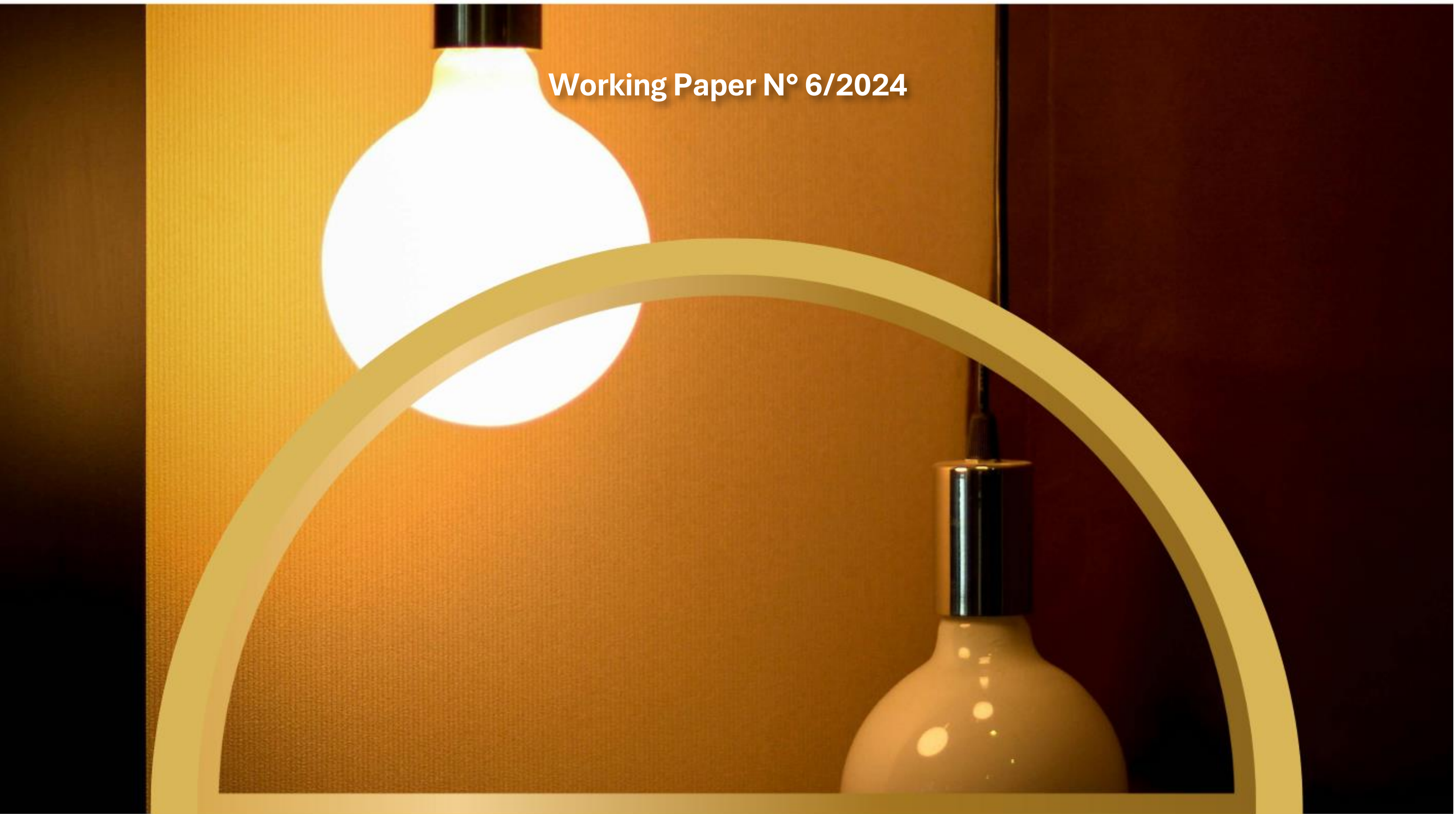
Working Paper N° 6/2024



Energy Poverty in Bolivia: Levels, trends, and inequalities at the Municipal level

By:

Erika Soliz
Ricardo Nogales

Energy Poverty in Bolivia: Levels, trends, and inequalities at the Municipal level

Erika Soliz[1]
Ricardo Nogales[1]

[1] Universidad Privada Boliviana (UPB).

Energy Poverty in Bolivia: Levels, trends, and inequalities at the Municipal level

Abstract

Access to clean energy is critical for economic development, poverty reduction, and enhancing individual well-being, aligning with Sen's capability approach which emphasizes the importance of energy services in achieving essential life functions. Despite its importance, energy poverty remains underexplored in Latin America, particularly in Bolivia. We address this gap by evaluating energy poverty convergence at the municipal level in Bolivia from 2012 to 2016. We employ a β-convergence analysis to compare observed and expected convergence rates, identifying municipalities that are energy poverty pockets—regions with high initial poverty levels and slow improvement rates. Our study also characterizes these lagging municipalities and projects their energy poverty levels for 2030. Findings from our study aim to inform targeted public policies by highlighting regional disparities and providing a nuanced understanding of energy poverty dynamics in Bolivia, thereby contributing to more effective interventions aligned with national and international development goals.

Keywords: Energy poverty; Bolivia; Convergence; Inequality

1. Introduction

Access to clean energy sources plays a crucial role in economic development and is fundamental for reducing poverty and inequality (Pereira et al., 2011; Acharya & Sadath, 2019). Energy and well-being are related because energy services enable household members to be productive, economically active, and have access to education, among others (Alkire et al., 2021). These ideas are in tune with one of the most influential model development paradigms, namely Sen's capability approach (1993, 1999). Considering that access to energy crucially affects individuals' ability to achieve functioning and expand opportunities to live a life they value, energy poverty is understood as the inability to achieve essential capabilities due to lack of access to energy services (Day et al., 2012).

Energy poverty reduction has become a central issue in virtually all national and international development agendas, and it figures prominently in the 2030 Agenda for Sustainable Development – goal 7 aims to ensure access to affordable, clean, and safe energy services for all. This has prompted increased efforts to accurately measure the proportion of people living in energy poverty, as only timely and robust information has the potential to positively influence policy design to address this crucial development issue (Nussbaumer et al., 2012).

While global literature on energy poverty is fast increasing, it is still relatively limited in Latin America. In a comprehensive recent literature review Thomson et al. (2022) stress this knowledge gap by signaling out only 62 publications related to poverty in the region compared with the much more evidence for European countries, with no studies available for Bolivia at that time. The need for such an analysis in Bolivia, the poorest country in South America, lies in the importance of generating public policies that consider the different contexts of various subnational regions. Each region may have different characteristics, such as climate, population size, or socioeconomic conditions, which can have differentiated effects on the magnitude of energy poverty and its changes over time.

One notable exception presenting rigorous evidence of energy poverty levels in Bolivia is Aliaga and Mansilla (2023) who estimated a multidimensional energy poverty index at the national level between 2015-2019, considering five dimensions related to energy and poverty. They found that energy poverty decreased during the analysis period, but its intensity is consistently higher in rural areas. To the best of our knowledge, thus far this is the only credible evidence in the literature about a decreasing trend of energy poverty in Bolivia, and its degree of geographical inequalities within the country.

One way to delve deeper into the evolution of energy poverty over time is by conducting β-convergence studies. These studies have primarily been used to analyze economic growth patterns across countries and establish convergence when poorer countries experience faster economic growth rates than richer ones, leading to a reduction in inequalities over time. A similar notion of convergence has been adopted within the field of energy economics. Han et al. (2018), for instance, found that the Belt and Road Initiative (BRI) promotes convergence in energy efficiency among the countries involved in this initiative, while Peng et al. (2022) identified three clubs of energy efficiency convergence in these countries. Mishra & Smyth (2014, 2017) conducted studies for ASEAN member countries and Australia, finding evidence of convergence in energy consumption in both cases. Liddle (2010) found evidence of convergence in energy intensity for a sample of over 100 countries in two different periods, while Mudler & De Groot (2012) found that lagging countries are catching up with the leading OECD countries. Evidence on the convergence of energy poverty is still limited. Only recent studies such as Huang et al. (2022) for 28 European countries, and Anastasiou & Zaroutieri (2023) and Salman et al. (2022) for European and developing countries respectively, show findings on conditional and unconditional convergence and the presence of convergence clubs towards different steady states.

Thus, based on the need to generate more empirical evidence on energy poverty in Bolivia, we evaluate energy poverty convergence at the municipal level in Bolivia from 2012 to 2016. It compares observed convergence with expected convergence for each municipality and identifies municipalities that are lagging behind: those with high initial levels of poverty and a slow convergence rate compared to other municipalities. These municipalities are considered energy poverty pockets.

