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Evolution of Multidimensional Energy Poverty Risk in Bolivia from 2005 to 2019*

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Abstract

"Energy poverty" is a multidimensional concept that reflects the need to achieve a variety of wellbeing outcomes, which has been scarcely studied and used in public policy agendas. Considering that the literature on energy poverty is still incipient in Bolivia, this paper's objective is to generate evidence about energy poverty evolution in the country, approximating measures of incidence (risk) and severity for the period 2005-2019. The methodological approach follows the one proposed by Alkire & Foster (2011), with five equally weighted dimensions (energy expenditure, lighting, cooking fuel and indoor pollution, food equipment, and education and communication) and using different cut-off options, at the urban and rural levels. Also, Multidimensional Energy Poverty results are compared with a Principal Component Analysis (PCA) based weight structure as a robustness exercise. Results show that the risk of being energy poor in Bolivia has decreased, but not structurally. Also, intensity has decreased in both urban and rural areas, but rural energy poor households continue to show at least 50% of deprivation in all dimensions evaluated.

JEL Classification: I32, O13, Q40.

Keywords: Multidimensional Poverty, Energy, Development.

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Resumen
La "Pobreza energética" es un concepto multidimensional que refleja la necesidad de alcanzar una diversidad de resultados de bienestar, lo cual ha sido poco estudiado y utilizado en las agendas de políticas públicas. Considerando que la literatura sobre pobreza energética es aún incipiente en Bolivia, el objetivo de este trabajo es generar evidencia sobre la evolución de la pobreza energética en el país, aproximando medidas de incidencia (riesgo) y severidad para el período 2005-2019. El enfoque metodológico sigue el propuesto por Alkire & Foster (2011), con cinco dimensiones (gasto energético, iluminación, combustible para cocinar y contaminación interior, equipamiento alimentario y educación y comunicación) y utilizando diferentes umbrales, a nivel urbano y rural. Además, los resultados de Pobreza Energética Multidimensional se comparan con un Análisis de Componentes Principales (ACP) basada en una estructura de pesos y un ejercicio de robustez. Los resultados muestran que el riesgo de ser pobre en términos de energía se ha reducido en Bolivia, pero no estructuralmente. La intensidad también ha disminuido en las zonas urbanas y rurales, pero los hogares rurales con pobreza energética siguen en situación de privación en al menos 50% de las dimensiones evaluadas.

Códigos JEL: I32, O13, Q40.
Palabras clave: Pobreza multidimensional, Energía, Desarrollo.

1. Introduction

"Energy poverty" is generally understood as the lack of access to modern energy services (Day *et al*., 2016), and cannot be evaluated as a fixed concept (Sovacool, 2014), due to economic, environmental and behavioral factors that can cause it (Fernández, 2019). This complexity reflects its multidimensional nature, as energy is needed to achieve a variety of wellbeing outcomes (Nussbaumer *et al*., 2012; Day *et al.*, 2016).

This multidimensional system concept is fundamental for the economic development of a country, but has scarcely been studied and used in public policy agendas. However, since the beginning of the last decade, there has been a growing interest in this issue (Barnes *et al.*, 2014), with existing evidence having confirmed the socio-economic benefits of providing modern energy services in terms of improving levels of wellbeing, productivity, health, education, and living conditions (Halff *et al.*, 2014; Sovacool, 2014; Altomonte *et al.*, 2020).

The alleviation of energy poverty has become a priority objective, to the point that some countries have included it as an official development goal in their long-term policies[1]. The risk of energy poverty translates into incidence, while vulnerability reflects, for example, the intensity with which certain populations use fossil fuels and/or biomass in their homes as firewood or dung mainly for cooking, cooling, thermal comfort, and lighting (Calvo, R. *et al.*, 2021).

The literature on energy poverty is still incipient in Bolivia; however, regional studies have shown that there are positive impacts of the transition to modern energy services (*e.g.*, Martínez and Ebenhack, 2008). In the country, measures of poverty only take into account monetary issues; therefore, measuring multidimensional poverty allows including a set of deficiencies in terms of health, food security, education, and, in this case, energy access and quality. The need to address this new type of methodological approach is the main motivating factor for the present research.

This paper seeks to answer if risk and energy vulnerability in Bolivia has gone down. In other words, to generate evidence to evaluate the evolution of energy poverty in the country, approximating measures of incidence and severity (severity intensity) for the period 2005-2019. Our methodological approach follows the one proposed by Alkire and Foster (2011), which constructs a Multidimensional Energy Poverty Index (MEPI) based on household data. The dimensional weights chosen follow the guidelines of OPHI (2019), with equal weights for the selected dimensions: energy expenditure, electricity and lighting, cooking fuel and indoor pollution, food equipment, education and communication, at the urban and rural levels. Also, MEPI results are compared with a Principal Component Analysis (PCA) based on weight structure as a robustness exercise, mainly for evaluating if results are consistent with

[1] Such is the case for Chile, as shown in Urquiza *et al.* (2019).

different weighting options, and, in case they are not, for assessing the magnitude of the changes between methods.

Finally, there are other relevant factors in the evolution of energy poverty, which are not a direct part of the present research. In this sense, the demarcation of our work does not address aspects of energy efficiency, economic growth, and the effect of exogenous factors. Firstly, we do not take into account factors such as geographical and ecological diversity, which give Bolivia great energy potential. Secondly, we do not analyze the availability of useful energy through technological access, which is one of the factors of economic development and social welfare. Thirdly, we do not include categories of territory, which is an explanatory factor in the generation of inequalities and vulnerabilities in access to energy services (Calvo, *et al.*, 2021). Finally, we do not take into account climate or asynchronous patterns of variability (Eyring *et al.*, 2021), which are promoting the use of clean energy, energy efficiency, and balanced reduction of energy poverty worldwide.

The results of the study suggest that the risk of energy poverty in Bolivia has decreased, but the vulnerability caused by the severity and intensity of rural deprivation persists. There are several latent threats identified – not analyzed in this research – that allow us to assume that the overall risk of reclassifying the energy non-poor is significant. Also, PCA results show clues that dimensional reduction techniques or even policy discussion-based weight structures may be more useful in contexts that report lower energy deprivation, since some dimensional deprivations may already be satisfied and their corresponding weights should be lower.

The document is structured as follows: the first section describes the context of the national energy sector, then there is an extensive literature review with a regional focus. The MEPI calculations for Bolivia are then performed, and the main results and conclusions are presented.

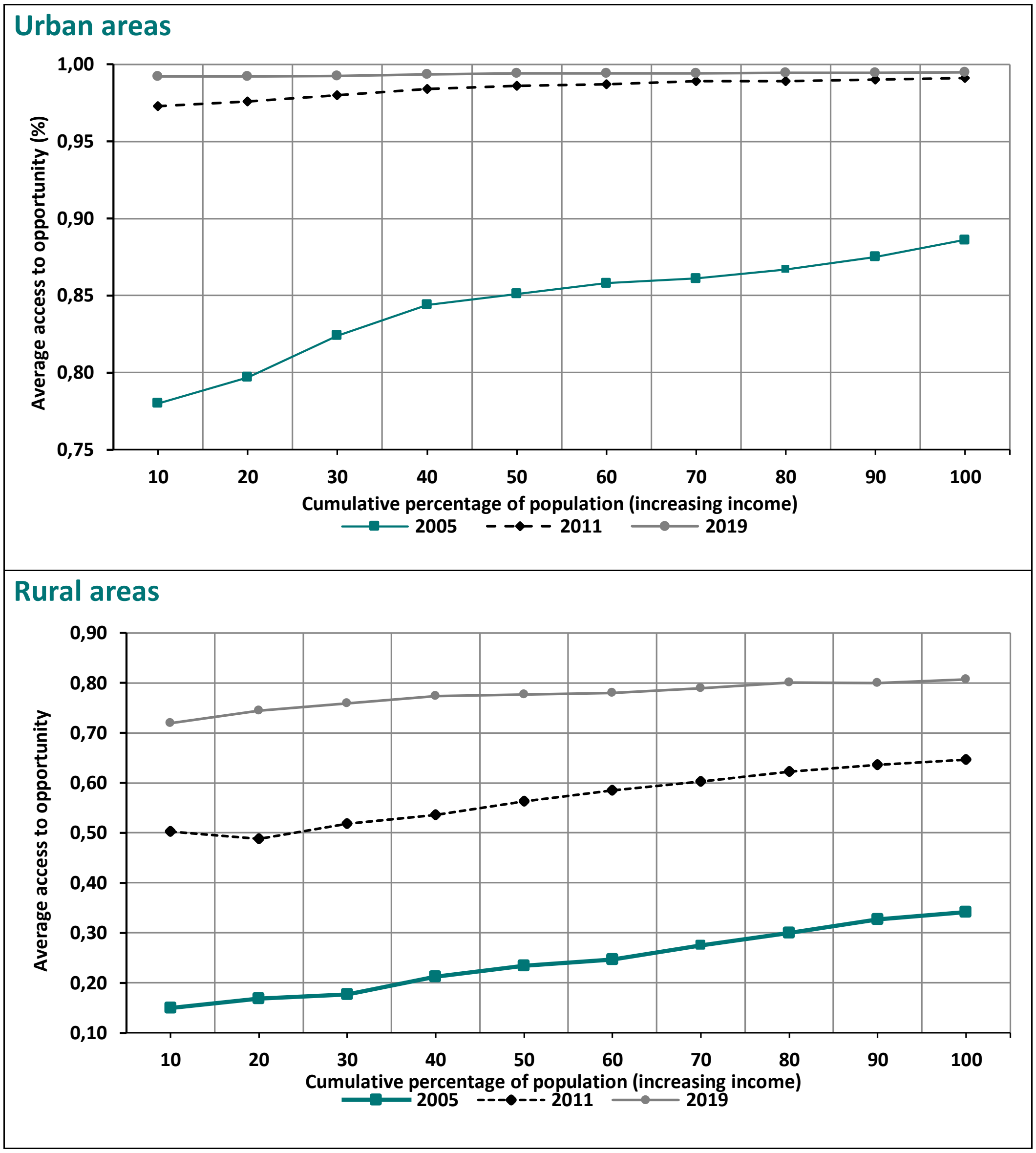
2. Energy context in Bolivia

The Political Constitution of the State (CPE) of Bolivia, promulgated in 2009, establishes in its Article 378.I, that "The different forms of energy and their sources constitute a strategic resource, their access is a fundamental and essential right for the integral and social development of the country, and will be governed by the principles of efficiency, continuity, adaptability and preservation of the environment". In this sense, CPE establishes the need to reduce energy poverty in a balanced way.

According to the World Bank (2020), nearly 800 million people still live without electricity worldwide, and they are considered energy poor. In the case of Bolivia, access to energy has improved significantly: urban electricity rose from 97.6% of the population in 1999 to 99.5% in 2019, while rural electricity rose from 27.1% in 1999 to about 80% in 2019 (Aliaga, 2020). However, significant gaps remain in the equity of electricity consumption, especially rural electricity, which can not be considered to have equitable consumption. Although 79% of rural households have access to some form of electricity, with 99.5% of urban households having access to electricity, the consumption gap between rich and poor households is high.

It should be noted that access to electricity at the household level improved substantially in 2005-2019, although universal coverage has not yet been achieved. In urban areas, 88.6% of families had access to this service in 2005, but in 2019 the rate reached 99.3%. In rural areas, the percentage increased from 34% to 80% between the same years (see *Figure 1*).

Figure 1. *Concentration curve of electricity opportunities, 2005-2019*
(In cumulative percentage of population)



Source: Own preparation based on household survey data from 2005 to 2019 (National Statistics Agency – Bolivia).

