Under a mean-risk behaviour framework, expression (6) allows us to establish a complete preference pre-order to compare any pair of random variables y_i^w, y_j^w, according to the following relation:[10]

[10] In fact, for a Bernulli variable y_i^w, the preference relationship in (6) could be simplified as $y_i^w \succ y_j^w \Leftrightarrow p_i > p_j$, given that the risk parameter σ_i^- is an increasing monotone function of p_i. However, for the vulnerability assessment under a downward risk approach, the relevant relationship is that indicated in (6), since the $p_i > p_j$ relationship instead is closer to an expected poverty comparison because it corresponds to a comparison of non-poverty expected values.

$$y_i^w \succ y_j^w \Leftrightarrow \mu_i^{ra} > \mu_j^{ra} \tag{7}$$

For γ values in the defined interval $(0, 1]$, the preference relationship in (7) is consistent with the second-order stochastic dominance criterion (see also: Ogryczak and Ruszczynski (1999, 2001). This relationship allows individuals vulnerable to multidimensional poverty to be identified according to the following criterion (Gallardo & Bekios, 2021):

Criterion 1 (identification): *Person i is vulnerable to poverty in the multidimensional space $\Re^m$ whenever $\mu_i^{ra} \leq z^v$, where z^v is the probability which defines the vulnerability threshold.*

For this research, we have defined 0.5 as the vulnerability threshold. This probability has been widely used as a threshold in applied research on unidimensional vulnerability to poverty, supported by the arguments that were pointed out by Pritchett et al. (2000, p. 5) and Suryahadi and Sumarto (2003, p. 48).[11]

This fixed threshold allows performing intertemporal and cross-country comparisons, which are the focus of this research. These comparisons would be unfeasible by using vulnerability thresholds selected by the receiver operating characteristic (ROC) curve criteria, as were done by Hohberget et al. (2018) and Gallardo (2020), given that in this case the probability threshold is data-dependent and therefore will change in each specific estimate.[12]

The identification step solves the problem of knowing who the multidimensionally vulnerable individuals are. The next step is to define a summary measure that informs how much vulnerability there is in a population, i.e. the aggregation step. To do this, we first define the individual vulnerability gap as follows:

[11] According to Suryahadi and Sumarto (2003, p. 48) '...it is intuitive to say a household is "vulnerable" if it faces at least 50% probability of falling into poverty...if a household is just at the poverty line and faces a mean zero shock, then this household has a one period ahead vulnerability of 0.5. This implies that, in the limit, as the time horizon goes to zero, then being "in current poverty" and being "currently vulnerable to poverty" coincide'.

[12] Note that, according to the concept of risk-adjusted mean defined in (5), in this framework, each individual has a different risk depending on his or her probability of being multidimensionally non-poor. However, under Criterion 1, there is a unique probability threshold which allows us to identify a multidimensionally vulnerable individual based only on his or her probability to be non-poor. This is because the non-linear equation $p_i - \gamma\sqrt{p_i^2(1-p_i)} = z^v$ has a unique solution for a real value $p_i \in [0, 1]$, given a value of z^v. For instance, for $z^v = 0.5$, this equation has a unique solution equal to 0.83756.

$$g_i = \begin{cases} \left(\frac{z^v - \mu_i^{ra}}{z^v}\right), \forall \mu_i^{ra} < z^v \\ Min\left(\frac{z^v - \mu_i^{ra}}{z^v}\right), \forall \mu_i^{ra} = z^v \\ 0, \forall \mu_i^{ra} > z^v \end{cases} \tag{8}$$

It may be worth noting that, for those individuals with a risk-adjusted probability of being non-poor exactly at the value of vulnerability threshold z^v, the minimum observed gap value is assigned. This is with the understanding that these individuals do face some degree of risk of becoming poor. In practice, however, the empirical effect of allocating the value of the minimum observed gap rather than zero is marginal, as it is an infrequent event to equalise the vulnerability threshold.

Next, we aggregate the individual vulnerability gaps in a summary measure using an FGT design, as indicated below:

$$V_\alpha = \frac{1}{N}\sum_{i=1}^{N} g_i^\alpha, \alpha \geq 0 \tag{9}$$

By analogy with the FGT family of poverty measurements, for $\alpha = 0$, the measure V_0 is the VMP headcount ratio, i.e. the percentage of people who are vulnerable to multidimensional poverty in a population. For $\alpha = 1$, the summary measure in (9) is the multidimensional vulnerability gap V_1, while for $\alpha = 2$, this is the squared multidimensional vulnerability gap V_2. Note that the V_1 measure indicates by how much the 'risk-adjusted mean' would have increased as a proportion of the vulnerability threshold in order to overcome multidimensional vulnerability.

Additionally, V_α can be decomposed into two indicators: the poverty-induced vulnerability V_α^P and the risk-induced vulnerability V_α^R. This decomposition is performed as follows:

$$\begin{aligned} &V_\alpha = V_\alpha^P + V_\alpha^R \\ &V_\alpha^P = \sum_{i=1}^{N} \tfrac{1}{N} g_i^\alpha I_{\mu_i \leq z^v}, \alpha \geqslant 0 \\ &V_\alpha^R = \sum_{i=1}^{N} \tfrac{1}{N} g_i^\alpha I_{z^v < \mu_i \leq z^v + \gamma\sigma^-}, \alpha \geqslant 0 \end{aligned} \tag{10}$$

where $I_{\mu_i z}$ and $I_{z^v < \mu_i \leq z^v + \gamma\sigma^-}$ are indicator functions that are equal to one when conditions $\mu_i \geq z^v$ or $z^v < \mu_i \leq z^v + \gamma\sigma^-$, respectively, are fulfilled for person i, and it takes value of zero otherwise.[13]

Finally, there are two additional indicators that arise from this framework when comparing the headcount ratio V_0 with the multidimensional poverty headcount ratio H. These indicators are the vulnerability-to-poverty ratio, and the over-rate-of-vulnerability headcount ratio (see Gallardo, 2020). The definitions of these indicators are as follows:

$$VPR = \frac{V_0}{H} \tag{11}$$

$$ORV = V_0 - H \tag{12}$$

VPR indicates how many vulnerable people there are per each poor person in a population, whereas the ORV indicates the additional proportion of people who are vulnerable to multidimensional poverty over the proportion of people who are multidimensionally poor. The measure will usually be more than one, as the fraction of the vulnerable in a population is often larger than the fraction of the poor. Only in very exceptional cases, when the incidence of poverty is very high, is it possible to find VPR values less than one. The ORV indicator, on the other hand, will usually be positive and very close to the value of the incidence rate of risk-induced vulnerability V_0^R because, if the MBC model predicts the outcomes of y_i^w with high accuracy, then the poverty headcount ratio H will be very close to the incidence rate of the poverty-induced vulnerability V_0^P.

3.3. Measurements of MBC performance assessment

A mandatory step when applying the MBC methodology is the assessment of its predictive performance. Several measures have been proposed in the research literature for that purpose (see Gil-Belgue et al., 2020 for a review). Amongst the proposed measures it is suitable to apply one measure to evaluate the average predictive performance over the class-dimensional variables and another for assessing the global performance of the model. Bielza et al. (2011) proposed to use the *average accuracy* of the dimensional class variables and the *global accuracy* (see also Gil-Belgue et al., 2020; Zaragoza et al., 2011). The average accuracy is the average of accuracy achieved by the model in predicting the class-dimensional variables, as defined below:

[13] Similar decomposition was performed by Günther and Harttgen (2009) and Gallardo (2013) for unidimensional vulnerability.

$$\overline{Acc_M} = \frac{1}{M}\sum_{m=1}^{M} Acc_m \tag{13}$$

where Acc_M is the accuracy of prediction in the class-dimensional variable m, i.e. the ratio between the number of correctly classified observations in that dimension to the total observations. On the other hand, *global accuracy* is a very strict evaluation measure that computes the accuracy over those correctly classified simultaneously in all class dimensional variables. Instead of such measurements, we use accuracy in predicting the outcomes of the super-class variable, since this class is by definition constructed from the class-dimensional variables. Following Gallardo and Bekios (2021), we will call this measurement the *overall accuracy*, which is defined as follows:

$$Acc_{mp} = \frac{1}{N}\sum_{i=1}^{N} I_{mp} \tag{14}$$

where I_{mp} is an indicator function equal to one if the observation i is correctly predicted by the model as multidimensionally poor or multidimensionally non-poor, and is equal to zero otherwise.

3.4. The reference indicator: A regional MPI for Latin America

As a reference indicator to identify and measure multidimensional poverty in this paper, we use the MPI-LA proposed by Santos and Villatoro (2018). This index was specially developed to fill the gap between national poverty measures and international poverty measures, with a regional perspective centred in Latin America. In fact, on the one hand, national measures, such as those developed in Mexico, Colombia and Chile, amongst other Latin American countries, are relevant for the particular country in question, but they do not allow for making cross-country comparisons. On the other hand, international poverty measures, such as the Global MPI, allow cross-country comparisons of widely disparate developing regions, but they fall short of accounting for what it is considered to be poor in Latin America.[14]

The MPI-LA follows the AF methodology. In a nutshell, the methodology entails the following steps, as described in Alkire and Santos (2014):

[14]The MPI-LA was estimated for 17 countries of the region at two points in time – one around 2005 and the other one around 2012 – and the figures were published in CEPAL (2014).