Additionally, a characterization of municipalities lagging behind compared to those that are not carried out. Finally, a projection of energy poverty levels for those municipalities identified as pockets of poverty is made for 2030.

2. Literature overview

Energy poverty is a problem that affects households around the world. This has led to the study of energy poverty to gain relevance due to the socioeconomic impacts it has on people's lives and the need to formulate better informed public policies (Rafi et al., 2021). However, currently there is no consensus on a definition of energy poverty, but a distinction between developed and developing countries can be found in the literature.

In developed countries, energy poverty is regularly defined as fuel poverty (Lewis, 1982). A household is fuel-poor if it cannot afford the necessary amount of fuel required to maintain thermal comfort within the household. Boardman (1991) posited that a household that needs to spend more than 10% of its total income on fuel costs to achieve an adequate indoor temperature is considered fuel-poor. Hills (2011) proposed the definition of Low-Income High Cost (LIHC) households. Under this definition, a household is fuel-poor if it has high energy costs (a bill above the median adjusted by household size), and if, after covering these costs, its disposable income falls below the monetary poverty line. Indeed, such high relative costs limit the available income to cover other basic needs, so households with low incomes, high energy needs, and high additional costs of living the home are considered energy-poor (Mahooney et al., 2020).

Importantly, many households in developing countries, especially in rural areas, lack access to clean energy. (Siksnelyte-Butkiene et al., 2021; Birol, 2007; Li et al., 2014). One reason for this are the barriers to equitable access due to low investment in electrical infrastructure (Calvo et al., 2021), leaving a large portion of the population with access to energy only through biomass sources, which are primarily used for cooking, boiling water, lighting, and heating (Pachauri et al., 2004; WHO, 2006). These sources have been linked to negative health effects as they generate indoor air pollution, causing respiratory illness (WHO, 2006; Barnes et al., 2011; WHO, 2016). Additionally, there is a high correlation between usage of these energy sources and risks to children's school attendance and women's participation in the labor market, as they spend part of their time searching for biomass fuels, (WHO, 2006, 2016; Birol, 2007). Inaccessibility to clean energy sources impacts the most vulnerable households the hardest thus exacerbating poverty (Calvo et al., 2021; CEPAL, 2009).

Complementing the concept of energy poverty as the lack of access to electrical grids or its high relative cost, another strand of the literature focuses on the amount of energy households or individuals need to achieve certain lifestyle outcomes. Thus, energy becomes a means through which other goods or services including lighting, heating, or cooking can be acquired sustainably (Sovacool et al., 2013). This idea is in line with a powerful development paradigm developed by Sen (1993) known as the capability approach. Deprivation in this approach is defined as the shortfall of individuals' capabilities to achieve functionings such as being well-nourished, having good health, being communicated with the rest of the world, or having access to remote education. (Sambodo and Novandra, 2019).

Day et al. (2016) propose a definition of energy poverty within Sen's capability approach enabling one to understand how energy and well-being are interconnected and how energy poverty should be understood. Indeed, consumption of energy services is a material prerequisite for achieving valuable capabilities, recognizing that energy is necessary for work, education, communication, and participation in social life.

Additionally, under Sen's capability approach it is likely that energy poor households are also deprived in various other aspects of well-being (Bartiaux, et al., 2021). Alkire et al., (2021) find that among those who lack access to electricity in over 100 developing countries, 83% also suffer from housing deprivation, 96% from cooking fuel deprivation, and 83% from sanitation deprivation. Simultaneous deprivations between electricity and these indicators are higher in rural areas (89%, 98%, and 85% respectively), and there is a gap between those simultaneously deprived of electricity and access to potable water in urban and rural areas (39% versus 63%).

Thus, within the literature on energy poverty, the focus is primarily on measurement, its implications on well-being (Sambodo & Novandra, 2019), or on the nexus between energy poverty and income inequality (Nguyen & Nasir, 2021). Other studies of energy poverty evaluate convergence in aspects related to energy access. Li & Lin (2015) found that the convergence of energy use and CO_2 emissions will have negative effects on economic growth in China. Han et al., (2018) found that the Belt and Road Initiative (BRI), through its role in trade integration and regional cooperation, could promote energy efficiency among countries. Peng et al. (2022) study convergence clubs in energy efficiency for all countries in BRI, finding that all countries together diverge, but evidence of the existence of three convergence clubs was found, each with different characteristics.

Similarly, there are several studies about convergence in terms of energy consumption. Mishra & Smyth (2014) examined conditional convergence for ASEAN countries using unit root tests and found that countries with low levels of energy consumption are catching up with countries with high levels of energy consumption. Mishra & Smyth (2017) conducted the same analysis, but this time for Australia between 1973 and 2014, finding evidence of energy consumption convergence in six out of seven sectors in Australia. Other studies evaluate convergence of energy intensity. For example, Liddle (2010) conducts the study for 111 countries between 1971-2006 and 134 countries for 1990-2006, finding in both cases continuous convergence at the level of the analyzed countries. Mudler & De Groot (2012) assessed convergence in energy intensity for 18 OECD countries and 50 sectors between 1970-2005 and found that lagging countries are catching up to the leading countries and that convergence rates are higher in the services sectors.

Considerably fewer studies evaluate how energy poverty evolves over time within a convergence analytical framework. One notable exception is Huang et al. (2022) who carried out a study on the convergence of energy poverty in 28 European Union countries between 2006 and 2008. They find that absolute and conditional convergence is faster in countries with higher poverty quantiles. Thus, countries with deeper levels of energy poverty reduce energy poverty more rapidly than countries with low levels.

Similarly, Salman et al. (2022) estimate the convergence of (multidimensional) energy poverty in 146 countries between 2002 and 2018. They use 33 OECD countries as a reference and evaluate the catch-up effect of the 113 developing countries in their study. They do not find evidence of overall convergence between these two sets of countries. Finally, Anastasiou & Zaroutieri (2023) evaluated the convergence of energy poverty for 27 member countries of the European Union between 2005 and 2020. They also reject the null hypothesis of convergence, thus finding that countries diverge in the long run.

3. Data and Methods

a. Data

The main database used for this paper is an anonymized research database, ELBOL, with monthly electricity consumption from all residential electricity meters in Bolivia during the period 2012 – 2016 (Andersen et al., 2023). It consists of a unique, unbalanced panel data of monthly residential electricity consumption data registered by 2.1 million energy meters across the country. The dataset contains information from 2012 to 2016, thus consisting of approximately 126 million observations.

The dataset combines official consumption records from two sources. First is the National Interconnected System, which is formed of eight regional electric distribution companies that supply electric energy to eight of the nine departmental capital cities – Cobija being the exception. These electricity providers account for approximately 93% of electricity supply in the country. The rest of the information in the dataset comes from official records in the Isolated Energy System formed of 24 small electricity distribution companies. This smaller System supplies electricity to areas not served by the National Interconnected System.

The unit of analysis in our study is the municipality. The original ELBOL data was used to estimate the mean monthly domestic electricity consumption in 329 out of the 339 municipalities in Bolivia. We are unable to calculate estimates for 10 municipalities because of lack of sufficient data. On one extreme, Table 1 shows that we have full information for 198 of the 329 municipalities, that is estimates of domestic electricity consumption for every month between 2012 and 2016 (60 months). On the other extreme, for 7 municipalities we only have information about domestic electricity consumption in 10 months or less within this time span.

Table 1: Number of Months for which Meter Information is Available at the Municipal Level in Bolivia (2012-2016)

Number of months with available information	Number of municipalities
60 months	198
between 50 and 59 months	32
between 40 and 49 months	44
between 30 and 39 months	31
between 10 and 29 months	17
Less than 10 months	7

Source: Own elaboration

The main dataset of electricity consumption at the municipal level was complemented by two variables that define core structural characteristics that are tightly related with their average electricity consumption. First, is a set of indicators coming from the 2020 Municipal Atlas of the Sustainable Development Goals created by SDSN Bolivia (Andersen et al., 2020). With municipal-level information gathered from records, censuses, and satellite data, the SDSN Bolivia Atlas consists of 62 indicators related to 17 Sustainable Development Goals.