On the other hand, in urban areas, the distribution of access to electricity benefited higher-income households more in 2005, with an equity of opportunities index (φ)[2] of 0.94, while in 2019 the distribution improved (φ=1.05). However, in rural areas there was an unequal distribution with a very low index (φ=0.67), which improved in 2019 (φ=0.905), but not enough to achieve equality of opportunity. In the rural regions, about 254,000 households do not have access to this service (approximately 30% of the rural population); and the problems of equity in consumption reveals the lack of energy inclusiveness.

Across Bolivia there are at least 1.2 million people living in energy poverty, due to problems of access to this service. At least remaining to be quantified are: i) the number of people with access to electricity, but with very low consumption levels, which is expected to be a significant proportion in rural areas; and ii) the number of people with access to electricity, but who do not have the necessary household appliances; all of these also live in conditions of energy poverty.

It is estimated that the first decile of the rural population ordered by income (approximately 278,000 people), despite having access to electricity, may be in conditions of extreme energy poverty, defined as the number of people whose energy consumption is below a minimum required for cooking and lighting – consumption ranging from 70 to 280 KWh per month. Between the second and fourth deciles of the population (approximately 834,000 people) moderate energy poverty is expected. Extreme Energy Poverty is found in the most isolated rural regions, where people do not access or consume very little electricity (56,000 households), while in the provincial capital cities, inclusiveness is greater. Across the country, it is estimated that there are more than 2 million people with some degree of energy poverty.

Finally, during the last three decades, the country has shown a loss of energy productivity of 17.34%; that is, that more and more energy is required to generate wealth, a clear symptom that the intensity of energy poverty remains a primary problem (Aliaga, 2020). About 56,000 rural households do not have access to electricity and their inclusion implies costly investments, as these families are often in very remote locations with low population density.

3. Energy Poverty definitions and measures

Access to and use of energy are both major factors for human development (Martínez and Ebenhack, 2008). Currently, there are multiple efforts to improve the energy situation across the world in order to achieve Sustainable Development Goal 7, related to access to affordable, reliable, sustainable and modern energy. That is why a formal definition of energy poverty and the existence of household energy indicators are fundamental to guide public policies that have a direct impact on reducing different types of energy deprivations.

[2] φ is the equal opportunities index; when φ>1 distribution is equitable, otherwise distribution is inequitable.

There have been several proposals to define what is understood as Energy Poverty, most of them related with low income or high energy costs and energy sources for household heating, cooking and lighting (*e.g.*, Osbaldeston, 1984; Meszerics *et al.*, 2016). Nevertheless, definitions across countries are highly conditioned to available data and their energy context. For example, García (2014) shows that Energy Poverty definitions across European Union (EU) countries are not homogeneous, and in fact they differ even in the indicators used to classify a household as energy poor.

For the case of Latin America, García (2014) proposed the definition: "A household is in energy poverty when the people who live there do not meet their energy needs, which are related to a series of satisfiers and economic goods that are considered essential, in a specific place and time, according to social and cultural conventions" (García, 2014, pg. 17). This definition provides a conceptual framework that can be adapted to different contexts, as the energy needs and satisfiers could vary between societies and can be constantly updated as time goes by.

There are various Energy Poverty measurement efforts in the literature[3] and they can be summarized in three categories of approaches that focus on different types of thresholds, as presented by González-Eguino (2015): 1) technological threshold approaches, that relate to access to "modern" energy services[4]; 2) physical threshold approaches, that estimate minimum energy consumption associated with basic necessities; and, 3) economic threshold approaches, that measure the household income percentage that is considered reasonable for energy spending. There are studies that measure Energy Poverty from the perspective of one of these approaches individually (*e.g.*, Pachauri, 2011), but there is also vast literature that seeks to combine all three kinds of thresholds as different types of energy deprivations that are important to be considered together. Among the latter, multidimensional index approximations stand out (*e.g.*, García, 2014; Nussbaumer *et al.*, 2014).

For example, Durán and Condori (2016) proposed a Synthetic Multidimensional Energy Poverty Index for Argentina in 2010. This index is composed of a set of six indicators of mean income, gas and electricity access, housing, social security, and energy spending; all at a department level. The indicators are weighted using Principal Components Analysis (PCA) and jointly they show a deprivation score for every department in urban and rural Argentina.

On the other hand, there is vast research that measures Energy Poverty on a household level. García (2014), for example, proposes an Unsatisfied Basic Needs Index for Mexico, that focuses on the absolute household necessities of subsistence, protection, understanding, pleasure, and recreation, which are satisfied with energy equipment and goods, such as refrigerators, computers, access to internet, fans or air conditioning, etc. This set of satisfiers allow classifying a household as energy poor when it lacks at least one of the goods and services considered, as at least one absolute energy necessity is left uncovered.

[3] For example, IAEA et al (2005) measure energy poverty with individual indicators, or Pachauri et al. (2004) that present energy consumption matrices for measuring poverty.
[4] For example, using gas or electricity instead of biomass for cooking (González-Eguino, 2015).

Among multidimensional studies, it is important for this paper to highlight the studies that estimate a multidimensional Energy Poverty Index (MEPI) using the Alkire and Foster (2011) method. This index, as explained in detail in Section III, uses a set of weighted dimensions to attribute to each household an energy poverty score that can later allow classifying whether it is poor or not, using a cut-off. Such is the case of Awan *et al.* (2013), that estimate the MEPI for Pakistan using five dimensions: type of fuel, indoor pollution, access to electricity, and having or not a refrigerator and a TV, radio or computer. The cut-off criteria used by Awan *et al*. (2013) classifies a household as energy poor when it suffers deprivation in at least two of the five dimensions.

An important aspect to consider is that, as mentioned above, the definition of Energy Poverty can vary across regions, so the dimensions and variables considered for the MEPI have to be selected according to the regional context. Since this paper is mainly focused on Bolivia, some evidence for Latin America and bordering countries of Bolivia is shown below.

Quishpe et al. (2019) prepared an MEPI for Ecuador using four variables: delayed payment of electricity bills, disproportionate energy expenditure[5], hidden energy poverty[6], and the Boardman Rule[7]. It is important to notice that there may be a problem with an MEPI-based on four indicators of a same dimension, as deprivation among them is excluding. In turn, Villalobos *et al.* (2021) proposes a perception-based MEPI for Chile, which considers five dimensions with different weights: household energy spending, neighborhood characteristics (that uses thermal comfort and public lighting indicators), energy saving behavior, quality of energy (for lighting and cooking), and energy education and information. Both Quishpe *et al*. (2019) and Villalobos *et al*. (2020) find the existence of significant gaps in multidimensional poverty incidence between urban and rural areas.

Regarding studies for the Latin American region, Santillán *et al*. (2020) applies the MEPI for seven Latin American countries, including Colombia and Peru. For this purpose, five dimensions are considered: cooking (fuel and indoor pollution), lighting, appliance ownership (having a refrigerator), entertainment/education (having a TV or radio) and communication (access to a mobile or landline phone). Also, Nussbaumer *et al*. (2013) uses an MEPI with the same dimensions for several Latin America, African and Asian countries, including Peru, Colombia and Bolivia. The results for all South American countries reveal that MEPI shows low to moderate Energy Poverty levels in comparison with the rest of the world, and Bolivia ranks as the second country in South America with the lowest MEPI value.

[5] Which considers that a household is in a deprivation condition when domestic energy spending is twice above the median.
[6] Which considers that a household is in a deprivation condition when domestic energy spending is below half of the median.
[7] Which considers that a household is in a deprivation condition when domestic energy spending is above 10% of total household income.

4. Calculating Energy Poverty in Bolivia

4. 1. The Alkire and Foster Multidimensional Poverty Index

The methodological approach selected for this research is the Multidimensional Poverty Index (MPI) proposed by Alkire and Foster (2011). The MPI combines FGT incidence and poverty severity; thus, the results will not only show the poverty incidence evolution across the period, but also how intense and severe the poverty was. The MPI is an index limited between the values 0 and 1, where 1 means that all the observations in the sample experience all the multidimensional deprivations.

Furthermore, the MPI consists of a composed set of dimensions that show deprivation in diverse aspects. Each of these dimensions has a weight assigned, so that the sum of all these weights equals one. Every time an observation experiences deprivation in one dimension, the corresponding weight is added up to the total weighted percentage of deprivations experienced. It is also possible that a dimension may contain multiple variables or indicators, as long as the sum of the weights of these indicators is equal to the weight assigned to that dimension (UNDP and OPHI, 2019).

Observations then identify multidimensional poverty if the total experienced deprivations are greater than or equal to a poverty cut-off "*k*", or if the total weighted percentage of experienced deprivations is greater than or equal to "*w*". This cut-off represents the minimum level of deprivations an observation must experience to be considered poor and it can be defined by different approaches. The two most extreme ones are the union and the intersection approaches. The union approach classifies as poor all observations that experience at least one deprivation (that is, k=1 or, if all dimensions have an equal weight of p, w=p). On the other hand, an observation is identified as poor with the intersection approach when it suffers all deprivations considered at the same time (k=total number of dimensions, or w=1) (Atkinson, 2003). What is most common when using the Alkire and Foster method is to choose k with a dual cut-off approach, so that the cut-off can range between one and the total number of deprivations[8] (UNDP and OPHI, 2019).

Once all the multidimensionally poor observations have been identified, the data can be used for building two indicators: Poverty Incidence (H) and Poverty Intensity (A) (UNDP and OPHI, 2019).

The Incidence of Multidimensional Poverty (H) is the proportion of observations identified as poor, as observed in the equation below:

$$H = \frac{q}{n} \tag{1}$$

, with q being the number of observations with a total weighted percentage of deprivations score equal to or above k; and n being the total number of households in the sample.

Conversely, the Poverty Intensity (A) is the average proportion of dimensions for which multidimensionally poor observations are deprived, as seen in the equation below:

[8] Union and intersection approaches are two specific cases when using a dual cut-off.

$$A = \frac{\sum_1^q w_i}{q} \qquad (2)$$

, where the numerator represents the sum of the total weighted percentages of deprivations experienced by the poor only, and the denominator is the total number of multidimensionally poor observations.

Finally, the MPI is computed as the product:

$$MPI = H \, x \, A \qquad (3)$$

, which represents "the total number of deprivations experienced by the poor divided by the maximum number of deprivations that could possibly be experienced by the entire sample" (Alkire and Foster, 2011, pg. 479).

4. 2. A Multidimensional Energy Poverty Index (MEPI) proposal for Bolivia

Since this paper focuses on energy poverty, a household data-based Multidimensional Energy Poverty Index (MEPI) is proposed. The structure of the MEPI consists of a total of five dimensions considered. These dimensions and the variables that make up each of them are described below.

The first dimension captures energy expenditure and household income characteristics. There are diverse indicators proposed in the literature for this purpose, like the Boardman Rule (Boardman, 1991) or late payment of electricity bills (Tirado *et al.*, 2018). The measure chosen for this research is the one known as Hidden Energy Poverty (Tirado *et al*., 2018), where all the households for which total energy expenditure is below half of the median are considered deprived. The median is calculated using the monthly energy spending ratio of total household income[9] and it varies according to the households' year and area (urban or rural) data.

The second dimension focuses on electricity and lighting energy access. The chosen indicator is household electricity access, considering households with no electricity as deprived.

The third dimension captures cooking fuel quality and indoor pollution. For this purpose, two indicators are used. The first indicator, related to cooking fuel quality, considers all households that use biomass fuel[10] as deprived. The second indicator identifies households that do not have a room exclusively for cooking as deprived.

The fourth dimension consists of two variables that allow measuring access to equipment for food purposes. The first variable is having a refrigerator and the second one is having a stove, oven or microwave. In both variables, if a household does not have the respective equipment, it is considered deprived.

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[9] Total energy spending is the sum of electricity and cooking fuel monthly spending.
[10] Firewood, dung or similar elements.