(1) Defining the set of *indicators* that will be considered in the measure, (2) Setting the *deprivation cut-offs* for each indicator, namely the level of achievement (normatively) considered sufficient in order to be non-deprived in each indicator, (3) Applying the cut-offs to ascertain whether each person is *deprived* or not in each indicator, (4) Selecting the relative weights that each indicator has, (5) Creating the weighted proportion of deprivations for each person, which can be called his/her *deprivation score* (6) Determining the *k-poverty cutoff*, namely, the proportion of weighted deprivations a person needs to experience in order to be considered multidimensionally poor, and identifying each person as multidimensionally poor or not according to the selected poverty cutoff, (7) Computing the proportion of people who have been identified as multidimensionally poor in the population: the *headcount ratio* of multidimensional poverty H, also called the *incidence* of multidimensional poverty, (8) Computing the average share of weighted indicators in which poor people are deprived. This entails adding up the deprivation scores of the poor and dividing them by the total number of poor people. This is the *intensity* of multidimensional poverty, A, and (9) Computing the M_0 measure as the product of the two previous partial indices: $M_0 = H \times A$.

Amongst other convenient properties, the M_0 measure can be decomposed by population subgroups, and it can be broken down by indicator. The overall M_0 can be expressed as the weighted sum of the proportion of the total population that has been identified as poor and is deprived in each indicator, and thus one can compute the relative contribution to total poverty by each deprivation.

The MPI-LA is composed of 13 indicators grouped into 5 dimensions. These dimensions and indicators are: *housing*, comprising the indicators of housing materials, overcrowding, and housing tenure; *basic services*, comprising the indicators of improved water sources, improved sanitation, and access to clean energy; *living standard*, comprising the indicators of monetary resources and durable goods; *education*, comprising the indicators of adult schooling achievement, children's school attendance and children's schooling gap; and *employment and social security*, comprising the indicator of employment and social protection (namely, health insurance and social security or pension).[15] A detailed description of each indicator is

[15] While the dimension is called employment and social protection in Santos and Villatoro (2018), given the indicators involved, it is more accurate to label it as employment and social security.

presented in Table A2 in the Appendix. It may be worth noting that the housing, basic services and education dimensions draw from the traditional unsatisfied basic needs (UBN) measures traditionally used in the region since the 1980s (Feres & Mancero, 2001), which are associated with structural poverty, although with updated thresholds in line with the currently higher living standards in the region. The living standard dimension captures monetary poverty, which may be transient or chronic, and the employment and social security dimension reflects what can be seen as a 'second generation' of poverty indicators, recently incorporated in official multidimensional poverty measures in the region. In this way, the MPI-LA offers quite a comprehensive yet synthetic measure of poverty. One almost missing dimension, however, is health, as only access to a contributive health insurance is included, a limitation imposed by the current data, which is detailed in the next section.

The housing, basic services, living standard and education dimensions are equally weighted at 22.22%, whereas the social protection dimension receives half of this weight at 11.11%. Weights within dimensions are equally distributed in the case of the housing, basic services and education dimensions, and unequally distributed within the living standard and the social protection dimensions, with income and employment receiving twice the weight of durable goods and social protection within the corresponding dimensions. As a result, all deprivations receive the same weight (7.4%), except for social protection (3.4%) and income (14.8%).

In the MPI-LA, someone is identified as poor if she lives in a household that experiences at least 25% of the weighted deprivations (i.e. $k = 25\%$). This is an intermediate cutoff criterion, in between the union criterion commonly used in the UBN approach in Latin America, by which experiencing one deprivation is sufficient for being identified as poor, and the intersection criterion by which deprivation must be experienced in all considered dimensions in order to be identified as poor, a criterion rarely used in practice.

Given the weighting structure, this poverty cutoff requires the household to experience deprivations in at least the equivalent of a full dimension of housing, basic services, education or living standard *plus* deprivation in one additional indicator, or, alternatively, at least in both indicators of employment and social security, *and* in the income poverty indicator. The 25% threshold may be considered rather conservative, as it demands several simultaneous deprivations to be identified as poor; in fact, with this cutoff, being income poor is not sufficient for being multidimensionally poor. However, the 25% poverty cutoff can be regarded as a threshold that places a focus on the population intensely deprived in structural or nuclear poverty.

Because it is based on the measure of the AF methodology, the MPI-LA overcomes some limitations of the UBN method. In particular, while it retains the simplicity of the counting approach to identify the multidimensionally poor, as the UBN method does, it allows accounting for poverty intensity and breaking down the overall poverty indicator (post-identification) by dimensions and indicators. Additionally, it allows the combination of cardinal indicators with ordinal ones in a methodologically robust way.

3.5. Feature variables

Table 1 presents the feature variables included in the vector $\mathrm{x_i}$ of our MBC model. These categorical variables are the household characteristics available in the data surveys used, which can be understood as proximate determinants of multidimensional poverty.

These variables include the level of education and the age of the household head (the latter variable can act as a proxy of maturity and experience).[16] There are also a set of demographic characteristics of the household, namely, the household head's sex and ethnicity, the household's size, composition, type (mono-parental or biparental), location (urban or rural) and the geographic unit in which the household is located. This last variable is not included in Table 1 because it contains so many categories that are different for each country.

3.6. Data sources

The data used correspond to the household surveys periodically performed in the countries of the region. Details of the name and survey years used are presented in Table 3. The different surveys have been harmonised by the Economic Comission for Latin America and the Caribbean (ECLAC)) in order to make the different variables as comparable across countries as possible. We perform estimations for 17 countries at three points in time with an average time span of 5 years between each observation: one estimate around 2005/6, another around 2012 and another around 2016/17, except for Guatemala, Nicaragua and Venezuela, for which we perform estimations at two points in time only due to lack of data for the year 2016/17.

The income poverty indicator corresponds to the one computed by the ECLAC using a revised and updated methodology detailed in CEPAL (2018).

[16]The arc of the household's deprivation in education to the household head's education was excluded from the model in Figure 1, as this proximate determinant of poverty intervenes in the deprivation indicator itself.

Table 1: Variables of household characteristics and their categories for the whole sample.

Variables	Categories	Circa 2006	Circa 2012	Circa 2017
Household head years of schooling	Complete Tertiary	6.8%	7.6%	8.9%
	Incomplete Tertiary	8.5%	10.6%	11.7%
	Complete Secondary	12.5%	15.2%	16.2%
	Incomplete Secondary	21.4%	24.1%	24.8%
	Complete Primary	19.8%	15.2%	13.6%
	Incomplete Primary	30.9%	27.3%	24.8%
	Not education	0.2%	0.1%	0.1%
Household head age	≤ 25	5.5%	5.4%	5.1%
	26-35	17.7%	17.1%	16.1%
	36-45	23.2%	21.6%	20.5%
	46-55	21.3%	21.8%	20.9%
	56-65	15.5%	16.8%	18.0%
	> 65	16.8%	17.4%	19.4%
Household head gender	Man	68.6%	64.1%	61.5%
	Woman	31.4%	35.9%	38.5%
Household type	Biparental	62.8%	60.6%	59.3%
	Monoparental	37.2%	39.4%	40.7%
Household composition	Adults, kids, elderly	7.8%	7.1%	6.3%
	Adults and kids	54.1%	50.3%	45.1%
	Adults and elderly	8.4%	9.0%	10.3%
	Elderly and kids	0.5%	0.5%	0.4%
	Only adults	23.0%	26.1%	29.1%
	Only elderly	6.2%	7.0%	8.7%
	Only kids	0.1%	0.1%	0.1%
Household size	1 person	11.1%	12.6%	14.8%
	2 persons	17.3%	19.5%	22.4%
	3 persons	20.9%	22.0%	22.8%
	4 persons	21.5%	20.9%	20.0%
	5 persons	13.8%	12.5%	10.8%
	6 persons	7.3%	6.2%	4.9%
	7 persons	3.8%	3.1%	2.2%
	8 persons or more	4.5%	3.2%	2.1%
Household location	Urban	78.5%	81.1%	78.6%
	Rural	21.6%	18.9%	21.4%
Household etnicity	No ethnic group	47.4%	48.0%	47.0%
	Ethnic group	52.6%	52.0%	53.0%

This methodology follows the cost of basic needs approach, defining a basic food basket and an inverse of the Engel coefficient in a homogenised and comparable way in as much as possible.[17]

[17] The poverty lines in the revised methodology have been constructed using data from more recent expenditure surveys in the region. Santos and Villatoro (2018) used the previous methodology employed by CEPAL, which computed monetary poverty using the national poverty lines and the income per capita definition. Thus, the income poverty rates as well as the MPI-LA results in this paper have some discrepancies with the results published in Santos and Villatoro (2018).

Table 2: Data sources, sample sizes and population size expanded. People.

Country	Survey	Years	Sample size	Population size
Argentina	Encuesta Permanente de Hogares	2005	47,004	23,348,651
		2012	58,139	27,595,578
		2017	54,515	25,364,874
Bolivia	Encuesta de Hogares	2007	16,726	9,850,513
		2012	31,852	10,373,231
		2017	38,179	11,210,084
Brazil	Pesquisa Nac. Por Amostra de Domicilios	2005	406,281	184,863,154
		2012	360,802	198,806,604
		2017	457,790	207,004,185
Chile	Encuesta de Caracterización Socioeconómica Nacional	2006	267,738	16,061,551
		2011	198,512	16,837,357
		2017	214,293	17,678,346
Colombia	Gran Encuesta Integrada de Hogares	2008	816,209	42,851,796
		2012	807,496	45,026,282
		2017	764,585	47,719,585
Costa Rica	Encuesta de Hogares de Propósitos Múltiples/	2005	43,132	4,208,446
	Encuesta Nacional de Hogares	2012	39,287	4,652,168
		2017	34,722	4,927,761
Ecuador	Encuesta de Empleo, Desempleo y Subempleo	2008	78,630	13,852,120
		2012	73,661	14,676,320
		2017	110,245	16,956,819
El Salvador	Encuesta de Hogares de Propósitos Múltiples	2005	69,999	6,857,538
		2012	84,228	6,185,917
		2017	72,295	6,358,077
Guatemala	Encuesta Nacional de Condiciones de Vida	2006	68,647	12,959,823
		2014	54,792	15,990,689
Honduras	Encuesta Permanente de Hogares de Propósitos Múltiples	2005	34,424	7,055,482
		2012	32,183	8,139,347
		2016	26,977	8,613,645
Mexico	Encuesta Nacional de Ingresos y Gastos de los Hogares	2006	80,970	105,799,259
		2012	212,678	117,310,503
		2016	245,284	116,803,541
Nicaragua	Encuesta Nacional de Hogares Sobre Medición de Niveles de Vida	2005	36,548	5,125,698
		2014	28,398	6,061,742
Perú	Encuesta Nacional de Hogares – Condiciones de Vida y Pobreza	2005	84,042	27,306,972
		2012	83,370	27,167,736
		2017	109,697	29,424,161
Paraguay	Encuesta Permanente de Hogares	2005	19,388	5,663,869
		2012	21,048	6,354,625
		2017	35,112	6,851,912
Rep. Dom.	Encuesta Nacional de Fuerza de Trabajo	2005	30,038	8,994,698
		2012	29,130	9,706,220
		2016	26,326	10,097,665
Uruguay	Encuesta Continua de Hogares	2007	142,852	3,369,890
		2012	120,072	3,363,538
		2017	118,122	3,489,311
Venezuela	Encuesta de Hogares por Muestreo	2008	164,810	27,748,279
		2012	154,158	28,817,782
Total			7,105,386	1,565,483,344