Second, is the official municipal population projection of the National Statistics Institute (INE). Based on population size in the 2012 census (the starting year of the analysis), municipalities were classified as type A (less than 5’000 habitants), type B (between 5’001 and 15’000), type C (15’001 and 50’000), or type D (more than 50’000). Additionally, we consider the altitude of each municipality over sea level. This variable is used to classify the municipalities into ecological zones which are relatively homogeneous in terms of climate, types of agricultural and economic activities, cultural and social habits, and volume of precipitation and temperature (Vásquez and Gallardo, 2012). The classification of each municipality according to the ecological zone is Andean, Valley, and Lowland municipalities.

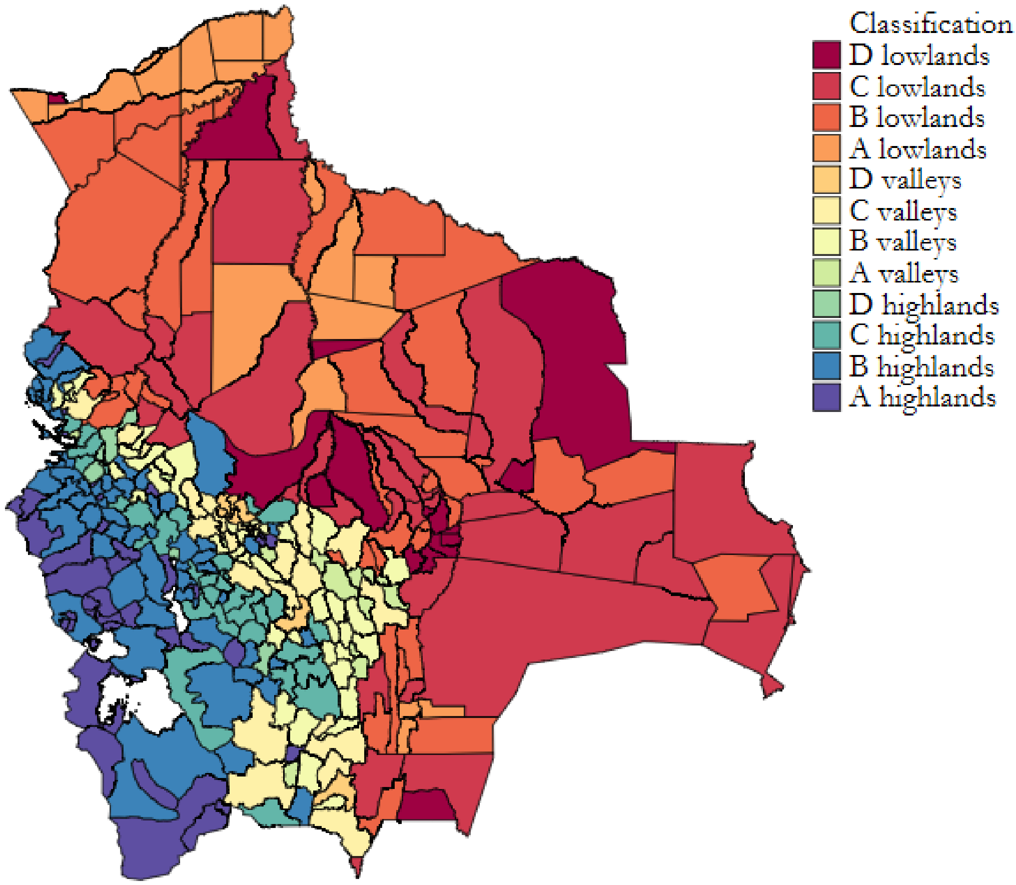
Most municipalities in 2012 had a population size between 5,001 and 15,000 inhabitants, while the number of municipalities with more than 50,001 inhabitants is considerably smaller (see Table 2). The full geographical coverage of our study, and the structural distribution of the considered municipalities based on altitude and population size is depicted in Figure 1.

Table 2: Classification of Municipalities according to Region and Population Size as of 2012

		Population Size				
		A (up to 5,000)	B (5,001 to 15,000)	C (15,001 to 50,000)	D (more than 50,001)	Total
Region-Altitude (meters above sea level)	Highlands: >3000 m	43	63	29	5	140
	Valleys: between 1500 and 3000 m	17	41	24	8	90
	Lowlands: < 1500 m	18	41	35	15	109
	Total	78	145	88	28	339

Source: Own elaboration based on Vásquez and Gallardo (2012), CEGIE, and data from the INE and the Municipios of Bolivia website

Figure 1: Classification of Municipalities according to Region and Population Size as of 2012



Source: Own elaboration based on Vásquez and Gallardo (2012), CEGIE, and data from the INE and the Municipios of Bolivia website

b. Methods

Measurement of energy poverty levels

To measure energy poverty, we estimate three indices within the FGT_α class of additively decomposable poverty measures proposed by Foster, Greer, and Thorbecke (1984). This class of measures is defined as:

$$FGT_\alpha = \frac{1}{n}\sum_{i=1}^{q}\left(\frac{z - x_i}{z}\right)^\alpha$$

In our context, x_i represents the level of monthly electricity consumption recorded by the electricity meter corresponding to household i, and z denotes the absolute energy poverty line. Thus, the difference $z - x_i$ is positive if meter i signals consumption levels corresponding to energy poor. The number of households identified as energy poor is denoted as q, and n denotes the total number of meters/households in the database. The parameter α can be interpreted as a measure of poverty aversion, where a larger α value puts additional emphasis on the poorest of the poor (Foster et al., 1984).

The incidence of energy poverty is measured by FGT_0, and it represents the percentage of households with levels of energy consumption below the poverty line. The poverty gap index corresponds to FGT_1, and it represents the depth of energy poverty as measured by the average relative shortfall of energy consumption from the poverty line among the energy poor households. The average squared poverty gap is captured by FGT_2 , and it measures the severity of energy poverty, considering not only the distance between consumption and the poverty line but also the inequality of gaps among the poor (Foster et al., 2000). The main reason for choosing this class of indices as our energy poverty measures is their adherence to important poverty measurement axioms (Foster et al., 1984). One of them is subgroup decomposability, by which when energy poverty increases in a group or the population, all the considered indices will increase as well. Similarly, the monotonicity axiom will always hold, as all indices will decrease when household energy consumption among the poor households increases.

To set the energy poverty line we use a minimum kWh/month consumption threshold (see Table 3). The idea behind these poverty lines is that there is a minimum energy consumption level necessary to maintain basic welfare levels (Barnes et al., 2011). The precise calculation of these lines is based on engineering calculations that take into account different aspects of basic energy-operated equipment and appliances to define the minimum electricity needed to meet basic needs (Pachauri et al., 2004). Our definition of these lines is conceptually aligned with Pachauri and Spreng (2011), Andersen et al. (2019) and Foster et al. (2000).

Thus, our energy poverty lines are based on the country's Tarifa Dignidad, an energy bill discount policy established in 2006 aiming to facilitate access and use of electricity for families with lower economic resources in the residential category, thus addressing the low coverage of electrical service (Espinoza and Jiménez, 2012). As of July 2024, this tariff has national coverage and consists of a 25% energy bill discount when monthly electricity consumption in a household is less than or equal to 180 kWh/month.

Based on Tarifa Dignidad, we define three absolute poverty lines. The first line corresponds to 100% of the minimum consumption level in this policy framework (70 kWh/month). Thus, households consuming less than 70 kWh/month are identified as energy poor. Our second poverty line consists of 50% of the Dignity Tariff (35 kWh/month), and the third line is equal to one-fourth of the Dignity Tariff (17.5 kWh/month). The 17.5 kWh/month line was also adopted by Andersen et al., (2019), who stress that it merely allows a household to maintain connection to 2-3 light bulbs, a radio, and one cell phone. This consumption level can thus be considered quite minimal so we posit it as an extreme energy poverty line.

Table 3: Absolute poverty lines based on "Tarifa Dignidad"

	Consumption kWh/month
Tarifa Dignidad (100%)	70
Tarifa Dignidad (50%)	35
Tarifa Dignidad (25%)	17.5

Assessing convergence of energy poverty levels

Building on the available data, we estimate monthly levels of energy poverty at the municipal level from January 2012 to December 2016. We feed these panel data into a β-convergence framework drawing directly from the seminal economic growth rate convergence analysis by Barro et al. (1991) and Barro and Sala-i-Martin (1992). We thus assess whether energy poverty is converging towards a common steady state in the country. There is evidence for β-convergence if energy poverty decreases more rapidly in municipalities with higher initial levels of energy poverty compared with municipalities with lower levels of energy poverty initially (see Huang et al. 2022 for a similar adaptation of the notion of β–convergence).