The fifth and last dimension measures access to education and communication items and services. This dimension, unlike the other, is composed of four distinct variables. The first variable is related to household access to internet, while the second, third and fourth variables capture computer (PC, laptop or tablet), television and radio possession, respectively. It is worth mentioning that cellphone access would be a better fitting variable for this dimension, but the data is not comparable across the period because of the question changing.

The chosen dimensional weights follow the normative arguments described by UNDP and OPHI (2019). Since it is difficult to justify that the relative importance of one dimension is higher than that of another (Alkire and Foster, 2011), equal weights are chosen for the five dimensions. Nevertheless, as this research seeks to evaluate energy poverty in urban and rural areas separately, the weighting structure within dimensions varies. More specifically, the weights of the variables of the fifth dimension differ according to the area of analysis. These weights are presented in *Table 1*. The dimensional weights are presented in bold font, and the variables weights are presented in regular font type and below each dimension. The total dimensional weight is the sum of the variable weights considered in each dimension.

Table 1. *MEPI weight structure, equal dimensional weights*
(Rural and urban weights)

	Equal weights		**PCA-based weights**	
Dimensions and variables	**Urban**	**Rural**	**Urban**	**Rural**
Dimension 1: Energy spending	**0.2**	**0.2**	**0.05**	**0.10**
V1: Hidden energy poverty	0.2	0.2	0.05	0.10
Dimension 2: Electricity and lighting	**0.2**	**0.2**	**0.05**	**0.15**
V1: Household electricity access	0.2	0.2	0.05	0.15
Dimension 3: Cooking fuel and indoor pollution	**0.2**	**0.2**	**0.20**	**0.20**
V1: Cooking fuel quality	0.1	0.1	0.10	0.15
V2: Room exclusively for cooking	0.1	0.1	0.10	0.05
Dimension 4: Equipment for food purposes	**0.2**	**0.2**	**0.25**	**0.25**
V1: Refrigerator holding	0.1	0.1	0.15	0.10
V2: Stove, oven or microwave possession	0.1	0.1	0.10	0.15
Dimension 5: Education and communication	**0.2**	**0.2**	**0.45**	**0.30**
V1: Internet access	0.1	0.1	0.15	0.05
V2: Computer, laptop or tablet possession	0.05	0	0.15	0.05
V3: TV possession	0.05	0.05	0.10	0.15
V4: Radio possession	0	0.05	0.05	0.05

Source: Own preparation.

As may be observed, the variable weights for dimensions one to four are equal, depending on the number of variables taken, but in dimension 5 the variable weights vary by region. First, the internet access weight is the same in both urban and rural areas, as it is the only variable capturing communication service access. On the other hand, the remaining variables that measure equipment possession have different weights by region, according to the national context of usage. In urban areas, an equal weight of 0.05 is given to both computer and TV possession, completely excluding the radio possession variable. At the same time, the rural MEPI considers only TV and radio possession in this dimension (with both variables having an equal weight of 0.05), since computer ownership is uncommon in the countryside.

Regarding the selected poverty cut-off *k*, this research evaluates the MEPI results with all the dual cut-off approach options. Thus, the MEPI is calculated for all the cut-off values between the union approach (*k*=1 or *w*=0.2) and the intersection approach (*k*=5 or *w*=1).

Also, as a robustness exercise, an alternative weight structure based on Principal Components Analysis (PCA) is carried out. The principal objective of this is to evaluate whether the MEPI results are consistent with different weighting options, and, in case they are not, to assess the magnitude of the changes between methods. For this purpose, 2019 data for the variables presented in Table 1 are used for urban and rural areas separately. The reason for using 2019 data only is to construct a weight structure that responds to current energy needs, such as internet access or ownership of some educational or communicational devices that were not common on the first years of the period analyzed.

The first Principal Component is selected for the weight definition, as it always explains a greater percentage of the total variance than the other components (see Annex A)[11]. In this sense, the variable weights found by PCA (*Table 2*) can be read as the relative contribution to the overall Energy Poverty component (Njong and Ningaye, 2008). PCA results show that computer ownership, internet access and refrigerator ownership are the three variables with the highest weights in urban areas, while TV possession, stove possession and cooking fuel quality are the most important in rural areas. It can be seen that only the third dimension maintains a weight of close to 0.2, while the first and second dimension have less importance, and the third and fourth dimensions have higher weights.

[11] It explains approximately 20% of the total variance in urban areas and 31% in rural areas.

Table 2. *MEPI weight structure, PCA resulting weights*
(Rural and urban weights)

Dimensions and variables	Urban weights	Rural weights
Dimension 1: Energy spending	**0.01**	**0.13**
V1: Hidden energy poverty	0.01	0.13
Dimension 2: Electricity and lighting	**0.06**	**0.14**
V1: Household electricity access	0.06	0.14
Dimension 3: Cooking fuel and indoor pollution	**0.21**	**0.23**
V1: Cooking fuel quality	0.09	0.15
V2: Room exclusively for cooking	0.12	0.07
Dimension 4: Equipment for food purposes	**0.24**	**0.26**
V1: Refrigerator ownership	0.14	0.11
V2: Stove, oven or microwave ownership	0.09	0.15
Dimension 5: Education and communication	**0.47**	**0.25**
V1: Internet access	0.14	0.02
V2: Computer or tablet ownership	0.15	0.05
V3: TV ownership	0.12	0.15
V4: Radio ownership	0.07	0.03

Source: Own preparation.

Despite the fact that PCA results show a completely different dimensional weight scenario that is worth examining, endogenous weights can infringe important properties of multidimensional poverty indices required for poverty evaluation and policy targeting (Dutta *et al*., 2021)[12]. In this sense, an alternative exogenous weight structure based on PCA results is proposed in *Table 3*. The poverty cut-offs selected to evaluate results with this alternative weight structure also range from *k*=1 to *k*=5.

[12] Such as monotonicity and subgroup consistency.

Table 3. *MEPI weight structure, PCA-based exogenous weights*
(Rural and urban weights)

Dimensions and variables	Urban weights	Rural weights
Dimension 1: Energy spending	**0.05**	**0.10**
V1: Hidden energy poverty	0.05	0.10
Dimension 2: Electricity and lighting	**0.05**	**0.15**
V1: Household electricity access	0.05	0.15
Dimension 3: Cooking fuel and indoor pollution	**0.20**	**0.20**
V1: Cooking fuel quality	0.10	0.15
V2: Room exclusively for cooking	0.10	0.05
Dimension 4: Equipment for food purposes	**0.25**	**0.25**
V1: Refrigerator ownership	0.15	0.10
V2: Stove, oven or microwave ownership	0.10	0.15
Dimension 5: Education and communication	**0.45**	**0.30**
V1: Internet access	0.15	0.05
V2: Computer or tablet ownership	0.15	0.05
V3: TV ownership	0.10	0.15
V4: Radio ownership	0.05	0.05

Source: Own preparation.

5. Data resources

For the MEPI calculation in this research, the Bolivian Household Surveys between 2005 and 2019[13] are used. The year 2020 is not taken into account for two main reasons: 1) changes in the survey questions, and 2) given that the relative importance of each dimension after the quarantine caused by COVID-19 must be reevaluated. Also, years 2008 and 2009 are left out of the analysis as the values reported in the considered variables for these years show patterns that do not follow the trend shown for the rest of the years considered in this research.

The dataset consists of a sample of 104,406 households distributed across years and regions as shown in *Table 4*.

Table 4. *Household sample, by year and area*
(Number of households)

Year	2005	2006	2007	2011	2012	2013	2014	2015	2016	2017	2018	2019
Urban	1,751	1,315	1,308	2,888	2,638	2,317	2,311	2,236	2,689	2,556	2,569	2,783
Rural	2,335	2,783	2,840	5,963	5,777	7,236	7,532	7,934	8,373	8,580	8,626	9,086

Source: Own preparation.

[13] Data collected by the National Statistical Institute of Bolivia (INE). No data is available for 2010, since the household survey was not carried out that year.

As seen in *Annex B*, the distribution of deprivations varies between regions. Firstly, it may be observed that the percentage of households that fall under Hidden Energy Poverty (the households with energy spending below half of the median) has fallen from 20.3% in 2005 to 15.5% in 2019 in urban areas, and from 41.4% to 26.6% in the same years for rural areas. It is interesting to see that between 2005 and 2007, deprivation in the rural areas in this indicator has an increasing tendency, reaching a maximum of 48% of households deprived in this regard.

Electricity access increased notably in both urban and rural areas, reaching a near-zero deprivation rate for urban areas in 2019. Also, electricity deprivation in rural areas decreased by 46.6% percentage points (p.p.) between 2005 (65.9%) and 2019 (19.3%).

For the variables of the third dimension, its shown that the deprivation rate in cooking fuel quality went down for both urban (from 6.8% in 2005 to 0.6% in 2019) and rural areas (from 67.7% in 2005 to 42.5% in 2019). In turn, deprivation in access to rooms only for cooking went down in urban areas between 2005 (24.1%) and 2019 (17.8%), but increased in almost 4 p.p. for rural areas between the same years (from 23.8% in 2005 to 27.6% in 2019). This may indicate that despite rural households using less harmful fuels, indoor pollution when cooking persists.

The case of equipment for food purposes reflects a reduction in the deprivation rate of approximately 28 p.p. in refrigerator ownership in urban areas (from 56.1% in 2005 to 28.2% in 2019) and 20.9 p.p. for rural areas (from 90% in 2005 to 69.1% in 2019). As for stove, oven or microwave ownership, rural areas show a reduction of 14.4 p.p. in the deprivation rate between 2005 (43.3%) and 2019 (29%), with the rate remaining almost constant in urban areas (6.1% in 2005 and 5.7% in 2019), as low values were already present at the beginning of the period.

Lastly, the evolution of deprivation rates for the variables in the dimension focusing on education and communication varies according to the region. Firstly, internet access had a major increase in access for urban areas between 2005 (deprivation rate of 95.9%) and 2019 (deprivation rate of 70%), but still has very low values for rural areas (deprivation rate of 98.9% in 2019)[14]. Secondly, computer (or tablet) and TV ownership increased, but the magnitude of this deprivation reduction differs across areas. It may be observed that the computer deprivation rate went down 20.2% p.p. in urban areas (from 83.8% in 2005 to 63.6% in 2019), but it still has values above 90% in rural areas at the end of the period. Deprivation in TV holding, in turn, reports a higher reduction in rural areas (30.4 p.p. between 2005 and 2019), as urban areas have values under 10% since 2007. Finally, radio ownership has a completely different behavior between urban and rural households, as the deprivation rate decreased from 44.3% in 2005 to 39.3% in 2019 for rural areas, but it increased by 17 p.p. among urban households. This last indicator does not necessarily mean that urban households are "deprived", as nowadays there are higher quality alternatives to replace use of the radio.

[14] It is worth mentioning that this variable takes into account only household internet access, not mobile internet. The latter would likely considerably increase access to internet services, but there is no data available to measure it.

A first look at deprivation rates reinforces the different dimensional weights chosen for urban and rural areas, which is explained in *Section III*.

6. Results

As explained before, the MEPI is calculated for all the dual cut-off options. Thus, the urban and rural Multidimensional Energy Poverty Incidence, Intensity and the MEPI are presented for every *k* between 1 and 5[15].