4. Results

Although the vulnerability measures V_α were computed for alternative values of the risk-aversion parameter γ, in this section, we present only the main results obtained with $\gamma = 1$. A reader with an interest in details regarding the estimates for the different γ values can see the alternative calculations in the Appendix (Table A3). In all calculations presented in this section, we use a cross-dimensional poverty threshold of $k = 25\%$ as in Santos and Villatoro (2018), and 0.5 as the vulnerability threshold. Although we concentrate most of our attention on results on the incidence of multidimensional vulnerability -V_0- and its relation with poverty, we also present results for the vulnerability gap measure V_1. Full estimation results of -V_0, V_1 and V_2- are available in the Appendix (Table A4).

In this section, we present the results on performance assessment of the MBC model, an overview of the recent trends of multidimensional poverty and vulnerability in Latin America, the results on decomposition of vulnerability in its risk and poverty constituents -V_0^R and V_0^P-, an analysis of dimensional decomposition of poverty amongst the different vulnerable groups, and an analysis of differences in the risk amongst the poverty dimensions.

4.1. Performance assessment of the MBC model

We carried out the performance assessment of the MBC model applying a *5-fold cross-validation* for each of the 17 countries in each time period.[18] That is, in each estimation, the sample was partitioned in 5 subsamples to carry out the cross-validation of each estimate outside the training sample. Table 3 presents the performance measures of the MBC obtained with the 5-fold cross-validation exercise. Naturally, given that the super-class variable y^w is predicted using the same deprivation indicators with which the MPI-LA is built, then the predictive accuracy of the model for this main variable, i.e. the *overall accuracy*, is very high. However, the objective here is not to predict the outcomes of y^w, which is already solved by calculating the MPI-LA. Instead, our aim is to model the uncertainty by estimating the

[18] The *k-fold* cross-validation consists of partitioning the sample in k subsamples. Then, $k-1$ subsamples are used for training the model and the remaining subsample is reserved to test the predictive accuracy of the model outside the training sample. In the next step, the test subsample is replaced by another partition, and the process is repeated until each of the k subsamples has served as a test set. When this process is completed, the average of the k prediction errors (or the average of the k predictions accuracy) is computed to obtain a robust performance metric for the model assessment.

conditional probabilities, which are then used for identifying those at risk of being multidimensionally poor. Regarding the prediction of dimensional class variables, the model performance is quite good. The measures of *average accuracy* are greater than 0.7, with the exception of Honduras and Nicaragua, and Guatemala and Paraguay in the first observation. However, even in these cases, the *average accuracy* is usually close to 0.7.

Table 3: Performance measures of the MBC using 5-fold cross-validation.

	Overall Accuracy			Average Accuracy over Deprivations		
	Circa 2006	Circa 2012	Circa 2017	Circa 2006	Circa 2012	Circa 2017
Argentina	0.997	0.997	0.997	0.864	0.903	0.896
Bolivia	0.972	0.962	0.969	0.701	0.786	0.799
Brazil	0.992	0.995	0.977	0.851	0.879	0.886
Chile	0.971	0.989	0.992	0.862	0.898	0.899
Colombia	0.981	0.983	0.982	0.869	0.872	0.888
Costa Rica	0.983	0.990	0.990	0.855	0.846	0.867
Ecuador	0.951	0.946	0.964	0.779	0.814	0.819
El Salvador	0.950	0.964	0.961	0.710	0.718	0.745
Guatemala	0.969	0.976		0.689	0.717	
Honduras	0.956	0.961	0.964	0.672	0.687	0.688
Mexico	0.967	0.956	0.963	0.795	0.828	0.847
Nicaragua	0.959	0.968		0.601	0.694	
Peru	0.952	0.962	0.957	0.715	0.760	0.800
Paraguay	0.944	0.969	0.948	0.684	0.732	0.773
Dominican Republic	0.953	0.950	0.935	0.756	0.735	0.783
Uruguay	0.994	0.992	0.997	0.876	0.901	0.922
Venezuela	0.953	0.966		0.855	0.860	

Table 4: Average accuracy of the MBC by deprivation using 5-fold cross-validation.

	Circa 2006	Circa 2012	Circa 2017	Average
Housing materials	0.808	0.842	0.879	0.843
People per room	0.806	0.836	0.866	0.836
Improved Water Sourced	0.787	0.820	0.852	0.820
Improved Sanitation	0.770	0.800	0.829	0.799
Energy	0.806	0.830	0.866	0.834
Housing tenure	0.774	0.793	0.804	0.790
Durable Goods	0.779	0.824	0.849	0.817
Adult Schooling Achievement	0.704	0.735	0.757	0.732
Children's School Attendance	0.814	0.850	0.883	0.849
Schooling Gap	0.815	0.852	0.883	0.850
Employment	0.732	0.767	0.787	0.762
Social Security	0.671	0.678	0.685	0.678
Monetary Resources	0.777	0.809	0.844	0.810

We also calculated the cross-country average accuracy by deprivation to see in which class-dimensional variables the model predicts better. These results are shown in Table 4. We see that the MBC performs better in predicting the outcomes of schooling gap, children's school attendance, housing materials, people per room, energy, improved water source and monetary resources, whereas in the indicators of employment and social security, the prediction of the model is understandably less accurate, as these are much more widespread deprivations and are thus less strongly associated with the proximate determinants of poverty.

4.2. Vulnerability vis-á-vis poverty: Incidence levels and trends

Figure 2 presents the comparisons of multidimensional poverty and vulnerability headcount ratios by country and year of estimation. The results are arranged clockwise from the least poor and vulnerable country to the poorest and most vulnerable one.

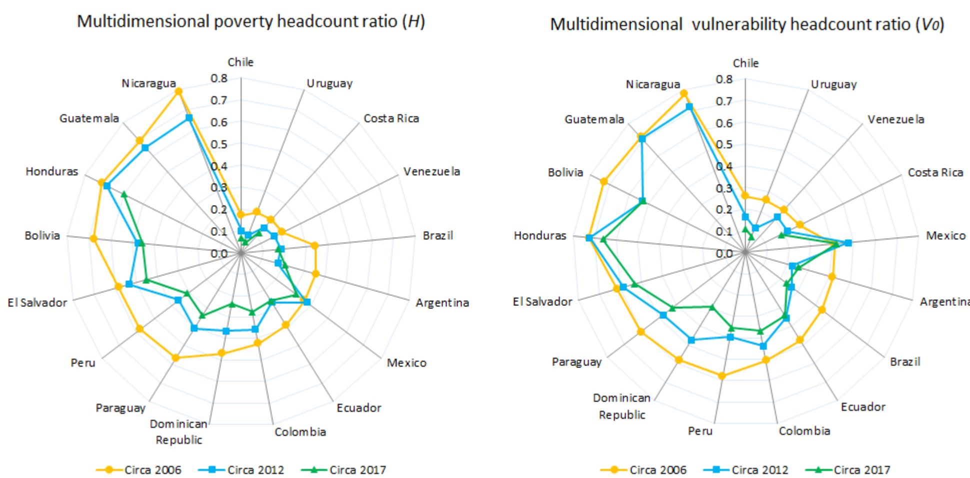

Figure 2: *Poverty headcount ratios and vulnerability headcount ratios by country and by period.*

This figure exhibits several results simultaneously. First, as expected, the poorest countries are also the most vulnerable. Three groups of countries at different levels of poverty and vulnerability can be distinguished in the graph. There is a group of four countries – Chile, Uruguay and Costa Rica, as well as Venezuela up to 2012 – with low poverty rates (below 20%) and low vulnerability rates (below 30%). There is a second group of countries – Brazil, Argentina, México, Ecuador and Colombia – with medium incidence levels of multidimensional poverty (ratios of around 20–50%), and medioum incidence levels of vulnerability, with headcounts 30–50%. A third group of countries – Honduras, Nicaragua, Guatemala, Bolivia, El Salvador, Peru and the Dominican Republic – is characterised by high incidence rates of multidimensional poverty and vulnerability.

Second, we observe that, in general, both multidimensional poverty and VMP have decreased in the region over the 15 years under study, with the biggest reduction occurring between the first and second observations, followed by a much milder reduction in the last period. The aggregate multidimensional poverty rate in the region decreased from 38% (circa 2006) to 29% (circa 2012) and to 24% (circa 2017), whereas the aggregate multidimensional vulnerability rate decreased from 45% to 36% and to 32%, correspondingly. This observed trend is consistent with results on monetary poverty (CEPAL, 2019) as well as on the observed economic cycle in the region, with a favourable international context that fuelled several years of significant economic growth in most countries, followed by a deacceleration since 2015. Clearly, the impact of the COVID-19 pandemic in the region and the associated lockdown measures are likely to undo much of the achieved progress in poverty and vulnerability reduction.