We study the two most well-known notions of β-convergence, namely absolute and conditional convergence (see Barro et al. (1991) and Barro and Sala-i-Martin (1992)). In our context, absolute convergence implies that energy poverty levels converge towards the same steady state across all municipalities, and thus inequalities in terms of energy poverty levels tend to reduce over time, ceteris paribus. The notion of conditional convergence opens up the possibility of having different steady states of energy poverty for different groups of municipalities. In this case, only municipalities with similar structural characteristics converge to the same steady state of energy poverty. (Barro and Sala-i-Martin, 1992).

We thus estimate the same equation in Barro and Sala-i-Martin (1992) to establish whether there is absolute convergence in terms of energy poverty across municipalities,

$$\frac{1}{T_i} ln\left(\frac{y_{i,t_0+T_i}}{y_{i,t_0}}\right) = a - b\, ln(y_{i,t_0}) + u_i \qquad (1)$$

where y_{i,t_0} represents the level of energy poverty in municipality *i* that we observe in the span covered by out study, and t_0 is the month of the first observation (normally January, 2012). Note that y can be any of the FGT_α indices defined previously. T_i represents the number of months in which we observe y for municipality *i* (generally, 60 months), and u_i represents the usual error term in a regression framework with zero mean and time-constant heteroscedastic variance.

In our case, changes of the ratio $\left(\frac{y_{i,t_0+T_i}}{y_{i,t_0}}\right)$ over time represents the relative rate of change of energy poverty levels, which are expected to be negative in general, depicting energy poverty reduction patterns. Thus convergence exists in our framework if municipalities with higher initial levels of energy poverty have a more negative change of the ratio $\left(\frac{y_{i,t_0+T_i}}{y_{i,t_0}}\right)$ over time, that is, they reduce poverty faster. This requires coefficient *b* in equation (1) to be positive (Young et al., 2008; Janekalne, 2016).

For a robustness check, we also estimate a version of equation (1) including a set of control variables x_{i,t_0} including population growth, classification by population size, and classification by altitude. These controls are associated with parameter vector *c* and they allow us to establish if structural municipal characteristics define specific steady states for groups of municipalities, thus bringing in the notion of conditional convergence:

$$\frac{1}{T_i} ln\left(\frac{y_{i,t_0+T_i}}{y_{i,t_0}}\right) = a - b ln y_{i,t_0} + c x_{i,t_0} + v_i \qquad (2)$$

In equation (2), the parameter of interest remains *b*. Here too, if *b* is positive then we can establish the existence of conditional convergence across municipalities.

Trends and pockets of poverty

Estimating equations (1) and (2) is sufficient to establish the existence of absolute or conditional convergence, respectively. Taking a step further, we aim to determine if there are municipalities that are systematically lagging behind the rest in terms of their pace of energy poverty reduction. We refer to these municipalities as pockets of energy poverty. It is possible to use the parameters of the absolute convergence equation (1) to identify these municipalities. Note that if there is significant evidence for absolute convergence, then after estimating equation (1) it is possible to estimate the expected monthly rate of reduction in energy poverty for each municipality (denoted as $\hat{\beta}_i^{lin}$) given the national context (captured through the model's parameters) and its initial level of energy poverty:

$$\hat{\beta}_i^{lin} \equiv \frac{1}{T_i} ln\left(\frac{y_{i,t_0+T_i}}{y_{i,t_0}}\right) = \hat{a} - \hat{b}\ ln(y_{i,t_0}) \qquad (3)$$

The rate $\hat{\beta}_i^{lin}$represents the annual absolute change in the measure of energy poverty between t_0 and T_i associated with a linear trajectory of this variable – hence the superscript *lin* in its definition. From this expected rate of energy poverty reduction with a linear trajectory, it is possible to deduce the corresponding expected reduction rate adjusted by a logistic model (see Alkire et al., 2023):

$$\beta_i^{log\,*} = \frac{\hat{\beta}_i^{lin}}{y_{i,t_0}(1-y_{i,t_0})} \qquad (4)$$

The adjusted rate defined in equation (4) represents the speed of reduction adjusted for the initial level of energy poverty in municipality *i* and the distance to the ideal situation where there is no poverty in that municipality. Since the rate calculated in equation (4) is calculated using the cross-municipality regression (1), it captures the <u>expected behavior</u> of poverty in municipality *i* given its situation with respect to all the other municipalities. With this equivalence, our methodological strategy to identify pockets of energy poverty consists of comparing the expected poverty reduction rate for each municipality *i*, $\beta_i^{log\,*}$, with the observed rate of reduction in energy poverty, calculated <u>solely</u> from the specific energy poverty levels of that municipality, denoted as β_i^{log}. Making use of all the available information to identify seasonal variations in the trajectories, β_i^{log} is calculated as the mean of monthly poverty rates deduced from calibrations of specific logistic models for each municipality *i* and month *m* (see Alkire et al., 2023):

$$y_{i,t,m} = \frac{1}{1 + exp\left(-\alpha_{i,m}^{log} + \beta_{i,m}^{log}\right)} \quad (5)$$

Thus:

$$\beta_i^{log} = E\left[\beta_{i,m}^{log}\right] = E\left[\frac{1}{T_i^m - t_0^m}\left[logit\,\left(y_{i,T_i^m}\right) - logit\,\left(y_{i,t_0^m}\right)\right]\right] \quad (6)$$

where *m* denotes the month, y_{i,t_0^m} is the initial observation of the energy poverty indicator for municipality *i* in month *m* (which typically occurs in 2012), and y_{i,T_i^m} is the corresponding final observation in the dataset (which typically occurs in December 2016). The logit operator denotes the logistic transformation such that $logit(y_{i,t_0^m}) = -ln\left(\frac{1-y_{i,t_0^m}}{y_{i,t_0^m}}\right)$ and $logit(y_{i,T_i^m}) = -ln\left(\frac{1-y_{i,T_i^m}}{y_{i,T_i^m}}\right)$. The logistic transformation has the advantage of respecting the limits of each of the energy poverty indices used in this study, as all three indices are within the interval 0 – 1 (see Alkire et al., 2023). Also, this transformation is adopted for its adequacy to reproduce smooth trajectories for municipalities with particularly high levels of energy poverty in both the initial and last periods of observation.

Note that the <u>observed</u> poverty reduction rate β_i^{log} takes a more negative value for municipalities that have reduced poverty the fastest, which is a positive trait. With this in mind, all municipalities can be classified into two groups based on β_i^{log}: i) those with an observed rate of poverty reduction below the median (good performers), and ii) those with an observed rate above the median (not good performers). Similarly, we can establish a complementary classification based on the <u>expected</u> poverty reduction rate β_i^{log*}. Again, more negative values of this rate denote faster expected poverty reduction rates. Moreover, note that there is a negative relationship between this rate and initial poverty levels given by equation (2) – higher initial poverty rates have more negative values of β_i^{log*}. Thus, all municipalities are, in turn, classified into i) those with an expected rate below the median (high levels of initial poverty rates), and ii) those with an expected rate of energy poverty reduction above the median (low levels of initial poverty rates). These two classifications allow each municipality to be regrouped according to the observed rate of poverty reduction and the expected reduction rate given the convergence pattern (which denotes its initial poverty levels). The four groups considered in this study are presented in Table 4 below:

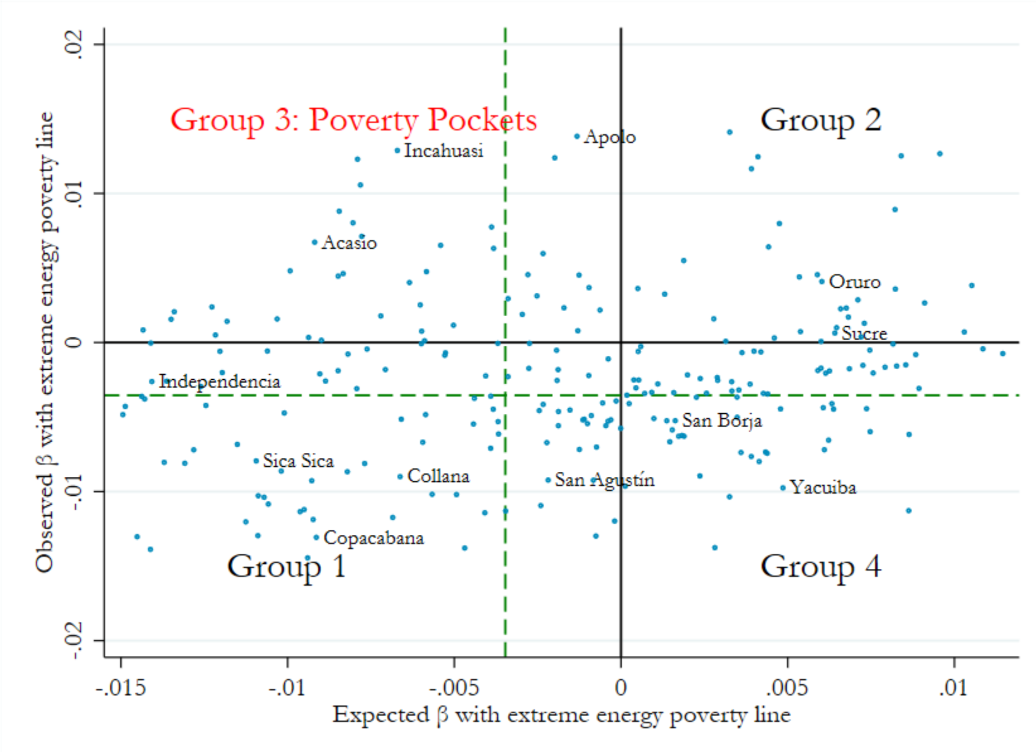
Table 4: Classification of Municipalities