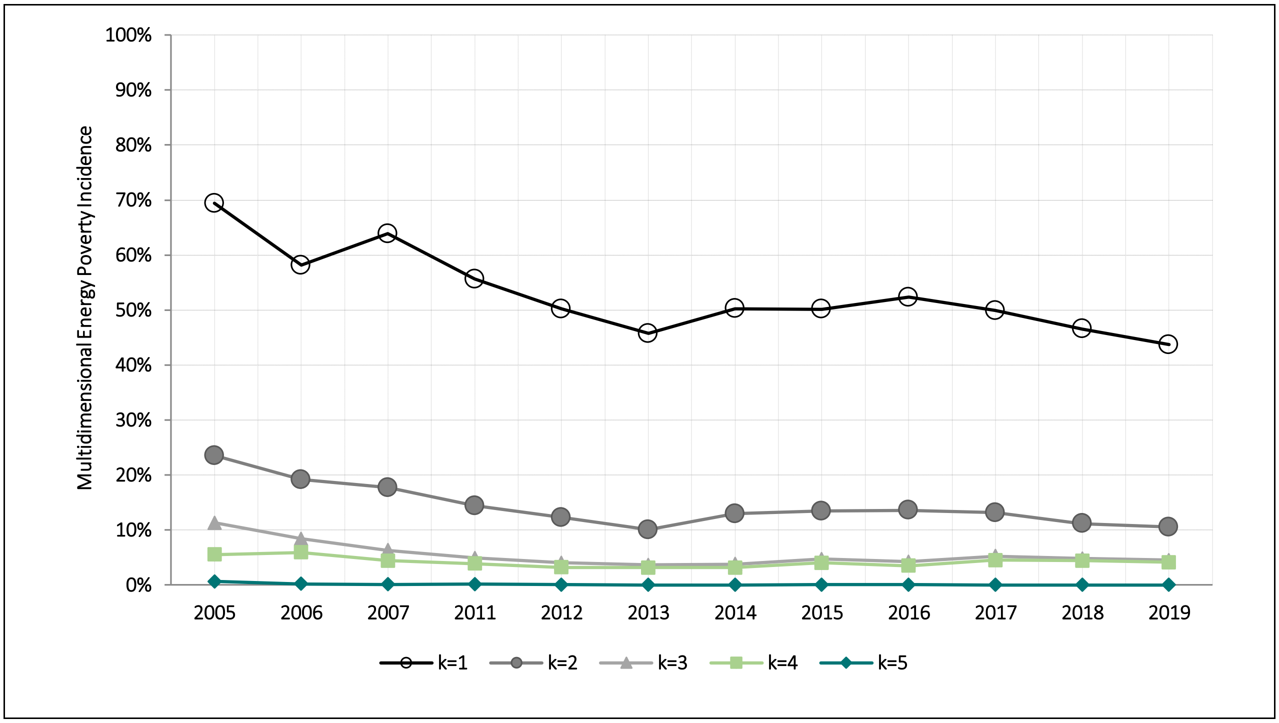
6. 1. Multidimensional Energy Poverty Incidence

Firstly, urban Multidimensional Energy Poverty Incidence according to different cut-off values is presented in *Figure 2*. As can be seen, the percentage of households suffering Multidimensional Energy Poverty fell between 2005 and 2019 for every *k* considered. Nevertheless, the incidence has a notable variation according to the poverty definition considered. For example, Incidence with *k*=1 had a value of 69% in 2005 and decreased to 44% in 2019, resulting in a reduction of 26 percentage points (p.p.); alternatively, if the cut-off value changes to *k*=3, the Multidimensional Energy Poverty Incidence moves from 11% in 2005 to 5% in 2019. It may also be seen that when considering as poor all households that experience deprivation in all dimensions (*k*=5), the incidence in urban areas is nearly 0 for every year across the period (see *Annex C*).

This variation is more evident when comparing incidence with *k*=1 and *k*=2, showing that 44% of urban households in 2019 were deprived in at least one dimension, but only 11% of them suffered two or more dimensional deprivations.

[15] Similarly for all weighted percentages of deprivations greater than or equal to 0.2, 0.4, 0.6, 0.8 and 1.

***Figure 2.** Urban multidimensional energy poverty incidence*
(In percentage of total urban households)

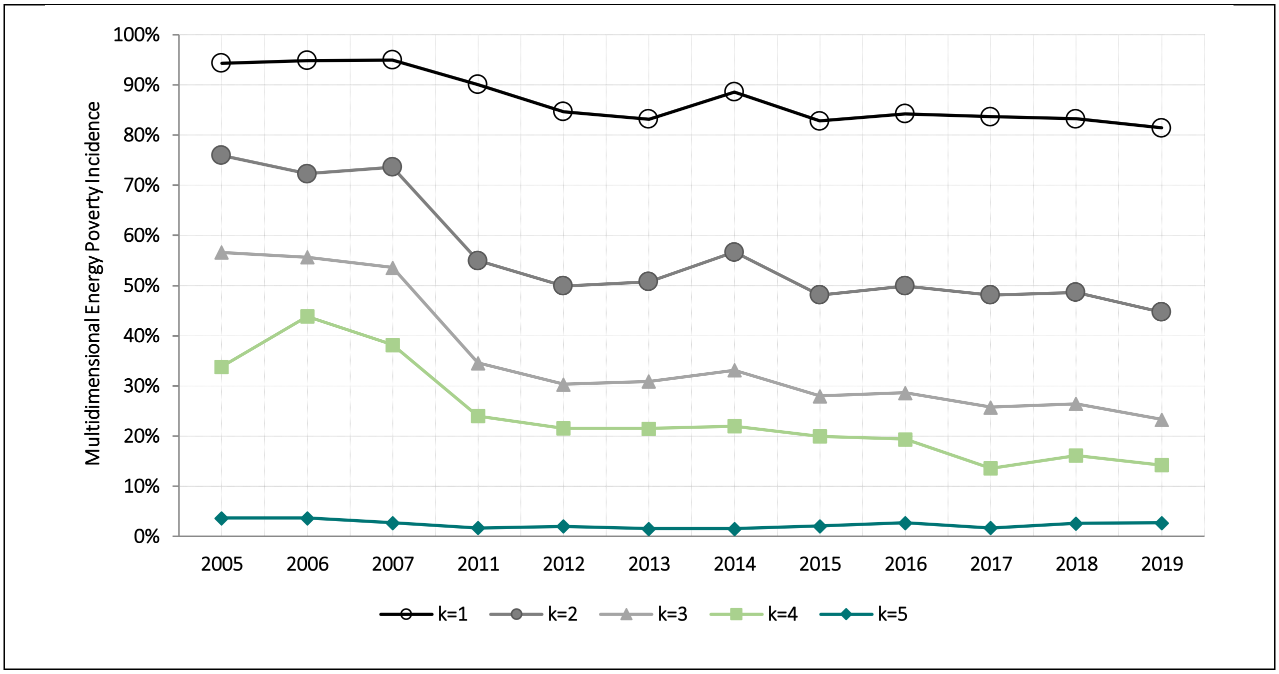


Source: Own preparation based on household survey data from 2005 to 2019 (National Statistics Agency – Bolivia).

On the other hand, rural Multidimensional Energy Poverty Incidence reveals a different situation. As shown in *Figure 3*, rural incidence decreased in greater magnitude than in urban areas across the period, which can be explained mainly because of the improvement in access to electricity and a reduced use of biomass as cooking fuel (see Annex B). Rural energy poverty incidence shows a reduction of 13 p.p. between 2005 (94%) and 2019 (81%) with the union approach (*k*=1), a reduction of 31, 33 and 20 p.p. with cut-offs equal to *k*=2, *k*=3 and *k*=4, respectively; and an almost constant behavior across the period, ranging from 4% to 2% with the intersection approach (*k*=5) (see *Annex C*).

It may also be observed that incidence according to different poverty cut-off criteria has a more uniform variation in rural areas than in urban areas. This may be evidence that a reduction in any dimensional deprivation can result in less rural energy poverty, which would facilitate public policies focused on this topic.

Figure 3. *Rural multidimensional energy poverty incidence*
(In percentage of total rural households)



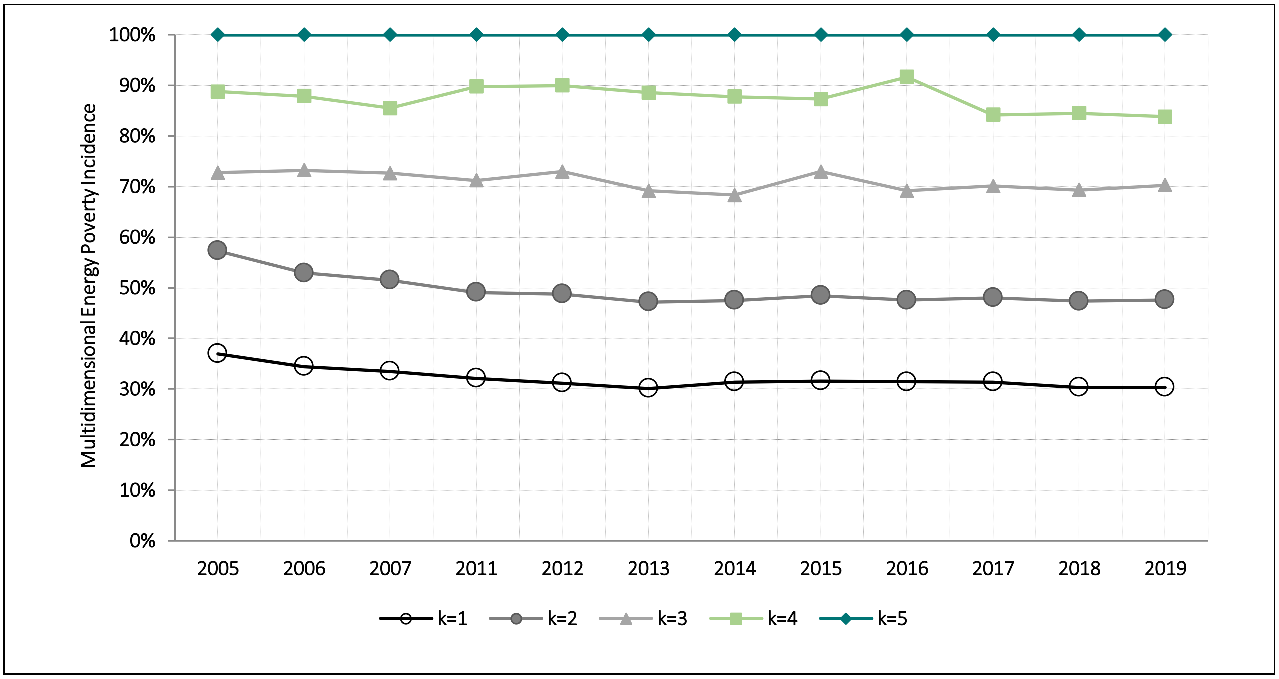
Source: Own preparation based on household survey data from 2005 to 2019 (National Statistics Agency – Bolivia).

6. 2. Multidimensional Energy Poverty Intensity

When examining the average proportion of dimensions in which urban energy poor households are deprived (urban Multidimensional Poverty Intensity), *Figure 4* shows that between 2005 and 2019 it decreased for every *k* considered. The highest reductions occur with *k*=2 (from 57% in 2005 to 48% in 2019), and with *k*=1 (from 37% in 2005 to 30% in 2019). For *k*=3 and *k*=4, the indicator decreased by 2 and 5 p.p., respectively. Considering that, by definition, the minimum value of Poverty Intensity increases with a higher *k* (*e.g.*, for *k*=1 the minimum Poverty Intensity should be 0.2, with *k*=3 it should be 0.6, and so on), it can be said that urban Energy Poverty Intensity does not take values much higher than the expected ones, as the series shown are close to their corresponding *w* cut-off values (see *Annex D*)[16].

[16] The case of *k*=5 is not examined since, by definition, multidimensional poverty intensity is always equal to 1.