Looking country by country, we observe that from circa 2006 to circa 2012, most countries succeeded in significantly reducing both poverty and vulnerability, with particularly large absolute reductions occurring in Peru, Paraguay, Bolivia, Argentina, Brazil, Ecuador, Uruguay and the Dominican Republic. In contrast, from circa 2012 to circa 2017, only the Dominican Republic achieved a significant reduction in both poverty and vulnerability. Several countries – Uruguay, Costa Rica, Chile, Bolivia, Brazil, Ecuador, Venezuela and Argentina – reduced poverty and vulnerability at 3 pp at most, and three of them (Bolivia, Ecuador and Venezuela) had zero reduction in vulnerability over this period. Attention should be drawn to the cases of Mexico, Nicaragua, and El Salvador, where progress in poverty reduction has been modest, while vulnerability remained stagnant at high incidence rates.[19]

One relevant result refers to the relationship between poverty and vulnerability rates when poverty decreases in the region. Figure 3 depicts the relationship between the vulnerability-to-poverty ratio and the incidence rate of multidimensional poverty H. We can observe that lower poverty headcount ratios are associated with higher over-rates of vulnerability to poverty. This suggests that the decrease in vulnerability is slower than the

[19] In the case of Mexico, both poverty and vulnerability increased slightly from 2006 to 2012, and then decreased again in 2016. The slight increase in poverty and vulnerability in Mexico is explained by the fact that, in 2012, Mexico was still suffering some effects of the subprime crisis of 2009 that strongly affected its trading partner, the United States.

decrease in poverty. In other words, the uncertainty around poverty does not disappear at the same speed as poverty decreases. A plausible explanation for this finding is that those who are no longer poor become part of the vulnerable group, while on the other hand, those who are vulnerable may tend to remain longer in an uncertain well-being situation. In developing countries, it is not surprising to find that between the poor and those who live in secure well-being, there always remains a significant group of people who are not poor but who face the uncertainty of a fragile situation for long-term periods. This is in line with Jalan and Ravallion's (1999) finding for China on the (income) poorest being much less insured than the richer deciles.

Figure 3: *Vulnerability to poverty ratio (VPR) and incidence rate of multidimensional poverty (H).*

This result emphasises the fragility of poverty reduction in the region. As long as a significant fraction of vulnerability remains, achievements in poverty reduction are not consolidated. This has strong implications for the SDGs: poverty reductions need to be substantial in order to endure. In fact, the impact of the COVID-19 pandemic – a covariate shock – has exposed this fragility, pushing households recently lifted out of poverty back to poverty again.

4.3. The vulnerability to multidimensional poverty gap

Section 4.2 depicted the size of the group of vulnerable in each country and in the region as a whole, but how vulnerable are the vulnerable to multidimensional poverty? The vulnerability gap V_1 measure can be interpreted in simple terms as the percentage of the average insurance deficit with respect to the vulnerability threshold of 0.5. In the region as a whole, the VMP gap was 39% circa 2006, then decreased to 29% circa 2012 and dropped to 24% in 2017.

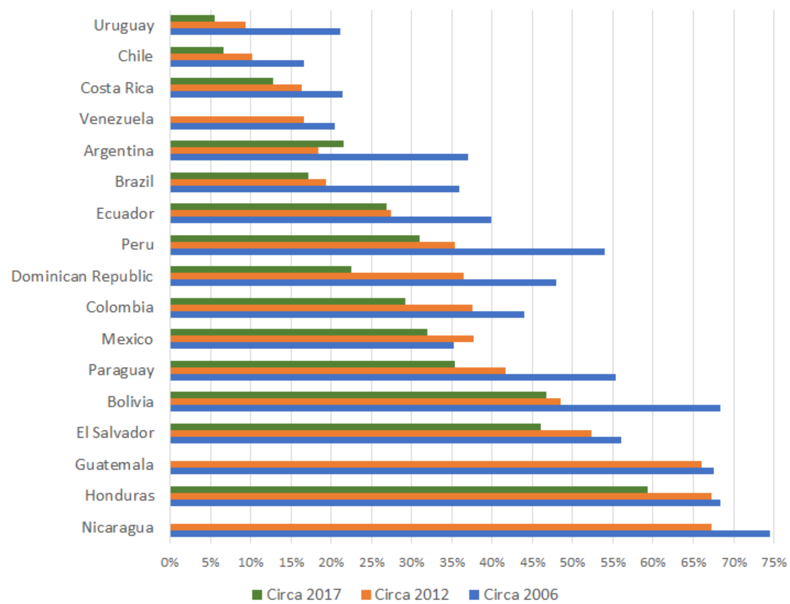

Figure 4: *Vulnerability gap over time by country.*

Figure 4 shows the country estimation of V_1 in each country. The figure shows that, in line with the trends in the vulnerability incidence rate, the vulnerability gap decreased systematically from 2006 to 2017 in all countries of our sample except for Mexico (with an increase in 2012, yet followed by a reduction). However, for many countries – Bolivia, Paraguay, the Dominican Republic, Peru, Ecuador, Brazil, Argentina, Chile and Uruguay – a significant fall was experienced from 2006 and 2012, with a subsequent much more modest reduction (and even an increase in the case of Argentina). Notably, the multidimensional vulnerability gap continued to be high in 2017 in the poorest and more vulnerable countries of the region. In Bolivia and El Salvador, this gap was greater than 45% in the last year of observation, whereas in Honduras, it was close to 60%.

4.4. Decomposing total vulnerability into poverty-induced and risk-induced

We now exploit the decomposition of the V_α measures into the group of the poor vulnerable – i.e. those whose probability of being non-poor below or equal to 50% – and the group of the risk-vulnerable — i.e. those who have a probability of being non-poor above 50%, but have a downside risk-adjusted probability of being non-poor below or equal to 50%. The observed higher inertia in vulnerability reduction as compared to poverty reduction pointed out before can be further analysed by decomposing the incidence rate V_0.

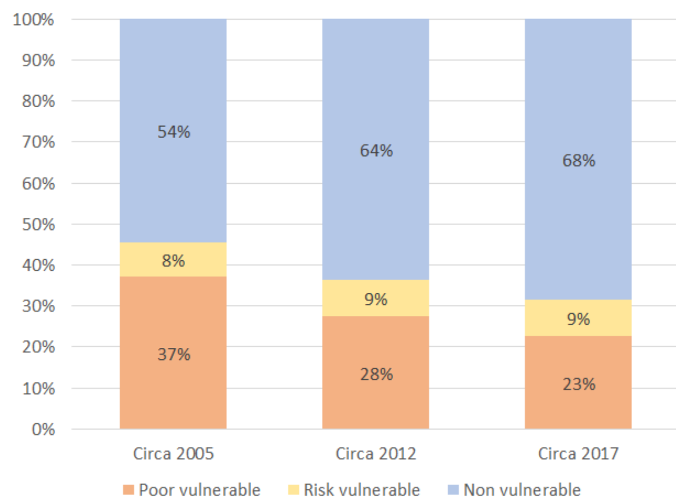

Figure 5: *Composition of vulnerability – Latin America aggregate – circa 2005, 2012 and 2017.*

Figure 5 shows such decomposition for the region as a whole in each observed period. It can be seen that, while the fraction of the population that is poor-vulnerable significantly decreased across the three observed years (more so from 2006 to 2012 than from 2012 to 2017), the fraction of the population that is risk-vulnerable remained with virtually no change throughout the 15 years (actually with an increase of 1 pp). These aggregate estimates of vulnerability in the region may appear somewhat low, especially when compared with estimates of vulnerability to income poverty, for example, those of CEPAL (2019). Yet, they are actually quite alarming, as they indicate that around 2017, a third of the region's population was vulnerable to falling into *multiple simultaneous deprivations*; recall that the k-value of multidimensional poverty is a conservative 25% (see Section 3.4). Moreover, it means that, for every 100 people who are in multidimensional poverty, there are another 39 (9%/23%) with a high risk of also falling into such a group.

Regional aggregates uncover a lot of country variation. Figure 6 depicts the estimated size of each vulnerability group looking country-by-country and period-by-period, verifying the significant reduction in the group of the poor-vulnerable alongside a much milder reduction or – in several countries – even an increase in the group of the risk-vulnerable. This means that, while poverty-induced vulnerability remains the most significant driver of total vulnerability, risk-induced vulnerability increased its preponderance over time. The graph also indicates that risk-induced vulnerability tends to have a higher share in less poor countries than in poorer ones, accounting for over a third of total vulnerability in Uruguay, Chile, Costa Rica and Brazil in the last observation. This intuitively indicates that, in less poor countries, the event of poverty is more often determined randomly by luck, while in poorest countries, poverty has a more deterministic character.

In some countries, the risk-induced vulnerability component has increased at the same time as the poverty-induced component of vulnerability has decreased. To see this more clearly, we calculated the percentage change in the rates of poverty-induced vulnerability and risk-induced vulnerability over the whole observation window. This is complementary information to that of Figure 6, as for poorer countries it is easier to experience big absolute changes (because their starting incidence is high) but more difficult to exhibit big relative changes, whereas for the less poor countries it is exactly the other way round. Indeed, Figure 7 shows that over the considered 15 years, the countries that experienced the greatest relative achievement in the reduction of both vulnerability components were Uruguay, Chile, Brazil and, remarkably, the Dominican Republic, despite its high initial incidence level. These four countries, together with Argentina, Costa Rica and Venezuela, experienced a reduction both in poverty and in the risk component of vulnerability. The other 10 countries have had a relative reduction in the poverty component of vulnerability together with an increase in the risk component. The Latin American country where the risk component of vulnerability increased the most during the observed period was Honduras, followed in decreasing order by Mexico, Bolivia, El Salvador and Paraguay.