Group 1	Below-median observed reduction rate and below-median expected reduction rate	Fast-progressing municipalities, departing from relatively high poverty levels
Group 2	Above-median observed reduction rate and above-median expected reduction rate	Slow-progressing municipalities, departing from relatively low poverty levels
Group 3 (Pockets of energy poverty)	**Above-median observed reduction rate and below-median expected reduction rate**	**Slow-progressing municipalities, departing from relatively high poverty levels**
Group 4	Below-median observed rate and above-median expected reduction rate	Fast-progressing municipalities, departing from relatively low poverty levels

Source: Own elaboration

In Figure 2 we observe the different groups of municipalities. Municipalities like Independencia, Acasio and Incahuasi are classified as energy poverty pockets since their observed rate of reduction of energy poverty is above median (green dashed line) and also their expected rate of reduction is below median (green dashed line). On the other hand, municipalities like Oruro or Sucre, were not good performers in terms of observed poverty reduction rates, but they had low initial levels of energy poverty, therefore are classified in Group 2.

Figure 2: Observed and expected *β* with 25% of Tarifa Dignidad as poverty line



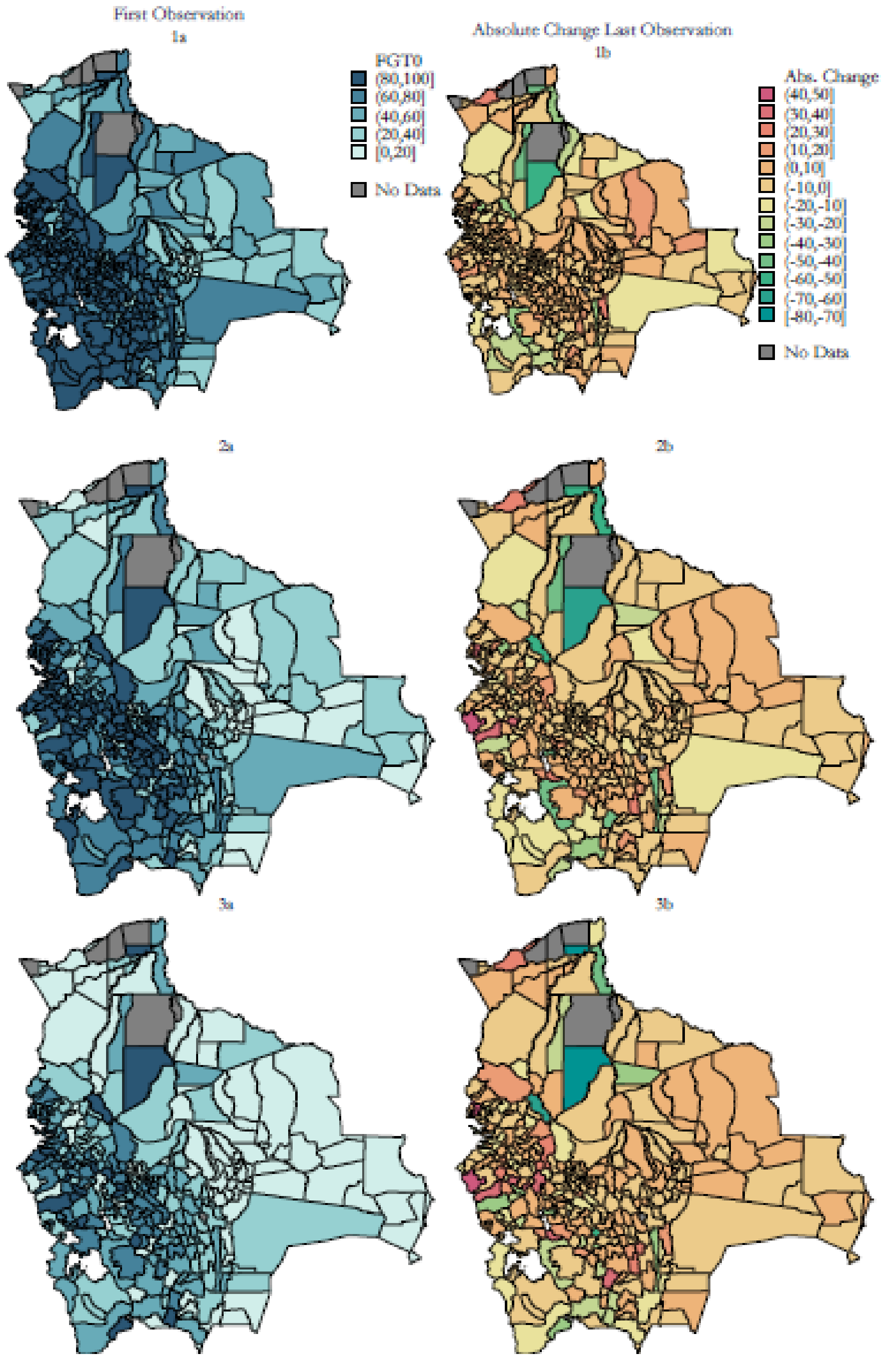
Source: Own elaboration

4. Results

a. Levels of energy poverty

Let's first examine the levels and changes in energy poverty incidence (*FGT_0*) according to our three absolute poverty lines: 100% of Tarifa Dignidad (Panel 1), 50% (Panel 2), and 25% (Panel 3). Initial levels of energy poverty are shown in the blue-shaded maps in Figure 3, while changes over time are depicted as total absolute changes in the orange-shaded maps. High incidences of energy poverty are heavily concentrated in the Highlands and the Valley, regardless of the poverty line. In this regard, the broad geographic distribution of energy poverty mirrors that of monetary poverty (see Arias and Robles, 2015). It is also important to note that the incidence of extreme energy poverty (consumption < 25 kWh/month) has largely decreased over time. This is true for 201 out of 327 municipalities, some of which had poverty incidence levels exceeding 80% in the initial observation.

Figure 3: FGT_0 for the first observation and absolute change for the last observation (%)



Source: Own elaboration

b. Convergence

Table 5 presents the results of estimating β-convergence using the intermediate poverty line of 70 kWh/month. The first column presents compelling evidence of absolute convergence, showing that energy poverty disparities across municipalities have decreased over time. Columns 2 through 7, which include additional variables to gauge conditional convergence, reveal that municipalities with similar structural characteristics converge to different steady states in the long run. All our results are consistent with one crucial finding: municipalities with higher initial levels of energy poverty experience a more rapid reduction in energy poverty compared to those with lower initial levels, irrespective of the notion of convergence or the controls used to identify distinct steady states. This observation aligns with the results of Huang et al. (2022), who also identify both absolute and conditional convergence in energy poverty when examining beta-convergence across 28 countries in the European Union.