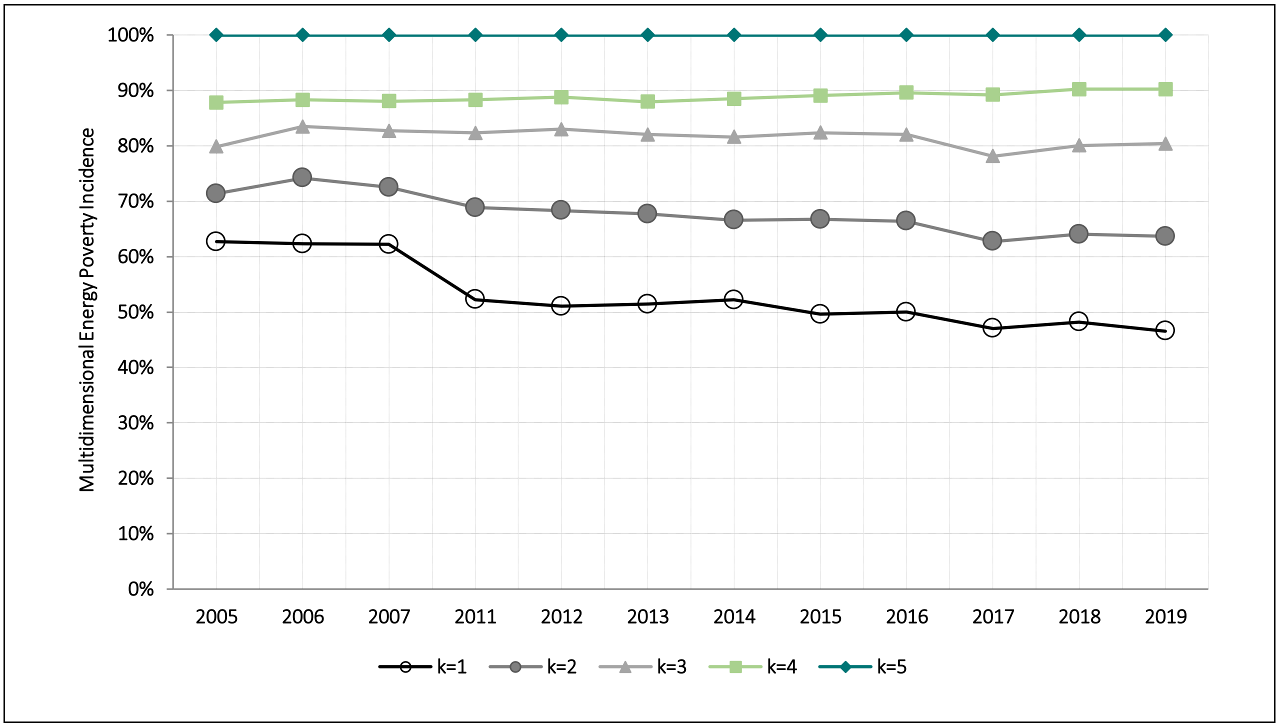
Figure 4. *Urban multidimensional energy poverty intensity*
(In percentage of urban multidimensionally energy poor households)



Source: Own preparation based on household survey data from 2005 to 2019 (National Statistics Agency – Bolivia).

In the case of rural areas, it may be observed in *Figure 5* that, with exception of *k*=1 (that gives a reduction of 16 p.p.), Multidimensional Energy Poverty Intensity went down by less than 10 p.p. or even increased, depending on the cut-off criteria. Also, it may be seen that, even with cut-offs *k*=1 and *k*=2, all poor households suffer from close to or more than 50% of the dimensional deprivations considered in this paper (see Annex D). Complementing with *Figure 3*, this is evidence that improvements in any indicator used in this paper may result in both Energy Poverty Incidence and Intensity reduction in rural areas.

Figure 5. *Rural multidimensional energy poverty intensity*
(In percentage of rural multidimensionally energy poor households)



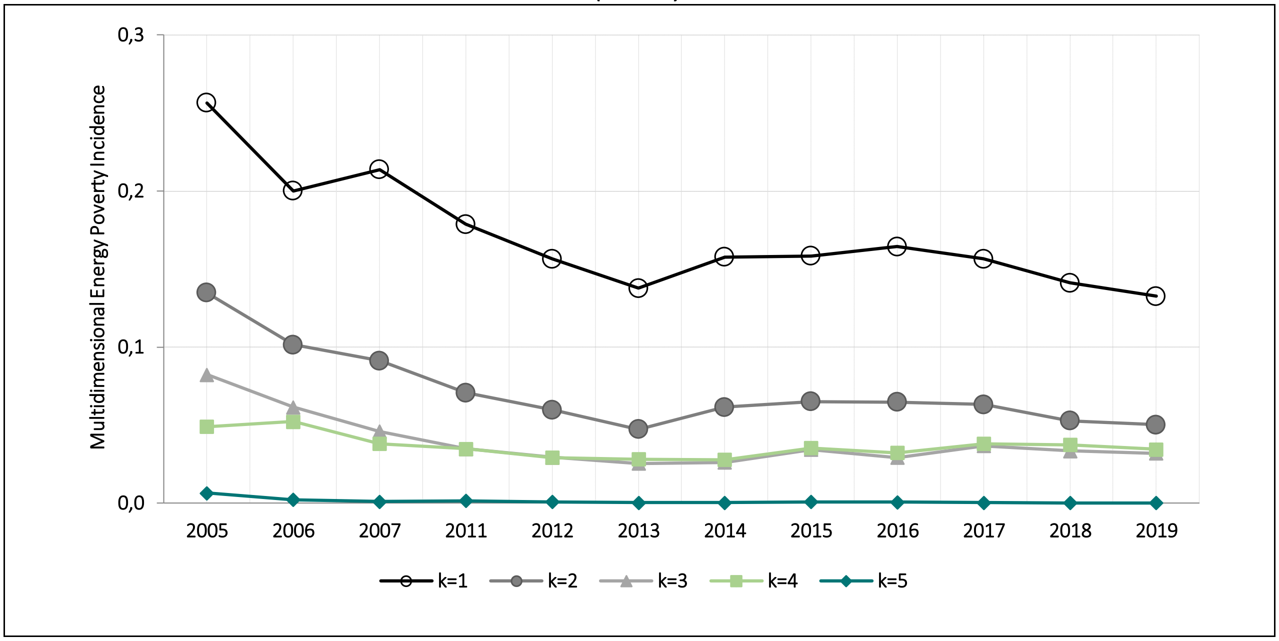
Source: Own preparation based on household survey data from 2005 to 2019 (National Statistics Agency – Bolivia).

6. 3. Multidimensional Energy Poverty Index (MEPI)

As explained in Section III, the interaction of Multidimensional Energy Poverty Incidence and Intensity results in the Multidimensional Energy Poverty Index (MEPI). As presented in *Figure 6*, the urban MEPI shows a reduction for every *k* considered. It is interesting to see that in 2019 the urban MEPI ranges from 0.13 to 0 according to the cut-off employed. In technical terms, this means that, in every multidimensional energy poverty classification approach, in 2019, urban Multidimensional Energy Poor Households experienced less than 13% of the total deprivations that can be experienced as a society (see *Annex E*).

Considering that MEPI goes down when a household rises out of energy poverty conditions, or when an energy poor household improves in at least one deprivation (even if the household remains energy poor), the urban results may be explained by both the Incidence and Intensity reductions presented in *Figures 2* and *4*.

Figure 6. *Urban multidimensional energy poverty index*
(Index)

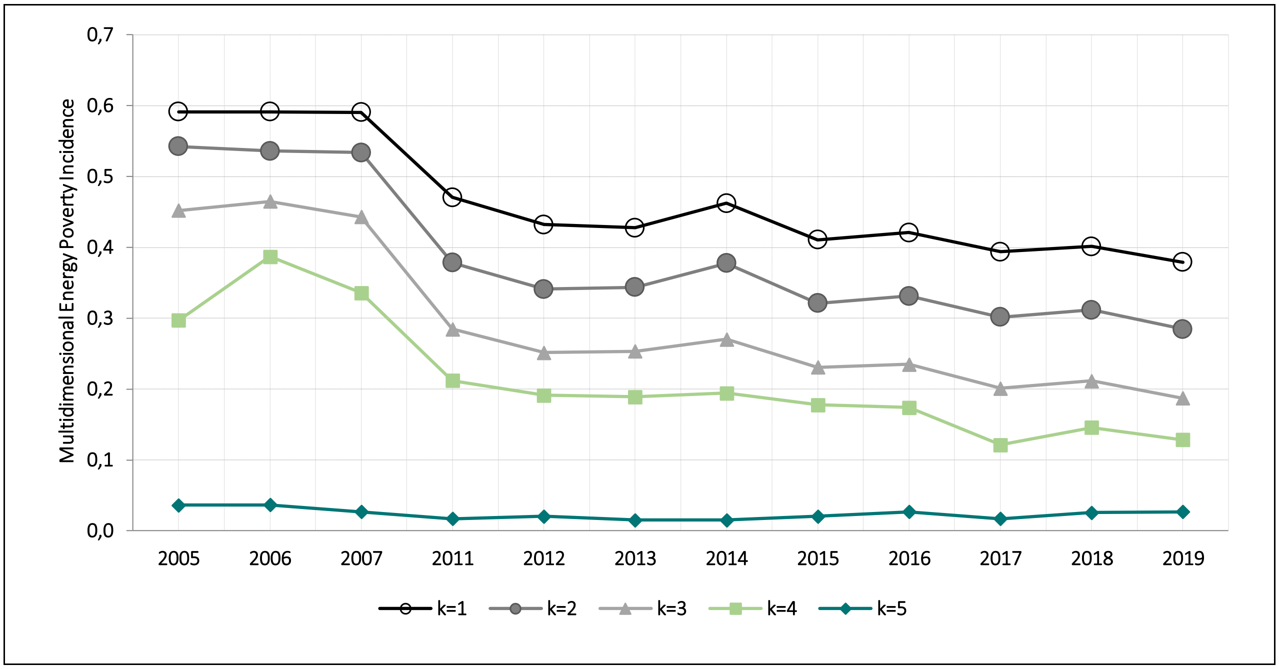


Source: Own preparation based on household survey data from 2005 to 2019 (National Statistics Agency – Bolivia).

The rural MEPI (See *Figure 7*) shows a decrease that ranges between 0.21 index points with *k*=1 and 0.01 index points with *k*=5. This decrease, as seen in Figures 3 and 5, may be is mainly explained by Incidence reduction, as Intensity has increased with some cut-off values. The rural MEPI results show that rural Multidimensional Energy Poor Households experienced between 38% and 3% of the total deprivations that can be encountered as a society in 2019 (see *Annex E*).

The rural MEPI can still be directly improved for the next few years with public policies focused on expanding coverage of telecommunications, electricity and pipeline gas services in rural areas in Bolivia.

Figure 7. *Rural multidimensional energy poverty index*
(Index)



Source: Own preparation based on household survey data from 2005 to 2019 (National Statistics Agency – Bolivia).