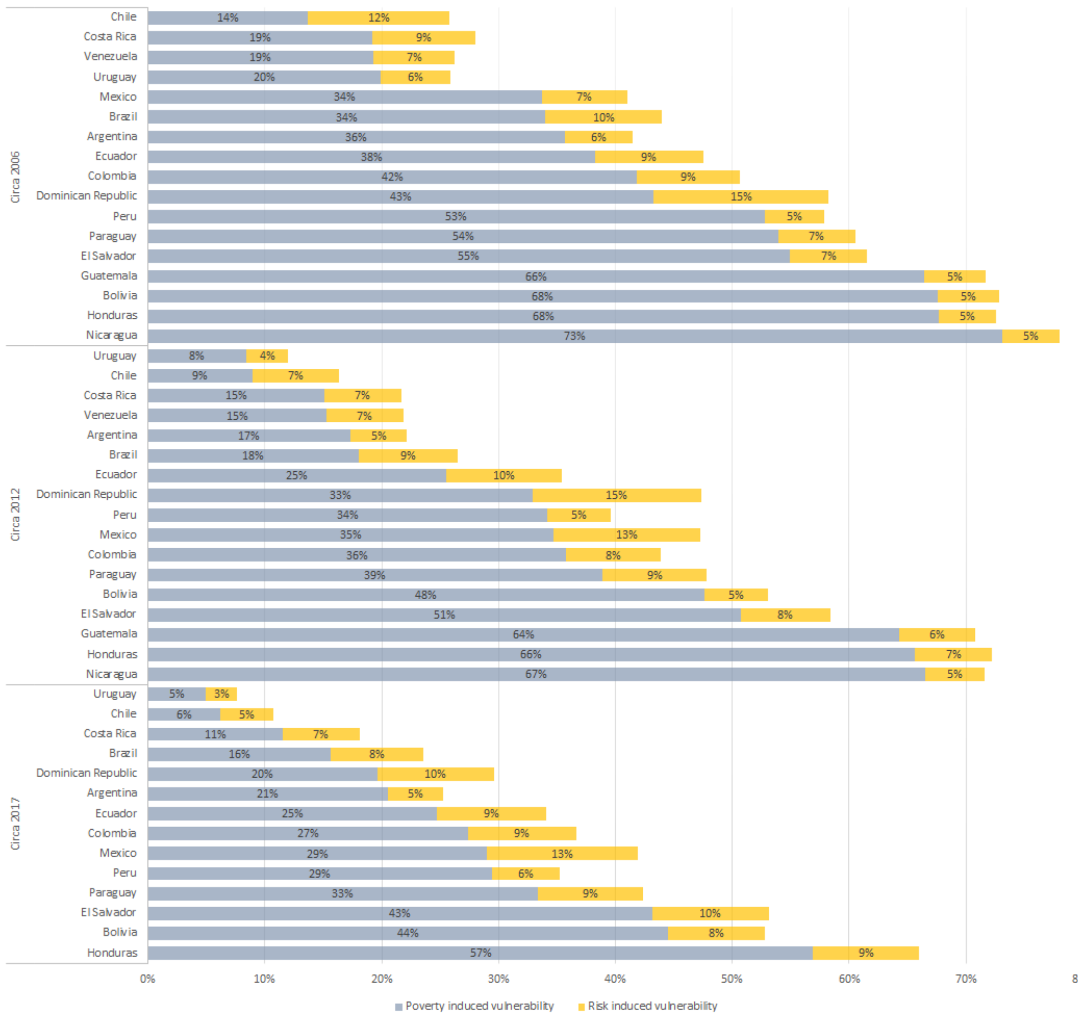

Figure 6: *Decomposition between poverty-induced and risk-induced vulnerability by country and period.*

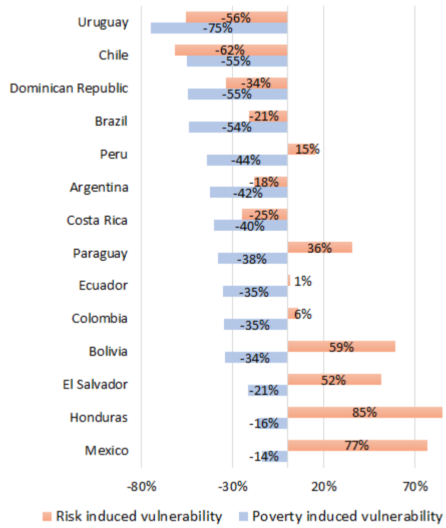

Figure 7: *Relative changes in poverty-induced and risk-induced vulnerability between circa 2017 and circa 2005. (Note: Guatemala is excluded because it does not have observation in the third period.)*

4.5. Dimensional composition of different vulnerable groups

One natural question to address is whether poverty-induced vulnerability differs from risk-induced vulnerability in terms of its dimensional composition. For that purpose, we performed two analyses. First, Figure 8 presents the regional-aggregate ratios of deprivation rates in each considered indicator amongst the poor-vulnerable to the deprivation rates amongst the risk-vulnerable. Naturally, the ratios are above one in all cases, indicating that there is a higher prevalence of each deprivation amongst the poor-vulnerable than amongst the risk-vulnerable. However, the interesting point is that ratios are substantially higher in indicators of structural poverty, namely, housing materials, energy, very basic durable goods (these three with ratios of 5 and over), water, overcrowding, sanitation and education: deprivations in these indicators are at least twice as prevalent amongst the poor vulnerable than amongst the risk vulnerable. In contrast, deprivations in income, social security, housing tenure and employment amongst the risk vulnerable are much more similar than incidences amongst the poor-vulnerable (ratios are closer to 1).

In our second analysis, we performed a dimensional breakdown of multidimensional poverty, which is shown in Figure 9. Noteworthy is a headcount ratio and, while it can be decomposed by subgroups, cannot be broken down

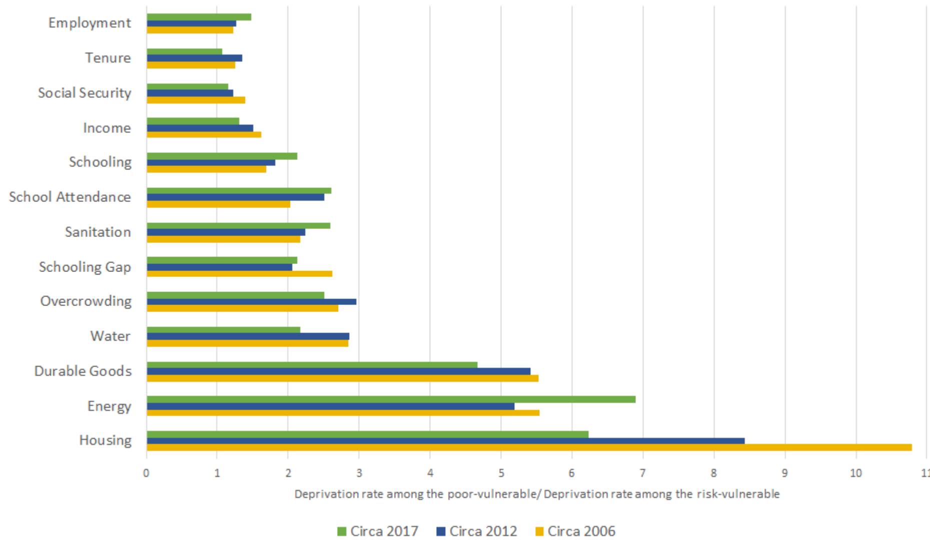

Figure 8: *Ratios of deprivation rates amongst the poor vulnerable to deprivation rates amongst the risk- vulnerable for 17 Latin American countries, circa 2005, 2012 and 2017.*

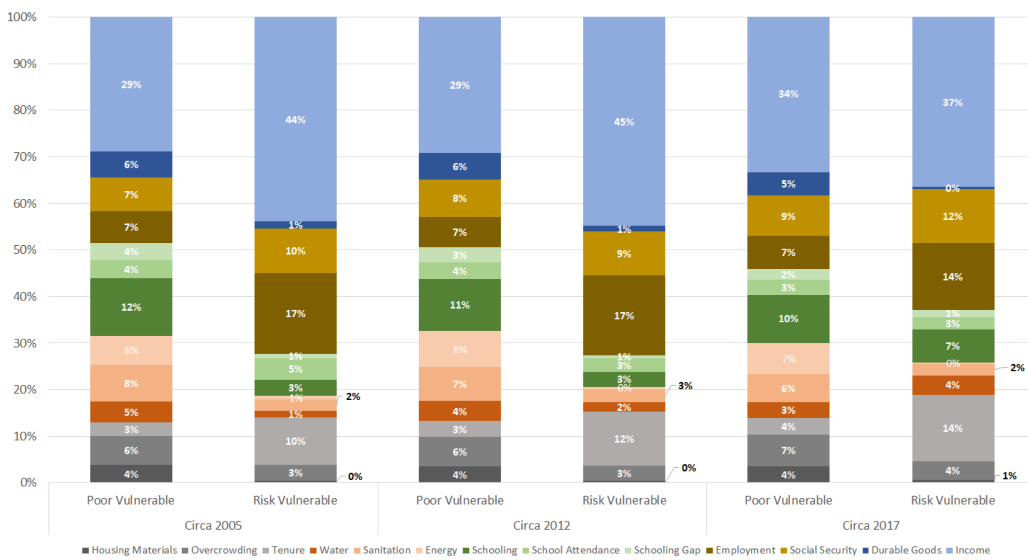

Figure 9: *Composition of poverty amongst the poor-vulnerable vs. amongstthe risk-vulnerable. Percent contributions to the MPI (M_0 measure) in each group-regional aggregate.*

by dimensions or indicators, as it does not incorporate poverty intensity. However, one can estimate the MPI (incidence rate times poverty intensity in the AF methodology) amongst those who have been identified as poor-vulnerable and amongst those who have been identified as risk-vulnerable, and then break down poverty into its components in each group. This is performed considering the LAC region as a whole. The estimates in Figure 9 confirm the analysis performed with the ratios of deprivation rates. Broadly speaking, across the three observed points in time, one can see that deprivations in the housing dimension (coloured in grey scale), basic services dimension (coloured in pink scale) and education dimension (coloured in green scale) – structural aspects of poverty – represent about 50% of total poverty amongst the poor vulnerable, whereas they represent a third or less of total poverty amongst the risk vulnerable. As a counterpart, deprivations in employment and social security, and in the living standard dimension (income and durable goods), account for 65–70% of the poverty amongst the risk vulnerable (vs. 50% amongst the poor vulnerable). Within those two dimensions, deprivations in income and employment are the leading sources of risk vulnerability.