Table 5: Unconditional Beta Convergence - Conditional Poverty Incidence *FGT_0* with 100% Tarifa Dignidad

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Δ FGT_0	Δ FGT_0	Δ FGT_0	Δ FGT_0	Δ FGT_0	Δ FGT_0	Δ FGT_0
FGT_0P1	-0.0016***	-0.0014***	-0.0020***	-0.0037***	-0.0047***	-0.0032***	-0.0042***
	(-3.64)	(-2.75)	(-3.15)	(-5.67)	(-5.37)	(-5.03)	(-5.64)
Δ Pop		0.0000				0.0001	0.0001
		(0.33)				(1.05)	(1.25)
B			-0.0004		-0.0002		-0.0003
			(-0.71)		(-0.36)		(-0.61)
C			-0.0007		-0.0006		-0.0007
			(-1.13)		(-1.03)		(-1.23)

D			-0.0013		-0.0022**		-0.0025**
			(-1.53)		(-2.36)		(-2.44)
Valleys				-0.0005**	-0.0005**	-0.0006**	-0.0007**
				(-2.03)	(-2.19)	(-2.11)	(-2.36)
Lowlands				-0.0030***	-0.0033***	-0.0033***	-0.0037***
				(-4.78)	(-5.13)	(-4.94)	(-5.22)
Constant	-0.0010***	-0.0010***	-0.0007*	-0.0007***	-0.0005	-0.0006***	-0.0003
	(-6.29)	(-5.73)	(-1.94)	(-5.21)	(-1.56)	(-3.08)	(-0.55)
N	320	320	320	320	320	320	320
R^2	0.055	0.057	0.066	0.165	0.195	0.179	0.215

t statistics in parentheses
* p<0.10, ** p<0.05, *** p<0.010

Tables A1 and A2 in the appendix show the results of β-convergence estimation with energy poverty incidence calculated using 50% and 25% of the Tarifa Dignidad, respectively. Consistent with the previous findings, these tables provide evidence of absolute convergence in the first column, and conditional convergence in columns 2 through 7. Thus, we show that convergence exists also irrespective of the chosen energy poverty line.

c. Pockets of poverty

Table 6 shows the number of municipalities classified into each of the four groups based on their energy poverty reduction rates and initial incidence levels. Importantly, to be categorized as an energy poverty pocket (Group 3), a municipality must be identified as part of this group under at least two different energy poverty lines. Our results identify 64 municipalities as energy poverty pockets, with 43 located in the Highlands and 20 in the Valleys and one in the Lowlands. Nearly 50 % of these municipalities have populations of less than 15,000. Overall, they are home to 806’000 approximately.

The majority of municipalities —97 out of 327— experienced slow progress but started from relatively low poverty levels. Among these, 51 are in the Lowlands, 31 in the Valleys, and 15 in the Highlands. In contrast, 92 municipalities that, despite starting from relatively high poverty levels, made rapid progress in reducing energy poverty are predominantly located in the Highlands (66 municipalities). These municipalities make up one-quarter of all municipalities, which supports our convergence results.

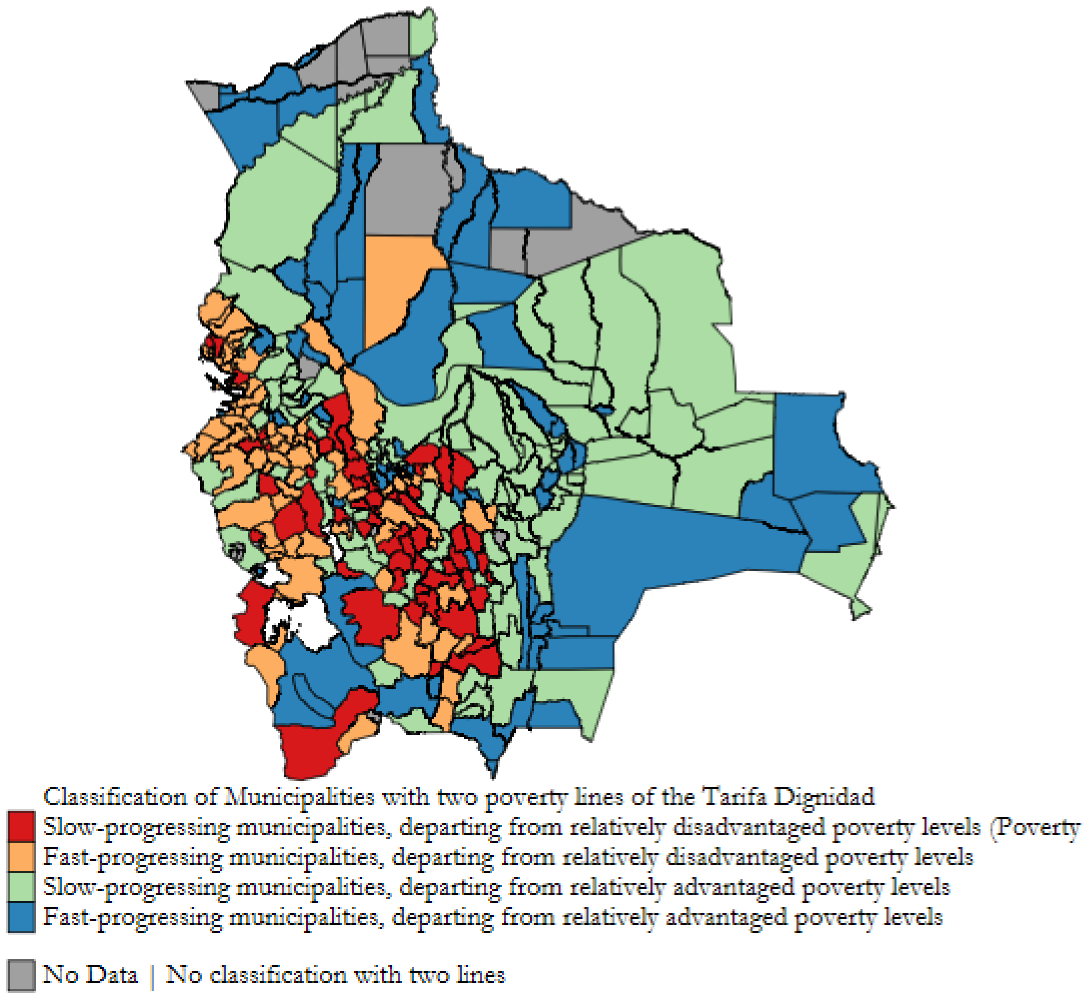
Table 6: Number of municipalities classified into each of the four categories based on their poverty reduction rate and initial incidence situation with at least two lines of energy poverty.

1) Fast-progressing municipalities, departing from relatively high poverty levels	92
2) Slow-progressing municipalities, departing from relatively low poverty levels	97
3) Slow-progressing municipalities, departing from relatively high poverty levels (Poverty pockets)	64
4) Fast-progressing municipalities, departing from relatively low poverty levels	64
No classification	3

Source: Own elaboration

Figure 4 illustrates the classification of each municipality. As previously noted, the majority of municipalities identified as energy poverty pockets are concentrated in the Highlands and Valley regions. In terms of population size, 12 municipalities had populations of less than 5,000 in 2016, 32 municipalities had populations ranging from 5,001 to 15,000, and 20 municipalities had populations between 15,001 and 50,000. Additionally, municipalities that started from relatively low poverty levels (groups 2 and 4) are predominantly located in the Lowlands.

Figure 4: Municipalities classified into each of the four categories based on their poverty reduction rate and initial incidence situation with at least two lines of energy poverty.



Source: Own elaboration

d. Expected trajectories of poverty incidence in municipalities classified energy poverty pockets

Having identified the energy poverty pockets municipalities, we now estimate their expected trajectories of poverty levels. For this, we project the incidence, depth and severity of extreme energy poverty (calculated with a 17.5 kWh/month poverty line). Our aim is to identify the pockets of poverty that can be expected to reach the goal of reducing poverty in half by 2030, and those that are not.

Regarding the incidence of extreme energy poverty in Table 7, we find that 25 out of 64 poverty pockets are expected to increase the percentage of households that live in extreme poverty by 2030 if the observed trends continue. This is aligned with the results found by the International Energy Agency (2010), who based on projections of access to electricity, argue that more people will lack electricity by 2030 if efforts to reduce poverty continue to be insufficient around the world, and in Latin America nearly 31 million people will lack access to electricity and 85 million people will still rely in biomass for cooking.

The remaining 39 poverty pockets are expected to reduce extreme poverty incidence by 2030 if observed trends continue. Of those, 10 are poised meet the 2030 goal; these 10 municipalities are some of the most populous ones (more than 15,000 habitants), with the exception of Villa Abecio, (under 5,000). Moreover, seven of them are located in the highlands and three in the valleys.

With respect to the poverty gap index (FGT1), 19 poverty pockets are expected to increase the depth of energy poverty. As a result, energy poor households within this set of municipalities are expected to further reduce their energy consumption by 2030, widening the gap between their energy consumption levels and the extreme energy poverty line. This index provides a more comprehensive overview of energy deprivation, as highlighted by (Croon et al., 2023), who emphasize the need of an index that helps the design and monitoring of energy poverty reduction policies.

The other 45 poverty pockets are expected to bridge the average gap in consumption with respect to the extreme energy poverty line. Of these, 12 municipalities are poised to decrease the depth of poverty by more than half, meaning that households within these municipalities will significantly increase their energy consumption.