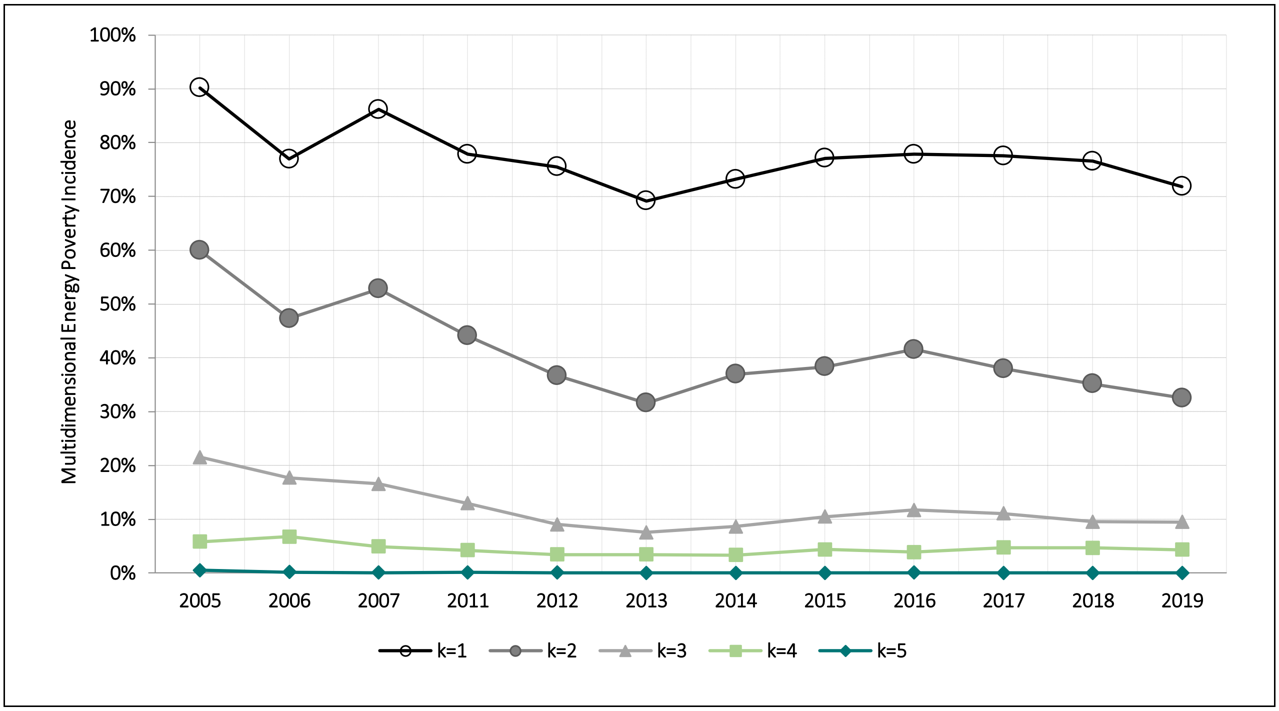
6. 4. Comparison with PCA-based variable weights

As a robustness exercise, Incidence, Intensity and MEPI results with the alternative weight structures based on PCA results are shown below.

First, urban Multidimensional Energy Poverty Incidence is shown in *Figure 8*. As indicated, Energy Poverty Incidence follows the same decreasing trajectory as the results for the equal weight structure for all cut-offs considered. Nevertheless, two important differences are noted. Firstly, Incidence with PCA-based weights is higher for almost every year and cut-off, especially when observing *k*=1 (see Annex F)[17]. Secondly, in comparison with the results show in Figure 2, the distance between Incidence with *k*=1 and *k*=2 is lower, but higher between *k*=2 and *k*=3. This may be explained by the fact that weights resulting from PCA are higher for variables that explain more variance of the total variable set. In this sense, variables that report higher deprivation rates in urban areas can have also higher weights, so that more households surpass the defined cut-offs, especially for the two lowest cut-offs.

[17] It is 25 p.p. higher than equal weight results, on average.

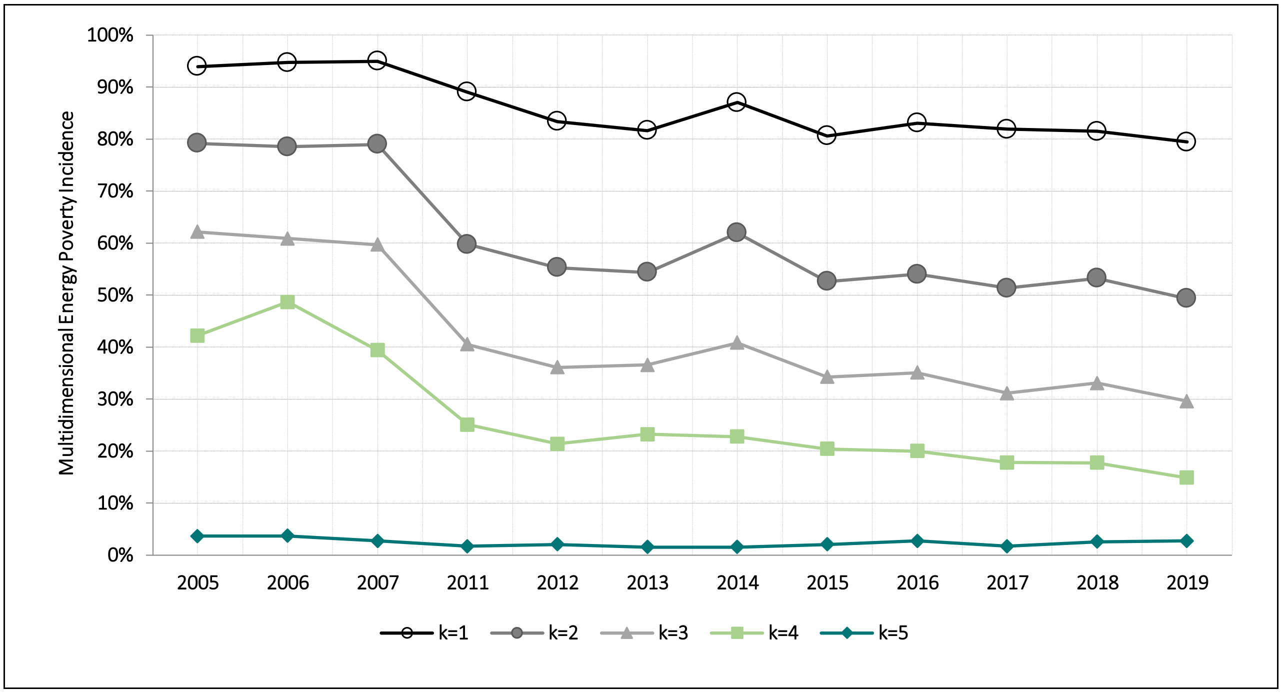
Figure 8. *Urban multidimensional energy poverty incidence, PCA-based weights*
(In percentage of total urban households)



Source: Own preparation based on household survey data from 2005 to 2019 (National Statistics Agency – Bolivia).

Meanwhile, rural Multidimensional Energy Poverty Incidence with PCA-based weights (*Figure 9*) shows values very similar to those of the original weight structure. As seen in *Annex B* and *F*, both weighting structures show the same decreasing trend in rural Incidence, even with similar values for the beginning and the end of the period and for all the cut-offs considered. In contrast to the urban case, PCA weights do not seem to have significant changes when classifying rural households, perhaps because they already had higher Energy Poverty Incidence rates to begin with.

Figure 9. Rural multidimensional energy poverty incidence, PCA-based weights
(In percentage of total urban households)

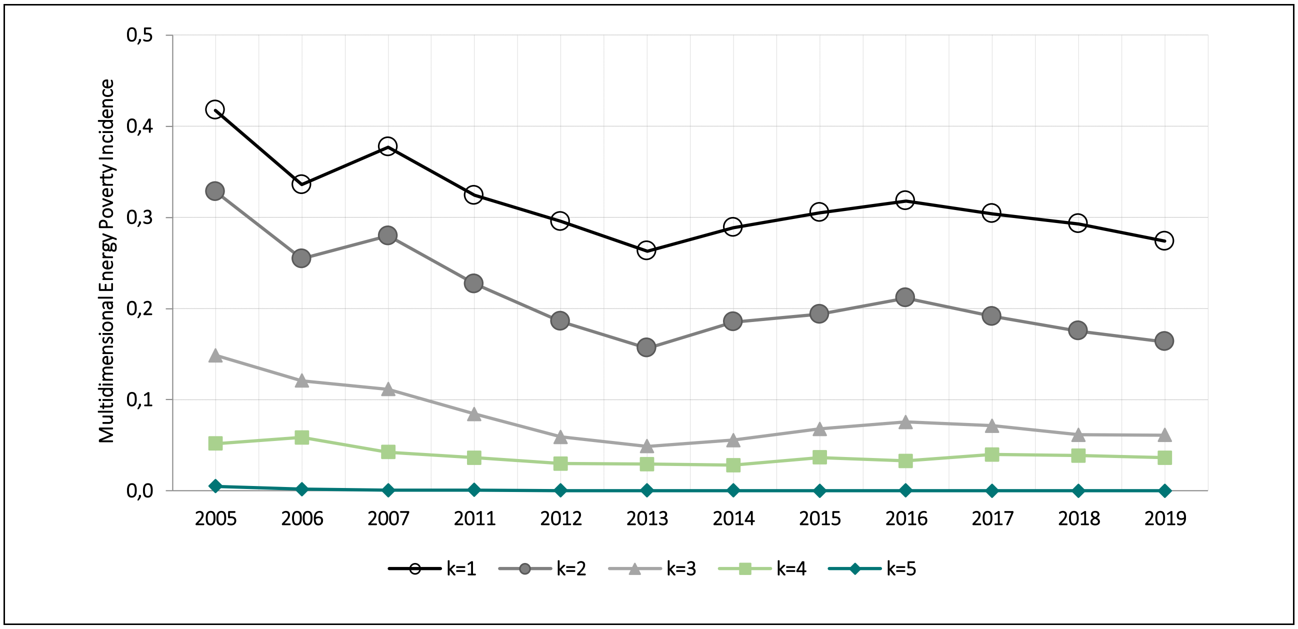


Source: Own preparation based on household survey data from 2005 to 2019 (National Statistics Agency – Bolivia).

When examining Energy Poverty Intensity, the values are similar for both urban and rural areas (see *Annex G*), reflecting that, with both weight structures, Energy Poor households are deprived at the same rate of dimensions.

When comparing the Urban MEPI (*Figure 10*) with both weight structures, the values for the PCA-based weights are higher, especially for *k*=1 and *k*=2 (see *Annex H*). This MEPI result is sustained mainly because of the Incidence results shown in Figure 8. PCA-based MEPI also shows a reduction across time, with the highest one observed (0.16) being at cut-off *k*=2. In 2019, urban Multidimensional Energy Poor Households experienced nearly 30% of the total deprivations that can be encountered as a society (less if other cut-offs are considered), in comparison to the 13% found with the original weight structure. In fact, MEPI reaches values below 10% in 2019 only with cut-offs *k*=3, *k*=4 and *k*=5.

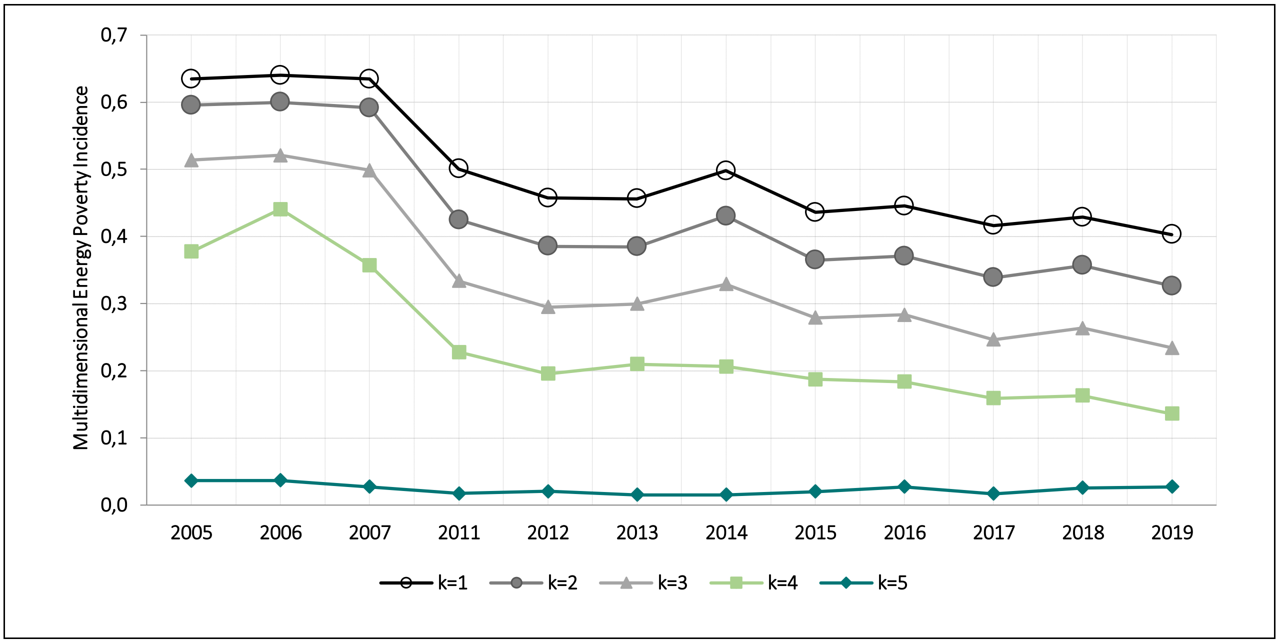
Figure 10. *Urban multidimensional energy poverty index, PCA-based weights (Index)*



Source: Own preparation based on household survey data from 2005 to 2019 (National Statistics Agency – Bolivia).