4.6. Dimensional vulnerability

So far, we have analysed results in terms of vulnerability to being multidimensionally poor. However, the MBC provides estimates of the conditional probabilities in each class-dimensional variable. Therefore, we can use this information to estimate vulnerability to being deprived in each considered indicator (i.e. when the risk-adjusted probability of being non-deprived is below or equal to 50%). Moreover, we can perform a decomposition between the poverty-induced and risk-induced vulnerability in each dimension in a similar way as we did for the multidimensional measure V_0. Figure 10 shows the boxplot of the distribution of vulnerability incidence rates by dimensions and years. We can see that not only the level but also the dispersion of dimensional vulnerabilities has decreased amongst countries in the dimensions of education, water, housing materials, energy, people per room and durable goods, suggesting some form of *convergence*. In contrast, deprivations in the dimensions of social security, monetary resources, employment, sanitation and housing tenure have not exhibited such convergence.

Finally, Figure 11 depicts the decomposition results between the poor-vulnerable and the risk-vulnerable in each dimension, which illustrates great heterogeneity of risk across dimensions. Out of the 13 considered indicators, vulnerability in social security stands out because of its very high incidence levels, as well as because this level increased in the observed time window.

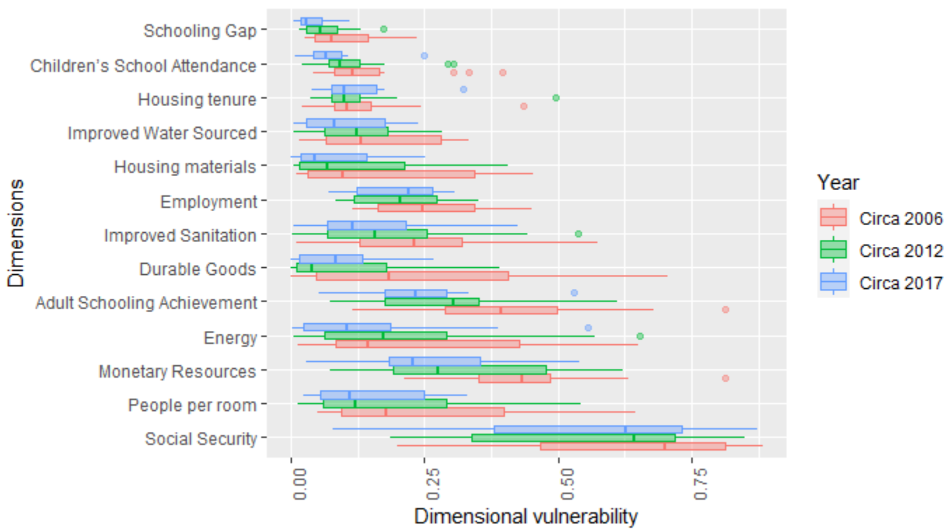

Figure 10: *Latin America: Boxplot of deprivations by countries.*

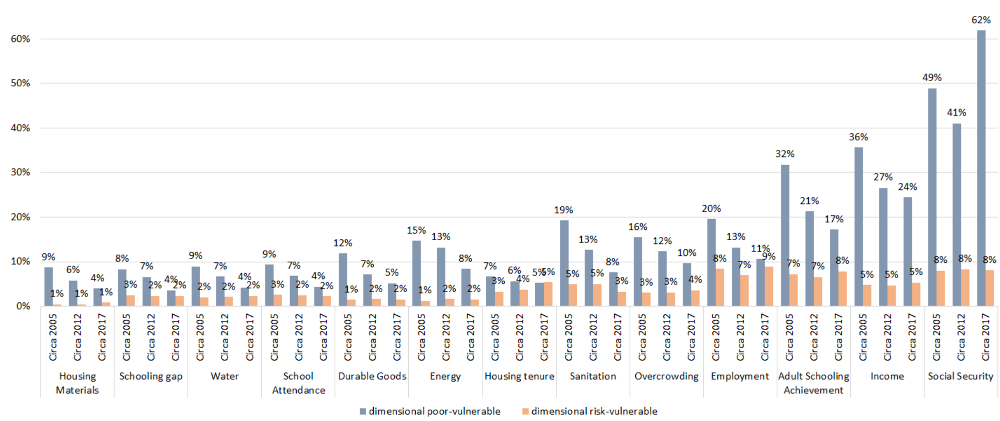

Figure 11: *Dimensionally-poor vulnerable and dimensionally-risk vulnerable – Latin America aggregate – circa 2005, 2012 and 2017.*

By 2017, only 30% of the region's inhabitants lived in households not vulnerable in this dimension, suggesting that the countries of the region have structurally informal economies. The region also remains highly vulnerable in the monetary dimension, in the educational attainment of adults (there is a lag in this for older people) and in employment. On the other hand, this figure shows that the region has already made significant welfare achievements in terms of children's school attendance, schooling gap, drinking water, housing materials and durable goods availability.

5. Discussion and concluding remarks

In this paper, we have implemented the Gallardo and Bekios (2021) methodology based on an MBC model for estimating VMP for the Latin America region, as measured by an application of the AF methodology for the region – the MPI-LA. We have performed estimates for 17 countries at three points in time over 15 years (circa 2006, 2012 and 2017) involving computations for over 7.1 million people. The MBC methodology has the advantage of solving, in a relatively easy way, the challenge of estimating VMP, respecting precisely the *multidimensionality.* We estimate the probability of being deprived in each welfare dimension and simultaneously the probability of being multidimensionally poor. Alternative methods, such as estimating probabilities by applying logit or probit models for each deprivation (Gallardo, 2020), or a probit model applied to the multidimensional score (Feeny & McDonald, 2016) are solutions that consist of transforming a multidimensional problem into a unidimensional one. These kinds of strategies are known as a *problem transformation method* in the specialised literature on multi-label classifiers (Tsoumakas et al., 2009). In contrast, the MBC estimation strategy belongs to the so-called *algorithm adaptation method* approaches, which, instead of transforming the problem into a unidimensional one, directly apply a multidimensional estimation algorithm.

We also provide wide empirical evidence that validates the use of this VMP estimation strategy, and this paper shows that this type of model works very well with a large diversity of data from different countries.

There are four particularly significant analytical results in this work. First, despite significant reductions over the study period, our estimates indicate that by 2017, 32% of the population in the region was vulnerable to multidimensional poverty. This means that approximately 200 million people – about the size of Brazil's population – were severely deprived. The VMP performance over the period reflects quite closely the economic cycle in most countries of the region. The important economic expansion from 2006 to 2012, even despite the 2009 crisis, enabled a substantial reduction in the vulnerability incidence as well as in the vulnerability gap. This was followed by years of deaccelerated growth and even recession in some countries, which translated into a smaller but still significant reduction of vulnerability.

Second, as the incidence of multidimensional poverty decreased, the overrate of vulnerability to poverty increased. Put differently, we observe that vulnerability to poverty is reduced at a much slower rate than poverty itself, which suggests that many of those who move out of poverty remain in the vulnerability zone. This implies that poverty reduction accomplishments can actually be quite fragile, compromising progress towards SDG1.

Third, the implemented methodology allows distinguishing two groups amongst the vulnerable: the poor vulnerable, those whose probability of being out of poverty is below or equal to 50%, and the risk vulnerable, those who, while having a probability of not being poor above 50%, when this probability is adjusted by the downside risk, fall below or equal to 50%. Discriminating these two groups reveals that, indeed, it is the group of poor-vulnerable that decreased the most in the study period, whereas the size of the risk-vulnerable group remained unchanged in the region as a whole, with some countries reducing it, and some others actually increasing it. While the poor-vulnerable are still the biggest group, the risk vulnerable are a significant group: for every 100 people who are already in multidimensional poverty in the region, there are another 39 with a relevant risk of also falling into such group.

Fourth, we also find that the poor-vulnerable and the risk-vulnerable are actually quite different in the deprivations they experience, in an intuitive way. The poor-vulnerable exhibit a more 'balanced' composition of deprivations, with deprivations in dimensions of structural poverty, such as housing and access to services and education, accounting for 50% of their total deprivations, and deprivations associated with the labour market – employment, access to social security and income – accounting for roughly the other 50% of their deprivations. In contrast, deprivations in structural dimensions of poverty amongst the risk vulnerable account for less than a third, whereas deprivations in dimensions associated with the labour market represent 70% of their total poverty.