Finally, we find that 13 poverty pockets are expected to increase their average severity of energy poverty (FGT2) by 2030. The increase in the severity of energy poverty will be a result of a greater gap between the energy consumption and the energy poverty line of the poorest households within the energy poor municipalities. This will result in greater levels of inequality, given that the poorest households will register less energy consumption. This result is aligned with Ye and Koch (2021) who identified households in the lowest decile of the income distribution in South Africa had the greater severity of energy poverty.

The remaining 51 poverty pockets are expected to reduce the severity of energy poverty, meaning their levels of inequality measured will fall. In fact, 13 out of 64 poverty pockets are expected to reduce the severity of poverty by half until 2030.

Table 7: Expected trajectories incidence, gap, and severity of energy poverty for municipalities classified as energy poverty pockets

			FGT0					FGT1					FGT2				
Municipality	Altitude	Population Size	2015	2030	Difference	2030	Increase	2015	2030	Difference	2030	Incre	2015	2030	Difference	2030	Increase

						Goal					Goal	ase				Goal	
Tinguipaya	Highlands	C	31.3%	31.5%	0.2%	0	1	58.9%	17.8%	-41.2%	1	0	70.5%	20.1%	-50.4%	1	0
Ravelo	Highlands	C	29.7%	31.2%	1.4%	0	1	58.7%	49.7%	-9.0%	0	0	70.9%	60.9%	-10.0%	0	0
Huachacalla	Highlands	A	50.1%	53.4%	3.3%	0	1	68.8%	69.0%	0.2%	0	1	76.7%	75.8%	-0.9%	0	0
Toledo	Highlands	B	53.6%	60.2%	6.6%	0	1	72.6%	70.8%	-1.9%	0	0	80.1%	74.8%	-5.4%	0	0
San Pablo de Lípez	Highlands	A	49.7%	56.9%	7.2%	0	1	70.1%	72.1%	2.0%	0	1	78.1%	77.6%	-0.6%	0	0
Tiraque	Highlands	C	60.0%	68.5%	8.5%	0	1	79.0%	81.8%	2.8%	0	1	85.6%	86.4%	0.8%	0	1
Nazacara de Pacajes	Highlands	A	24.0%	33.0%	9.0%	0	1	48.9%	27.8%	-21.1%	0	0	60.5%	30.0%	-30.6%	1	0
Villa de Sacaca	Highlands	C	46.8%	56.5%	9.7%	0	1	78.1%	68.9%	-9.2%	0	0	87.5%	77.3%	-10.3%	0	0
Vacas	Highlands	B	40.3%	51.6%	11.3%	0	1	64.9%	68.3%	3.4%	0	1	74.6%	75.1%	0.5%	0	1
Tacopaya	Highlands	B	19.1%	31.8%	12.7%	0	1	51.8%	55.3%	3.5%	0	1	65.6%	65.2%	-0.4%	0	0
Ocurí	Highlands	C	37.2%	52.4%	15.1%	0	1	64.5%	72.1%	7.6%	0	1	75.6%	83.4%	7.9%	0	1
Yocalla	Highlands	B	46.9%	72.6%	25.6%	0	1	74.0%	83.8%	9.9%	0	1	83.1%	84.5%	1.4%	0	1

Chayanta	Highlands	C	42.6%	73.0%	30.4%	0	1	73.5%	92.7%	19.2%	0	1	84.3%	97.2%	12.9%	0	1
Chaquí	Highlands	B	58.6%	90.8%	32.1%	0	1	82.5%	97.3%	14.8%	0	1	89.7%	98.3%	8.6%	0	1
Cruz de Machacamarca	Highlands	A	27.9%	67.9%	40.0%	0	1	50.0%	78.6%	28.6%	0	1	60.9%	80.9%	19.9%	0	1
Caranavi	Lowlands	C	59.0%	67.7%	8.7%	0	1	76.5%	81.1%	4.6%	0	1	83.2%	86.2%	2.9%	0	1
Independencia	Valles	C	38.1%	49.4%	11.3%	0	1	64.3%	66.4%	2.1%	0	1	74.8%	74.2%	-0.5%	0	0
Totora	Valleys	C	51.0%	51.4%	0.4%	0	1	72.6%	66.7%	-5.9%	0	0	80.7%	73.8%	-6.9%	0	0
Arque	Valleys	B	38.8%	39.9%	1.1%	0	1	65.2%	64.6%	-0.6%	0	0	75.7%	73.8%	-2.0%	0	0
Icla	Valleys	B	44.2%	47.3%	3.1%	0	1	69.3%	62.0%	-7.3%	0	0	78.7%	69.1%	-9.6%	0	0
Pojo	Valleys	B	53.2%	56.6%	3.5%	0	1	74.5%	71.5%	-3.0%	0	0	82.3%	78.4%	-3.9%	0	0
Vila Vila	Valleys	A	43.7%	52.6%	8.9%	0	1	67.3%	67.5%	0.2%	0	1	76.6%	73.8%	-2.8%	0	0
Villa Alcalá	Valleys	A	46.8%	55.9%	9.1%	0	1	67.7%	72.9%	5.2%	0	1	76.1%	78.9%	2.7%	0	1
Tacobamba	Valleys	B	59.4%	73.3%	13.9%	0	1	83.5%	90.2%	6.7%	0	1	91.1%	93.3%	2.2%	0	1
Tapacarí	Valleys	C	39.8%	57.3%	17.5%	0	1	65.6%	74.9%	9.3%	0	1	75.6%	81.3%	5.7%	0	1

Uncía	Highlands	C	64.1%	21.4%	-42.7%	1	0	78.9%	10.0%	-68.9%	1	0	84.6%	5.2%	-79.4%	1	0
Colquencha	Highlands	B	58.4%	17.0%	-41.3%	1	0	78.5%	18.5%	-60.0%	1	0	85.7%	17.7%	-67.9%	1	0
San Pedro de Curahuara	Highlands	B	43.4%	7.3%	-36.1%	1	0	66.7%	14.6%	-52.2%	1	0	76.8%	17.3%	-59.5%	1	0
Mocomoco	Highlands	B	33.1%	0.2%	-32.9%	1	0	62.5%	2.4%	-60.1%	1	0	73.9%	6.2%	-67.7%	1	0
Achacachi	Highlands	C	55.5%	24.6%	-31.0%	1	0	75.5%	45.3%	-30.2%	0	0	82.9%	56.1%	-26.7%	0	0
Villa Abecia	Highlands	A	53.8%	23.0%	-30.8%	1	0	72.4%	33.2%	-39.2%	1	0	79.8%	37.8%	-42.0%	1	0
San Pedro de Totora	Highlands	B	30.1%	3.5%	-26.6%	1	0	58.8%	6.8%	-52.0%	1	0	70.1%	8.4%	-61.7%	1	0
Eucaliptus	Highlands	B	47.4%	25.3%	-22.1%	0	0	70.9%	45.6%	-25.3%	0	0	79.6%	53.5%	-26.1%	0	0
Challapata	Highlands	C	62.0%	42.0%	-19.9%	0	0	79.0%	60.1%	-18.9%	0	0	85.1%	67.1%	-18.0%	0	0
Palca	Highlands	C	56.9%	37.2%	-19.8%	0	0	77.0%	60.1%	-16.9%	0	0	84.3%	70.7%	-13.6%	0	0
San Lucas	Highlands	C	49.3%	31.2%	-18.2%	0	0	73.3%	57.0%	-16.4%	0	0	82.1%	71.2%	-10.9%	0	0