Finally, as seen in *Annex G* and *Figure 11*, Rural MEPI also shows higher values for PCA weights results, being very similar than the urban case. In 2019, rural Multidimensional Energy Poor Households experienced over 40% of the total deprivations that can be encountered as a society (less if other cut-offs are considered), which reflects a reduction of approximately 0.2 index points in comparison to 2005.

Figure 11. *Rural multidimensional energy poverty index, PCA-based weights (Index)*



Source: Own preparation based on household survey data from 2005 to 2019 (National Statistics Agency – Bolivia).

7. Conclusions and final remarks

On the one hand, the risk of being ***urban energy poor*** in Bolivia has fallen, because the percentage of households with multidimensional energy poverty decreased in 2015-2019, for all the indicators identified. However, this incidence result is not robust; *e.g.*, when comparing the incidence with *k*=1 and *k*=2, it is observed that 44% of urban households in 2019 presented deficiencies in at least one dimension, but only 11% suffered deficiencies in two or more dimensions of deprivation.

Similarly, the risk of being ***rural energy poor*** in Bolivia has decreased, as expected, more significantly than in the urban area, mainly because access to rural electricity has increased significantly over the last decade (Aliaga, 2021), but also due to a change in the pattern of rural energy consumption, with a greater substitution of biomass consumption in favor of fuel and other derivatives. The improvement in rural energy poverty is a more robust result than at the rural level; *e.g.*, rural energy poverty decreased 31% and 33%, at cut-offs of *k*=2 and *k*=3, respectively.

In general, the risk of being energy poor has decreased in the country for the period of analysis 2005-2019, but not structurally. In other words, there are households that can be classified as non-poor whose category can be reclassified in the face of marginal changes in their living conditions. Reducing the risk of being energy poor is a necessary condition, but not enough to imply a reduction in energy poverty in Bolivia. Several latent risks persist, which are not part of this work, that could pose higher levels of risk than those presented here; *e.g.*, decreases in the rate of access to electrical energy or there being less availability of diesel oil, etc.

On the other hand, the vulnerability caused by the intensity of urban energy poverty also decreased in the period under review and for all the indicators evaluated. In the case of rural areas, there is also a fall in energy vulnerability measured by the intensity of deprivations, with the exception of $k=1$. This is an unsteady result, because it depends on the criterion of the cut-off; in addition, all rural energy poor households continue to show at least 50% of dimensional deprivations.

Also, the improvement in the reduction of urban energy poverty is explained both by reductions in incidence and intensity, for each k considered. In the case of rural areas, the reduction of energy poverty is mainly explained by the reduction in incidence, since the intensity has increased with some cut-off values. We estimate that in 2019 urban households experienced 13% less of the total deprivation experienced by society, while in rural areas poor households experienced up to 38% of the total shortages that can be experienced as a society.

Finally, when comparing results from an equal dimensional weight and a PCA-based dimensional weight structure, it is clear that urban MEPI is higher with the second option. This may reflect that dimensional reduction techniques, such as PCA, and even policy discussion-based weight structures, may be more useful in contexts that report lower energy deprivation, and thus lower Incidence and Intensity of Multidimensional Energy Poverty. In turn, contexts with high values of Multidimensional Energy Poverty can be well identified with equal dimensional weight structures, since an improvement in any dimension can improve the general energy poverty situation.

In short, the risk of being energy poor in Bolivia has decreased, but not sufficiently, as there is evidence that the vulnerability caused by the severity and intensity of rural deprivation has remained constant or even worsened, depending on the cut-off considered. There are several latent threats identified – not analyzed in this research – that allow us to assume that the global risk of reclassifying being energy non-poor is growing. In addition, the work does not address energy productivity, understood as the ability of households to translate energy into growth, which is a key factor for reducing the overall risk of being energy poor.

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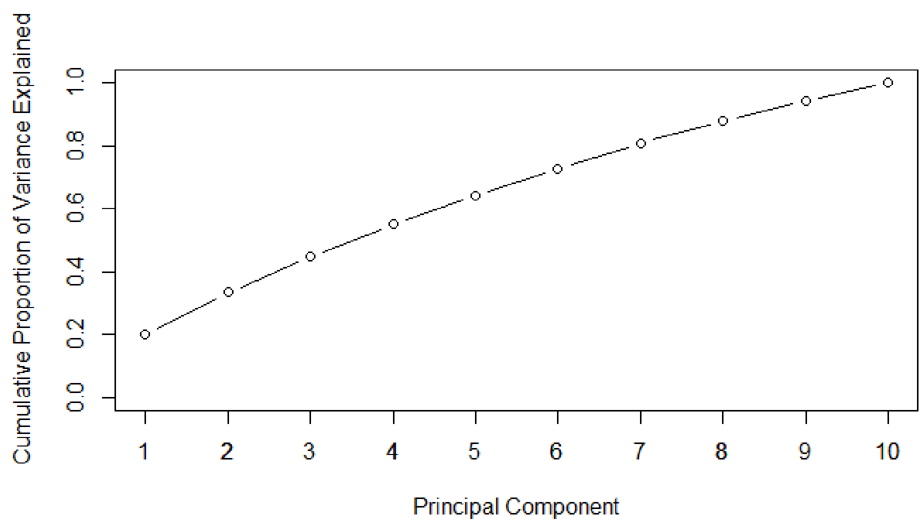
Annexes

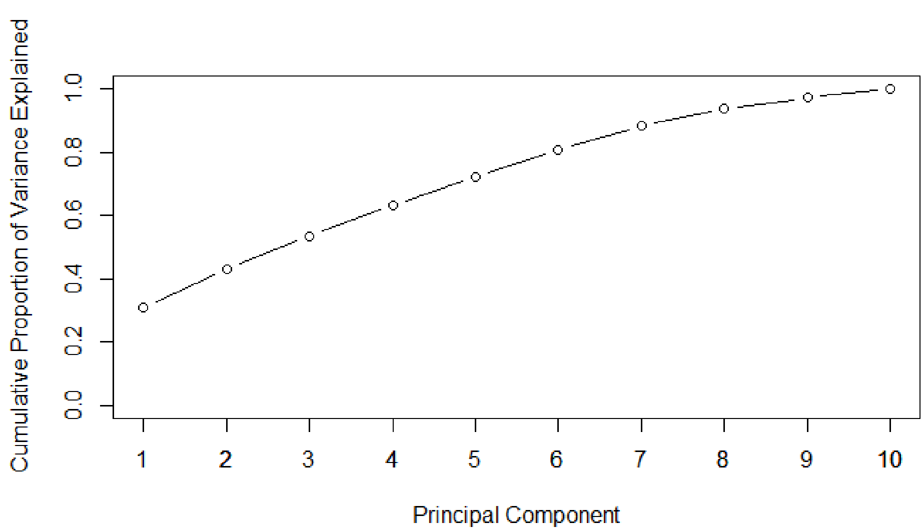
Annex A. ***Cumulative proportion of variance explained by each Principal Component***

(Cumulative percentage)

Urban households



Rural households



Source: Own preparation based on household survey data from 2005 to 2019 (National Statistics Agency – Bolivia).

Annex B. ***Deprivation rate in variables used for the MEPI, by year and areas***

(Percentage of deprived households)

Variables	2005	2006	2007	2011	2012	2013	2014	2015	2016	2017	2018	2019
Urban areas												
Hidden energy poverty	20.3%	19.9%	18.8%	17.4%	17.6%	16.4%	18.8%	18.1%	18.5%	17.7%	15.8%	15.5%
Household electricity access	11.4%	4.7%	2.0%	0.9%	1.0%	0.4%	0.6%	0.6%	0.5%	0.8%	0.5%	0.5%
Cooking fuel quality	6.8%	5.0%	8.5%	2.7%	2.0%	1.3%	1.5%	1.4%	1.1%	1.1%	0.8%	0.6%
Room exclusively for cooking	24.1%	28.1%	22.4%	21.5%	15.7%	15.5%	17.4%	20.3%	22.0%	20.2%	18.5%	17.8%
Refrigerator ownership	56.1%	51.4%	48.5%	40.4%	36.1%	29.6%	35.8%	33.3%	34.9%	30.7%	28.5%	28.2%
Stove, oven or microwave ownership	6.1%	6.5%	4.5%	4.9%	3.8%	4.1%	5.8%	6.1%	5.6%	6.7%	6.0%	5.7%
Internet access	95.9%	61.0%	95.7%	90.0%	84.1%	81.9%	79.4%	81.4%	80.0%	83.9%	79.1%	70.2%
Computer or tablet ownership	83.8%	80.1%	77.6%	66.3%	57.3%	55.1%	61.0%	67.3%	65.2%	64.9%	66.2%	63.6%
TV ownership	14.7%	11.4%	8.5%	6.1%	4.2%	3.4%	3.6%	4.2%	5.4%	4.7%	4.8%	5.5%
Radio ownership	25.3%	24.0%	23.7%	26.8%	40.0%	24.5%	29.5%	35.4%	52.7%	40.1%	40.7%	42.9%
Rural areas												
Hidden energy poverty	41.4%	45.5%	48.0%	37.2%	34.1%	34.9%	35.9%	34.0%	33.9%	29.2%	29.4%	27.6%
Household electricity access	65.9%	58.1%	59.1%	35.3%	31.4%	30.4%	30.9%	25.0%	25.7%	21.6%	23.2%	19.3%
Cooking fuel quality	67.7%	71.8%	77.1%	54.4%	48.5%	53.4%	62.2%	49.3%	46.8%	41.9%	42.0%	42.5%
Room exclusively for cooking	23.8%	26.6%	20.4%	22.4%	22.8%	16.1%	22.9%	22.4%	27.7%	31.8%	26.7%	27.6%
Refrigerator ownership	90.0%	91.0%	90.0%	84.4%	77.2%	75.5%	78.1%	70.7%	75.2%	71.5%	72.4%	69.1%
Stove, oven or microwave ownership	43.3%	48.7%	42.6%	35.1%	32.3%	35.5%	40.3%	34.9%	31.5%	29.8%	33.8%	29.0%
Internet access	100.0%	98.6%	100.0%	99.7%	99.3%	98.4%	98.9%	95.7%	98.0%	98.7%	98.9%	98.9%
Computer or tablet ownership	99.2%	99.0%	98.3%	96.5%	93.7%	90.8%	93.5%	93.4%	93.2%	93.5%	93.6%	92.9%
TV ownership	74.2%	73.8%	71.5%	53.4%	48.7%	46.1%	50.7%	44.5%	48.6%	46.4%	47.5%	43.8%
Radio ownership	44.3%	42.1%	39.2%	30.4%	31.7%	27.1%	29.0%	32.0%	38.5%	35.7%	41.6%	39.3%

Source: Own preparation based on household survey data from 2005 to 2019 (National Statistics Agency – Bolivia).