What are the policy implications of these results? It is commonplace to say that economic growth is a necessary yet insufficient condition for reducing poverty. Nevertheless, the estimates in this paper support the idea one more time. When growth deaccelerated in the region, so did poverty and vulnerability reduction. We need growth, and we need it to be sustained over time. However, countries with very different growth performances achieved the same vulnerability reduction. Thus, there is something else than just growth.[20] Indeed, in the 15 years under study, countries in the region either implemented, expanded or consolidated social protection

[20] In fact, Santos et al. (2019) found a modest 0.53 elasticity of multidimensional poverty to economic growth.

policies, mainly consisting of conditional cash transfer (CCT) programmes – a hallmark of social policy in the region (Shifter, 2013; Villatoro, 2007) – and non-contributive pensions for the poor. To a lesser extent, countries in the LAC region also implemented employment programmes, although with great heterogeneity in their design across countries and in fragmented ways within countries.[21]

Of course, the region is greatly heterogeneous, and surely there is no 'one fits all' policy recommendation. However, the results here offer some compelling guidance. Our results suggest two target groups of vulnerable populations. There is the group of the *poor-vulnerable*, who actually constitute the core vulnerability group. They experience deprivations in infrastructure and basic services, including education, as much as deprivations in income, employment and social security. In other words, they fail 'to acquire a basic minimum set of capabilities that excludes people from participating in social and economic activity on par with the rest of society', a condition that is hardly temporary (Mookherjee, 2006). As Banerjee and Duflo (2011) have noted, 'risk is a central fact of their lives; for them a bad break can have disastrous consequences' (p. 133). There is also the group of the *risk-vulnerable*, for whom structural deprivations are much less prevalent, but experience exclusion from the economic autonomy and security that formal employment can facilitate.

Thus, we understand that the region needs to evolve into a new generation of social policy, currently strongly based on income transfers, into a much more *integrated (social policy) design* across sectorial ministries differently targeted. For the poor-vulnerable, the CCT programmes that are already in place need to be articulated with three other areas. First, for many beneficiaries, the transfer needs to be accompanied by expanding access to basic infrastructure services. Second, it is also key to develop some link between the transfers and training programmes, which is accurately tuned to the needs of this segment in each country, to facilitate a transition from unemployment or being outside the labour force into the labour market. Third, it is also of fundamental importance to keep encouraging long-term investments in education and capability-building. One option may be complementary programmes that offer a closer follow-up of the most vulnerable families from infancy until ensuring completion of the secondary school level. In this regard, there is overwhelming evidence regarding the long-term

[21]See Abramo et al. (2019) for a detailed discussion on each kind of these policies implemented in the region and their impacts, scope and limitations.

impact of investments in the first years of life (Cunha & Heckman, 2006). Articulated programmes that offer support for the most vulnerable mothers, including child-care services that guarantee early childhood stimulation allowing, at the same time, female labour participation, parenthood training workshops and nutritional supplements for infants, can promote permanent changes in the life trajectories for these children.[22] Improving school quality in schools with disadvantaged children, developing strategic ways to enhance cognitive development, would be a further incentive from the supply side for secondary school completion.

For the risk-vulnerable, the emphasis needs to be placed on insurance mechanisms against employment and income losses. Naturally, the big barrier is the high informality level structurally embedded in the Latin American economies, which is reflected in the very high vulnerability rates we observe in the social security dimension. Prevailing systems in the region are actually limited to formal sector wage earners (Velasquez Pinto, 2016). Thus, it is key to design and strengthen policies to increase formality (both for the employed and the self-employed), such as tax and registry simplification, alongside compulsory employment insurance schemes learning from successful experiences in developed countries (see, for example, van Breugel, 2016). However, while the region progresses towards higher levels of formality, a minimum income level should be assured for the dependent population (children and the elderly) building upon the already well-established CCTs, extending them to vulnerable sectors not yet reached by them (which differs in each country), in order to advance towards a more complete protection system.

Certainly, the Covid-19 pandemic shock has already impacted the group of vulnerable in the region and has surely increased its size. Rather than interpreting this shock as a limitation for improvement, it must be taken as a compelling nudge to build upon policies already in place, articulating across them and complementing them with new elements in order to amplify their vulnerability and poverty reduction potential. This does not necessarily need to place further pressure on fiscal resources. As suggested by Lustig and Tommasi (2020), the exceptionality of the circumstances can make budget reallocations much more politically palatable.

[22] There are some experiences in the region, such as Chile Crece Contigo, with successful results in several dimensions (Torres et al., 2017).

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Acknowledgements: This work was supported by the National Research and Development Agency (ANID), corresponding to the Fondecyt project No. 11170650 'Measuring Vulnerability to Multidimensional Poverty: Methodology and Applications in Latin America'.

Appendix A

Table A1. Natural disasters that have affected more than 5% of the national population of Latin American countries, 2001 to 2017.

Country	Year	Disaster	National population affected (
El Salvador	2001	Earthquakes	26.9
El Salvador	2001	Drought	6.8
Perú	2003	Extreme weather	6.8
Perú	2004	Extreme weather	7.8
Bolivia	2007	Floods	8.8
Colombia	2007	Floods	6
Guatemala	2009	Drought	17.8
Chile	2010	Earthquake	15.6
Colombia	2010	Floods	6.1
Guatemala	2012	Earthquake	8.8
Paraguay	2012	Drought	21.8
Bolivia	2013	Drought, floods	7.9
Brazil	2014	Drought	13.1
Guatemala	2014	Drought	8.3
Honduras	2014	Drought	6.4
Nicaragua	2014	Drought	7.6
Ecuador	2015	Volcanic eruption	5.8
El Salvador	2015	Drought	11.1
Bolivia	2016	Drought	6.1
Perú	2016	Floods	5.7
Dominican Republic	2016	Floods	26.2

Source: Elaborated by the authors, based on ECLAC database, https://cepalstat-prod.cepal.org/cepalstat/tabulador/ConsultaIntegrada.asp?idIndicador=1837&idioma=e and CELADE database, https://www.cepal.org/es/temas/proyecciones-demograficas/estimaciones-proyecciones-poblacion-total-urbana-rural-economicamente-activa.

Table A2. MPI-AL: Selected dimensions, deprivation indicators and weights.

Dimensions	Deprivation Indicators: People Who Live In...	Weights (%)
Housing		**22,2**
Housing materials [a]	Households with dirt floor or precarious roof or wall materials (waste, cardboard, tin, cane, palm, straw, other materials).	7,4
People per room [b]	Households with three or more people per room, in urban and rural areas (overcrowding).	7,4
Housing tenure [c]	Households which live in i) an illegally occupied house or ii) in a ceded or borrowed house	7,4
Basic Services		**22,2**
Improved Water Sourced [d]	Urban areas: Households with some of the following water sources: - piped outside yard/plot; - unprotected well or without mechanic pump; - cart with small tank; - bottled water; - river, spring, dam, lake, ponds, stream, rainwater, other. Rural areas: Households with some of the following water sources: - unprotected well or without mechanic pump; - cart with small tank; - bottled water; - river, spring, dam, lake, ponds, stream, rainwater, other.	7,4
Improved Sanitation [d]	Urban areas: Households with some of the following: - toilet or latrine not connected to piped sewer system or septic tank; - shared toilet facility; - no toilet facility (bush/field). Rural areas: Households with some of the following: - no toilet facility (bush/field); - shared toilet facility; - toilet or latrine flushed without treatment to surface, river or sea.	7,4
Energy [e]	Households with no access to electricity or which use wood, coal or dung as cooking fuel.	7,4
Living Standard		**22,2**
Monetary Resources	Households with insufficient per capita income to cover food and non-food needs.	14,8
Durable Goods [f]	Households which do not own any of the following items: car, refrigerator or washing machine.	7,4
Education		**22,2**
Children's School Attendance	Households where there is at least one child or adolescent (6 to 17 years) not attending school.	7,4
Schooling Gap	Households where there is at least one child or adolescent (6 to 17 years) who is over two years delayed with respect to his/her schooling grade for age.	7,4
Adult Schooling Achievement	Households where no member 20 years or older has achieved a minimum schooling level, defined as: - complete lower secondary school for people between 20 and 59 years, and - complete primary school for people of 60 years or more.	7,4
Employment and Social Protection		**11,1**
Employment	Households with at least one member between 15 and 65 years old being one of the following: - unemployed; - employed without a pay; or - a discouraged worker.	7,4
Social Security [g]	Households experiencing at least one of the following characteristics: - no member has some form of contributory health insurance; - no member is contributing to a social security system; - no member is receiving a pension or retirement income.	3,7

Notes: [a] There was no available information on the following items for the following countries and years: walls for Argentina (2005, 2012), floor for Brazil (2005, 2012), roof for Colombia (2008, 2012), housing materials for Uruguay (2005). See details of surveys used in Table 2. [b] Given that in the case of Brazil, Costa Rica and Mexico, the number of rooms does not exclude kitchen and/or toilets, we corrected the number of rooms in the house using Kaztman's (2011) suggestion of subtracting one from the total number of rooms. [c] Households living in houses given in usufruct were not considered as deprived. [d] In the case of the Dominican Republic (2005 and 2012), we applied the same deprivation definition for urban areas to rural ones because the survey question does not allow us to differentiate between the two. [e] There is no information on access to electricity for Argentina (2005 and 2012), the Dominican Republic (2005) and Uruguay (2005), and there is no information on cooking fuel for Chile (2006 and 2011). [f] There is no information on durable goods for Argentina (2005 and 2012). There is no information on car ownership for Brazil (2005); it has been replaced by ownership of a stove. There is no information on washing machines for Costa Rica (2012), and it has been replaced by a TV with plasma or LCD screen. [g] There is no information on health insurance for Brazil (2005 and 2012).

Table A3. Poverty and vulnerability headcount ratios for different γ values, in percent.