Annex C. Multidimensional Energy Poverty Incidence, by area

(In percentage of total households by area)

Cut-off value	2005	2006	2007	2011	2012	2013	2014	2015	2016	2017	2018	2019
Urban areas												
k=1	69%	58%	64%	56%	50%	46%	50%	50%	52%	50%	47%	44%
k=2	24%	19%	18%	14%	12%	10%	13%	13%	14%	13%	11%	11%
k=3	11%	8%	6%	5%	4%	4%	4%	5%	4%	5%	5%	5%
k=4	6%	6%	4%	4%	3%	3%	3%	4%	4%	5%	4%	4%
k=5	1%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
Rural areas												
k=1	94%	95%	95%	90%	85%	83%	89%	83%	84%	84%	83%	81%
k=2	76%	72%	74%	55%	50%	51%	57%	48%	50%	48%	49%	45%
k=3	57%	56%	54%	35%	30%	31%	33%	28%	29%	26%	26%	23%
k=4	34%	44%	38%	24%	22%	22%	22%	20%	19%	14%	16%	14%
k=5	4%	4%	3%	2%	2%	2%	2%	2%	3%	2%	3%	3%

Source: Own preparation based on household survey data from 2005 to 2019 (National Statistics Agency – Bolivia).

Annex D. *Multidimensional Energy Poverty Intensity, by area*

(In percentage of rural multidimensionally energy poor households)

Cut-off value	2005	2006	2007	2011	2012	2013	2014	2015	2016	2017	2018	2019
Urban areas												
k=1	37%	34%	33%	32%	31%	30%	31%	32%	31%	31%	30%	30%
k=2	57%	53%	52%	49%	49%	47%	47%	48%	48%	48%	47%	48%
k=3	73%	73%	73%	71%	73%	69%	68%	73%	69%	70%	69%	70%
k=4	89%	88%	86%	90%	90%	89%	88%	87%	92%	84%	85%	84%
k=5	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%
Rural areas												
k=1	63%	62%	62%	52%	51%	51%	52%	50%	50%	47%	48%	47%
k=2	71%	74%	72%	69%	68%	68%	67%	67%	66%	63%	64%	64%
k=3	80%	83%	83%	82%	83%	82%	82%	82%	82%	78%	80%	80%
k=4	88%	88%	88%	88%	89%	88%	89%	89%	90%	89%	90%	90%
k=5	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%

Source: Own preparation based on household survey data from 2005 to 2019 (National Statistics Agency – Bolivia).

Annex E. Multidimensional Energy Poverty Index, by area

(Index)

Cut-off value	2005	2006	2007	2011	2012	2013	2014	2015	2016	2017	2018	2019
Urban areas												
k=1	0.26	0.20	0.21	0.18	0.16	0.14	0.16	0.16	0.16	0.16	0.14	0.13
k=2	0.13	0.10	0.09	0.07	0.06	0.05	0.06	0.07	0.06	0.06	0.05	0.05
k=3	0.08	0.06	0.05	0.03	0.03	0.03	0.03	0.03	0.03	0.04	0.03	0.03
k=4	0.05	0.05	0.04	0.03	0.03	0.03	0.03	0.04	0.03	0.04	0.04	0.03
k=5	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Rural areas												
k=1	0.59	0.59	0.59	0.47	0.43	0.43	0.46	0.41	0.42	0.39	0.40	0.38
k=2	0.54	0.54	0.53	0.38	0.34	0.34	0.38	0.32	0.33	0.30	0.31	0.28
k=3	0.45	0.46	0.44	0.28	0.25	0.25	0.27	0.23	0.23	0.20	0.21	0.19
k=4	0.30	0.39	0.34	0.21	0.19	0.19	0.19	0.18	0.17	0.12	0.15	0.13
k=5	0.04	0.04	0.03	0.02	0.02	0.02	0.02	0.02	0.03	0.02	0.03	0.03

Source: Own preparation based on household survey from 2005 to 2019 (National Statistics Agency – Bolivia).

Annex F. ***Multidimensional Energy Poverty Incidence with PCA-based weights, by area***

(In percentage of total households by area)

Cut-off value	2005	2006	2007	2011	2012	2013	2014	2015	2016	2017	2018	2019
Urban areas												
k=1	90%	77%	86%	78%	76%	69%	73%	77%	78%	78%	77%	72%
k=2	60%	47%	53%	44%	37%	32%	37%	38%	42%	38%	35%	33%
k=3	22%	18%	17%	13%	9%	8%	9%	10%	12%	11%	10%	9%
k=4	6%	7%	5%	4%	3%	3%	3%	4%	4%	5%	5%	4%
k=5	1%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
Rural areas												
k=1	94%	95%	95%	89%	83%	82%	87%	81%	83%	82%	81%	79%
k=2	79%	79%	79%	60%	55%	54%	62%	53%	54%	51%	53%	49%
k=3	62%	61%	60%	41%	36%	37%	41%	34%	35%	31%	33%	30%
k=4	42%	49%	39%	25%	21%	23%	23%	20%	20%	18%	18%	15%
k=5	4%	4%	3%	2%	2%	2%	2%	2%	3%	2%	3%	3%

Source: Own preparation based on household survey data from 2005 to 2019 (National Statistics Agency – Bolivia).

Annex G. Multidimensional Energy Poverty Intensity with PCA-based weights, by area

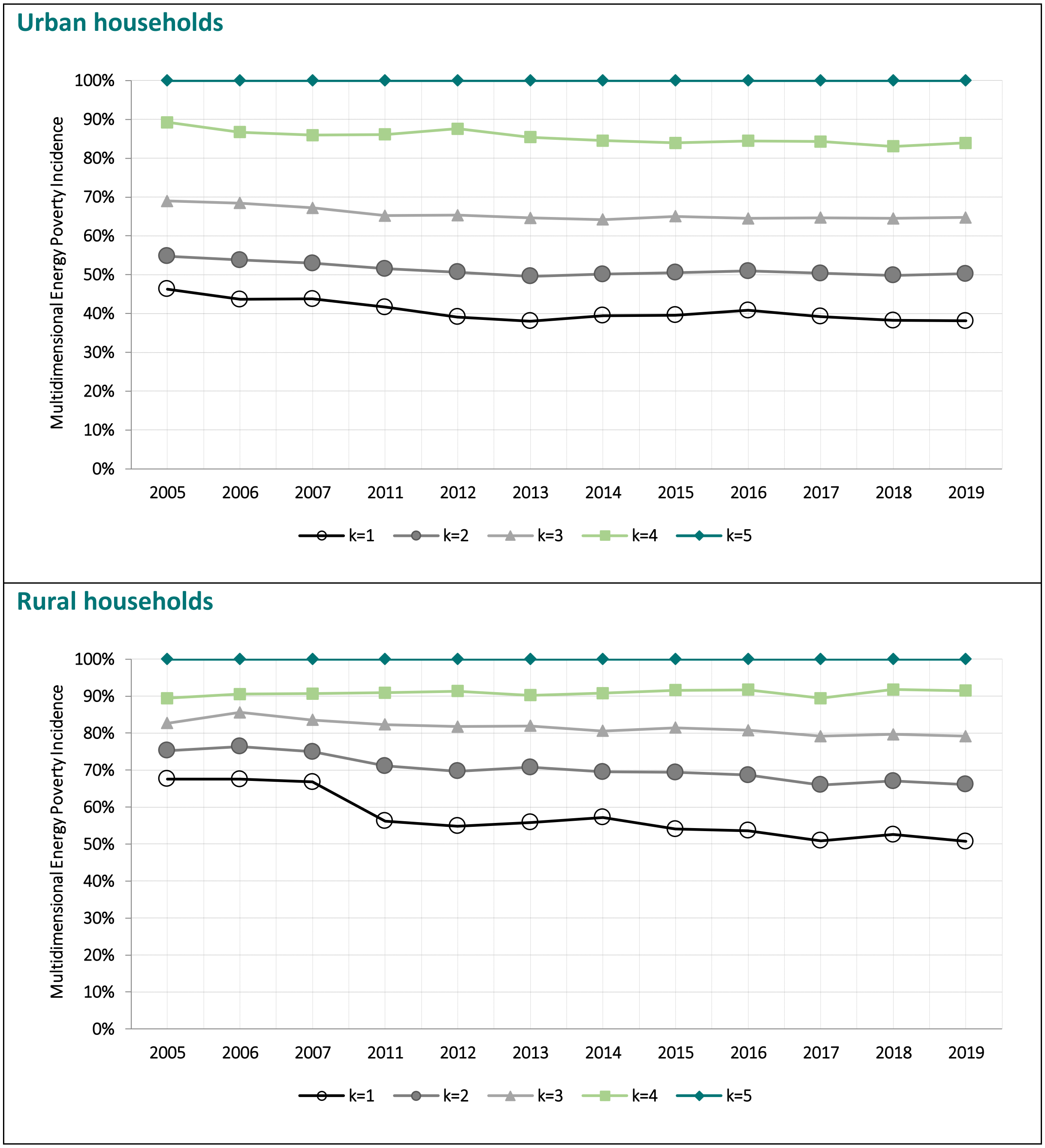
(In percentage of rural multidimensionally energy poor households)

Cut-off value	2005	2006	2007	2011	2012	2013	2014	2015	2016	2017	2018	2019
Urban areas												
k=1	46%	44%	44%	42%	39%	38%	39%	40%	41%	39%	38%	38%
k=2	55%	54%	53%	52%	51%	50%	50%	51%	51%	50%	50%	50%
k=3	69%	68%	67%	65%	65%	65%	64%	65%	65%	65%	64%	65%
k=4	89%	87%	86%	86%	88%	85%	85%	84%	84%	84%	83%	84%
k=5	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%
Rural areas												
k=1	68%	68%	67%	56%	55%	56%	57%	54%	54%	51%	53%	51%
k=2	75%	76%	75%	71%	70%	71%	69%	69%	69%	66%	67%	66%
k=3	83%	86%	84%	82%	82%	82%	81%	81%	81%	79%	80%	79%
k=4	89%	91%	91%	91%	91%	90%	91%	92%	92%	89%	92%	91%
k=5	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%

Source: Own preparation based on household survey data from 2005 to 2019 (National Statistics Agency – Bolivia).

Multidimensional Energy Poverty Intensity with PCA-based weights, by area

(In percentage of total urban households)



Source: Own preparation based on household survey data from 2005 to 2019 (National Statistics Agency – Bolivia).

Annex H. Multidimensional Energy Poverty Index with PCA-based weights, by area

(Index)

Cut-off value	2005	2006	2007	2011	2012	2013	2014	2015	2016	2017	2018	2019
Urban areas												
k=1	0.42	0.34	0.38	0.32	0.30	0.26	0.29	0.31	0.32	0.30	0.29	0.27
k=2	0.33	0.25	0.28	0.23	0.19	0.16	0.19	0.19	0.21	0.19	0.18	0.16
k=3	0.15	0.12	0.11	0.08	0.06	0.05	0.06	0.07	0.08	0.07	0.06	0.06
k=4	0.05	0.06	0.04	0.04	0.03	0.03	0.03	0.04	0.03	0.04	0.04	0.04
k=5	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Rural areas												
k=1	0.63	0.64	0.63	0.50	0.46	0.46	0.50	0.44	0.45	0.42	0.43	0.40
k=2	0.60	0.60	0.59	0.42	0.39	0.38	0.43	0.36	0.37	0.34	0.36	0.33
k=3	0.51	0.52	0.50	0.33	0.29	0.30	0.33	0.28	0.28	0.25	0.26	0.23
k=4	0.38	0.44	0.36	0.23	0.20	0.21	0.21	0.19	0.18	0.16	0.16	0.14
k=5	0.04	0.04	0.03	0.02	0.02	0.02	0.02	0.02	0.03	0.02	0.03	0.03

Source: Own preparation based on household survey data from 2005 to 2019 (National Statistics Agency – Bolivia).