	Year	H	V_0 $(\gamma = 0.5)$	V_0 $(\gamma = 0.6)$	V_0 $(\gamma = 0.75)$	V_0 $(\gamma = 0.8)$	V_0 $(\gamma = 0.9)$	V_0 $(\gamma = 1)$
Circa 2006								
Argentina	2005	35.7	37.4	39.6	40.6	41.0	41.3	41.5
Bolivia	2007	67.7	69.4	70.0	70.6	71.0	71.4	72.8
Brazil	2005	34.0	36.9	39.0	40.6	41.8	42.9	44.0
Chile	2006	17.1	17.4	18.5	20.5	24.1	25.4	25.8
Colombia	2008	42.3	45.2	48.0	49.2	49.5	49.9	50.6
Costa Rica	2005	20.4	23.5	24.2	24.7	26.0	27.4	28.0
Ecuador	2008	39.0	42.2	42.9	43.4	43.9	45.5	47.5
El Salvador	2005	58.2	57.7	58.3	59.0	59.4	60.5	61.5
Guatemala	2006	68.9	68.8	69.5	69.9	70.5	71.0	71.7
Honduras	2005	71.1	69.7	70.3	70.7	71.1	71.7	72.6
Mexico	2006	36.3	36.8	38.0	38.7	39.4	39.9	41.0
Nicaragua	2005	78.9	75.6	76.2	76.7	77.2	77.5	78.0
Peru	2005	58.0	55.4	55.8	56.0	56.5	56.8	57.9
Paraguay	2005	56.6	57.7	57.9	58.2	58.8	59.6	60.6
Dominican Republic	2005	46.8	50.5	51.2	53.7	56.0	57.1	58.2
Uruguay	2007	19.8	21.8	23.0	23.9	24.6	25.3	25.9
Venezuela	2008	21.1	21.7	22.4	23.6	24.5	25.5	26.2
Circa 2012								
Argentina	2012	17.6	19.4	20.4	20.7	21.0	21.6	22.2
Bolivia	2012	47.6	50.3	51.4	51.9	52.5	52.8	53.1
Brazil	2012	18.3	19.4	20.3	22.5	24.4	25.6	26.5
Chile	2011	10.0	10.2	11.6	14.2	15.4	15.9	16.3
Colombia	2012	35.8	39.5	41.7	42.4	42.7	43.1	43.9
Costa Rica	2012	15.3	17.5	18.4	19.2	20.0	20.7	21.6
Ecuador	2012	26.7	29.7	30.4	30.7	31.8	34.3	35.4
El Salvador	2012	53.2	54.1	55.2	55.8	56.7	57.5	58.4
Guatemala	2014	65.0	67.4	68.7	69.3	69.9	70.5	70.8
Honduras	2012	68.7	69.1	69.6	70.7	71.5	72.0	72.2
Mexico	2012	37.6	39.6	39.9	40.3	42.5	46.2	47.3
Nicaragua	2014	66.0	68.9	69.3	69.7	70.1	70.9	71.6
Peru	2012	35.9	36.5	37.0	37.8	38.4	38.9	39.6
Paraguay	2012	40.8	43.1	44.2	45.5	46.6	47.4	47.8
Dominican Republic	2012	36.5	40.0	41.3	42.3	44.5	46.5	47.4
Uruguay	2012	8.5	9.9	10.3	10.8	11.1	11.6	12.0
Venezuela	2012	17.0	18.5	19.0	19.5	20.4	21.0	21.9
Circa 2017								
Argentina	2017	20.7	22.5	23.5	23.8	24.1	24.8	25.3
Bolivia	2017	45.3	48.2	49.2	50.7	51.4	52.0	52.8
Brazil	2017	17.0	19.2	19.5	20.0	21.2	22.7	23.5
Chile	2017	6.9	7.0	7.3	7.7	8.6	9.7	10.8
Colombia	2017	27.5	30.1	31.3	34.2	35.7	36.2	36.7
Costa Rica	2017	12.2	13.4	14.1	14.7	15.9	17.3	18.1
Ecuador	2017	25.8	28.7	29.9	31.1	32.3	33.6	34.1
El Salvador	2017	45.1	48.1	48.8	50.7	52.3	52.8	53.2
Honduras	2016	60.0	61.6	62.1	62.9	63.4	64.8	65.9
Mexico	2016	31.7	33.2	33.7	34.9	38.7	40.9	41.9
Peru	2017	30.9	32.3	32.9	33.5	34.1	34.5	35.2
Paraguay	2017	33.8	36.7	37.9	40.1	41.3	42.0	42.4
Dominican Republic	2016	23.8	24.2	26.4	27.8	28.2	28.9	29.6
Uruguay	2017	5.0	5.8	6.1	6.4	6.8	7.1	7.6

Notice that, by definition, V_0 increases for higher γ values. When compared with the headcount ratio of multidimensional poverty H, even for the lowest γ value of 0.5, vulnerability usually has a higher incidence than poverty, which is an intuitive result. Some exceptions could occur for the poorest countries of the sample. However, these exceptions could be explained by the fact that, when a high proportion of the population is poor with certainty and with deprivation in several dimensions, vulnerability could be underestimated because the certainty of poverty in several dimensions is an extreme risk. In other words, a high incidence of acute multidimensional poverty in some sense outweighs the estimated vulnerability. It is noteworthy that, for γ value of one, we only observe two cases (Nicaragua and Peru in period 1) when the incidence of poverty is slightly greater than that of vulnerability.

Table A4. Poverty and vulnerability measures ($\gamma = 1$) in fractions.

	Year	H	A	M_0	V_0	V_1	V_2	VPR	ORV
Circa 2006									
Argentina	2005	0.36	0.39	0.14	0.41	0.37	0.35	1.16	0.06
Bolivia	2007	0.68	0.49	0.33	0.73	0.68	0.67	1.08	0.05
Brazil	2005	0.34	0.39	0.13	0.44	0.36	0.33	1.29	0.10
Chile	2006	0.17	0.32	0.06	0.26	0.17	0.14	1.51	0.09
Colombia	2008	0.42	0.40	0.17	0.51	0.44	0.41	1.20	0.08
Costa Rica	2005	0.20	0.36	0.07	0.28	0.21	0.19	1.37	0.08
Dominican Republic	2005	0.47	0.39	0.18	0.58	0.48	0.44	1.24	0.11
Ecuador	2008	0.39	0.40	0.16	0.48	0.40	0.37	1.22	0.09
El Salvador	2005	0.58	0.49	0.29	0.62	0.56	0.54	1.06	0.03
Guatemala	2006	0.69	0.51	0.35	0.72	0.67	0.66	1.04	0.03
Honduras	2005	0.71	0.53	0.38	0.73	0.68	0.67	1.02	0.01
Mexico	2006	0.36	0.40	0.14	0.41	0.35	0.33	1.13	0.05
Nicaragua	2005	0.79	0.58	0.46	0.78	0.75	0.73	0.99	-0.01
Paraguay	2005	0.57	0.46	0.26	0.61	0.55	0.53	1.07	0.04
Peru	2005	0.58	0.50	0.29	0.58	0.54	0.53	1.00	0.00
Uruguay	2007	0.20	0.40	0.08	0.26	0.21	0.20	1.31	0.06
Venezuela	2008	0.21	0.36	0.08	0.26	0.20	0.18	1.25	0.05
Circa 2012									
Argentina	2012	0.18	0.36	0.06	0.22	0.18	0.17	1.26	0.05
Bolivia	2012	0.48	0.46	0.22	0.53	0.48	0.46	1.12	0.05
Brazil	2012	0.18	0.36	0.07	0.27	0.19	0.17	1.45	0.08
Chile	2011	0.10	0.30	0.03	0.16	0.10	0.08	1.64	0.06
Colombia	2012	0.36	0.40	0.14	0.44	0.38	0.35	1.23	0.08
Costa Rica	2012	0.15	0.36	0.06	0.22	0.16	0.15	1.41	0.06
Dominican Republic	2012	0.36	0.37	0.13	0.47	0.37	0.32	1.30	0.11
Ecuador	2012	0.27	0.37	0.10	0.35	0.27	0.25	1.33	0.09
El Salvador	2012	0.53	0.46	0.25	0.58	0.52	0.50	1.10	0.05
Guatemala	2014	0.65	0.51	0.33	0.71	0.66	0.64	1.09	0.06
Honduras	2012	0.69	0.49	0.34	0.72	0.67	0.65	1.05	0.04
Mexico	2012	0.38	0.39	0.15	0.47	0.38	0.35	1.26	0.10
Nicaragua	2014	0.66	0.52	0.35	0.72	0.67	0.66	1.08	0.06
Paraguay	2012	0.41	0.43	0.17	0.48	0.42	0.39	1.17	0.07
Peru	2012	0.36	0.43	0.15	0.40	0.35	0.34	1.10	0.04
Uruguay	2012	0.09	0.36	0.03	0.12	0.09	0.08	1.41	0.03
Venezuela	2012	0.17	0.35	0.06	0.22	0.17	0.15	1.29	0.05
Circa 2017									
Argentina	2017	0.21	0.36	0.08	0.25	0.22	0.20	1.22	0.05
Bolivia	2017	0.45	0.45	0.20	0.53	0.47	0.45	1.17	0.08
Brazil	2017	0.17	0.33	0.06	0.24	0.17	0.15	1.38	0.06
Chile	2017	0.07	0.32	0.02	0.11	0.07	0.06	1.56	0.04
Colombia	2017	0.28	0.37	0.10	0.37	0.29	0.26	1.33	0.09
Costa Rica	2017	0.12	0.35	0.04	0.18	0.13	0.11	1.49	0.06
Dominican Republic	2016	0.24	0.36	0.08	0.30	0.23	0.20	1.24	0.06
Ecuador	2017	0.26	0.37	0.10	0.34	0.27	0.24	1.32	0.08
El Salvador	2017	0.45	0.42	0.19	0.53	0.46	0.43	1.18	0.08
Honduras	2016	0.60	0.45	0.27	0.66	0.59	0.57	1.10	0.06
Mexico	2016	0.32	0.37	0.12	0.42	0.32	0.29	1.32	0.10
Paraguay	2017	0.34	0.39	0.13	0.42	0.35	0.33	1.25	0.09
Peru	2017	0.31	0.40	0.13	0.35	0.31	0.29	1.14	0.04
Uruguay	2017	0.05	0.34	0.02	0.08	0.06	0.05	1.51	0.03