Ichoca	Highlands	B	36.8%	19.6%	-17.1%	0	0	62.2%	28.8%	-33.5%	1	0	72.6%	34.6%	-38.0%	1	0
Puna	Highlands	C	42.1%	25.2%	-17.0%	0	0	68.4%	43.8%	-24.5%	0	0	77.6%	48.1%	-29.5%	0	0
Quillacas	Highlands	A	45.6%	29.3%	-16.3%	0	0	66.0%	39.5%	-26.5%	0	0	75.0%	45.3%	-29.7%	0	0
Corque	Highlands	B	40.6%	26.0%	-14.6%	0	0	63.1%	40.8%	-22.3%	0	0	72.6%	49.2%	-23.4%	0	0
Caripuyo	Highlands	B	43.3%	31.4%	-11.9%	0	0	78.3%	61.2%	-17.1%	0	0	88.5%	75.7%	-12.8%	0	0
Poopó	Highlands	B	24.9%	13.6%	-11.2%	0	0	51.4%	33.9%	-17.5%	0	0	63.4%	41.6%	-21.7%	0	0
Tarabuco	Highlands	C	50.9%	39.9%	-11.0%	0	0	74.9%	67.5%	-7.5%	0	0	83.5%	77.9%	-5.6%	0	0
Caiza D	Highlands	B	50.2%	43.9%	-6.3%	0	0	74.0%	68.2%	-5.8%	0	0	81.9%	71.5%	-10.4%	0	0
Yamparáez	Highlands	B	45.6%	39.4%	-6.2%	0	0	68.1%	60.6%	-7.5%	0	0	77.1%	70.6%	-6.5%	0	0
Tomave	Highlands	B	40.8%	35.9%	-4.9%	0	0	70.4%	57.7%	-12.8%	0	0	80.7%	63.8%	-16.9%	0	0
Corocoro	Highlands	B	39.9%	35.4%	-4.5%	0	0	62.5%	59.4%	-3.1%	0	0	72.3%	70.8%	-1.5%	0	0
Malla	Highlands	A	39.9%	35.7%	-4.3%	0	0	63.2%	63.3%	0.2%	0	1	72.8%	73.4%	0.6%	0	1

Humanata	Highlands	B	26.7%	23.5%	-3.2%	0	0	58.5%	4.8%	-53.7%	1	0	71.3%	6.1%	-65.2%	1	0
Llica	Highlands	A	57.9%	56.3%	-1.6%	0	0	74.8%	70.4%	-4.5%	0	0	81.6%	76.4%	-5.2%	0	0
Colquechaca	Highlands	C	37.9%	36.5%	-1.3%	0	0	66.4%	41.5%	-24.9%	0	0	77.3%	51.3%	-26.0%	0	0
Betanzos	Highlands	C	53.0%	52.3%	-0.6%	0	0	75.7%	76.8%	1.1%	0	1	83.8%	86.1%	2.3%	0	1
Sabaya	Highlands	B	54.2%	54.0%	-0.3%	0	0	71.6%	67.3%	-4.4%	0	0	78.8%	73.0%	-5.8%	0	0
Culpina	Valleys	C	57.1%	19.1%	-38.0%	1	0	77.2%	21.9%	-55.3%	1	0	84.4%	22.8%	-61.5%	1	0
Incahuasi	Valleys	B	56.8%	28.5%	-28.3%	0	0	77.7%	41.0%	-36.7%	0	0	84.9%	46.8%	-38.1%	0	0
Inquisivi	Valleys	B	33.2%	5.3%	-28.0%	1	0	60.3%	22.5%	-37.8%	1	0	71.5%	34.1%	-37.4%	1	0
Tarvita	Valleys	B	39.9%	12.9%	-27.0%	1	0	62.2%	23.6%	-38.5%	1	0	71.7%	30.7%	-41.1%	1	0
El Villar	Valleys	A	47.0%	23.8%	-23.2%	0	0	66.7%	38.7%	-28.0%	0	0	75.1%	46.7%	-28.4%	0	0
Presto	Valleys	B	44.4%	27.7%	-16.7%	0	0	68.6%	54.3%	-14.3%	0	0	78.1%	68.1%	-10.0%	0	0
Mojocoya	Valleys	B	59.2%	42.6%	-16.7%	0	0	78.7%	60.2%	-18.6%	0	0	85.6%	68.8%	-16.8%	0	0

Acasio	Valleys	B	31.5%	18.4%	-13.0%	0	0	58.9%	44.6%	-14.3%	0	0	70.5%	54.1%	-16.4%	0	0
Villa Libertad Licoma	Valleys	A	58.8%	50.5%	-8.3%	0	0	78.2%	66.3%	-11.9%	0	0	85.2%	74.4%	-10.9%	0	0
Tomina	Valleys	B	57.9%	52.4%	-5.5%	0	0	76.2%	64.9%	-11.3%	0	0	83.1%	69.9%	-13.3%	0	0
Toro Toro	Valleys	B	52.0%	48.6%	-3.4%	0	0	75.2%	75.5%	0.4%	0	1	83.1%	81.7%	-1.4%	0	0

Source: Own elaboration

e. Characterization of the pockets of poverty

To better understand the differences in the speed of progress in reducing energy poverty, we compared the characteristics of municipalities classified as poverty pockets with those in other groups. We used data from the Atlas of Sustainable Development Goals of Bolivia, which provides detailed municipal-level information on various aspects such as poverty levels, health, education, and more.

Based on the literature on poverty determinants, variables such as urbanization (Ren et al., 2017; Abbas et al., 2020), education (Motuma, 2020; Qurat-ul-Ann and Mizra, 2020; Eyasu, 2020), population growth rate (Salvador, 2018; Vista and Murayama, 2011), elevation (topographic) (Salvación, 2018; Vista and Murayama, 2011), access to sanitation or clean water (Vista and Murayama, 2011), labor market variables such as unemployment rate, occupation, or labor force (Motuma, 2016; Salvación, 2018; Abbas et al., 2020), region (Islam and Hossain, 2015), and distance to health centers (Salvación, 2018) are selected for the characterization.

Our results are summarized in Table 8, which provides a comparison between municipalities classified as energy poverty pockets and those in groups 1, 2, and 4. Column 2 compares poverty pockets with all other municipalities. Column 3 compares group 3 with group 1, while Column 4 compares group 3 with group 2. Finally, column 5 contrasts group 3 with group 4.

Table 8: Characterization of municipalities

	(1)	(2)	(3)	(4)	(5)
Chronic malnutrition in children (< 5 years), 2016 (%)	0.0065***	0.0050***	0.0091***	0.0057*	0.0085***
	(2.79)	(2.66)	(2.88)	(1.90)	(3.71)
Population with higher education (>= 19 years), 2012 (%)	0.0009				
	(0.18)				
Literacy rate (>= 15 years), 2012 (%)	0.0032			-0.0089**	
	(0.37)			(-2.06)	
Drinking water coverage, 2017 (% of population)	0.0024			0.0044**	
	(1.62)			(2.42)	
Sanitation coverage, 2017 (% of population)	-0.0017	-0.0027**		-0.0035**	
	(-1.30)	(-2.33)		(-2.44)	
Overall participation rate of men (>= 10 years), 2012 (%)	-0.0075	-0.0098***	-0.0148**		
	(-1.59)	(-2.93)	(-2.36)		

Overall participation rate of women (>= 10 years), 2012 (%)	0.0008				
	(0.30)				
Density of bank branches, 2018 (per 100,000 inhabitants)	-0.0003				
	(-0.17)				
Number of railway/primary roads entering/exiting the municipality, 2019	-0.0035				
	(-0.16)				
Gini coefficient of years of education, 2012	0.9958	0.8549***	1.4456***		0.8078***
	(1.60)	(3.90)	(3.74)		(2.80)
Urbanization rate, 2012 (% of population)	-0.0024*	-0.0026***		-0.0037***	-0.0021**
	(-1.75)	(-2.93)		(-2.94)	(-2.01)
Population Growth	-0.0069			-0.0206***	
	(-1.29)			(-3.36)	
Population Logarithm	0.0390				
	(1.33)				

Average Maximum Temperature	-0.0104				-0.0261***
	(-1.55)				(-6.94)
Observations	317	317	156	161	128
R^2					

t statistics in parentheses
* p<0.10, ** p<0.05, *** p<0.010

The characterization shows energy poverty pockets have lower urbanization rates compared to other municipalities (column 2) and to those in groups 2 and 4, which experienced rapid poverty reduction. This aligns with Ren et al. (2017), who found a negative link between poverty incidence and urbanization rates. Lower urbanization is associated with reduced access to education and health services, greater distances between communities, and higher vulnerability to shocks (Qurat-ul-Ann and Mirza, 2020). Additionally, poverty pockets have slower population growth, further limiting access to infrastructure and services.

The effects of having limited access to healthcare is evident in the higher rates of chronic malnutrition among children in group 3 municipalities. The lack of nearby health centers likely hinders access to essential medical services and nutritional supplements, given this municipalities have dispersed communities, making health centers hard to reach due to poor road conditions, as noted by Salvacion (2020).

Additionally, the lower male labor force participation rate in these areas suggests a limited job market, exacerbated by the small population size and insufficient services.

In terms of education, municipalities classified as energy poverty pockets show a higher Gini coefficient for educational attainment, indicating greater inequality in education. This finding aligns with existing literature suggesting that higher educational attainment is linked to lower multidimensional energy poverty (Crentsil et al., 2020). This elevated Gini coefficient further reflects significant educational inequality, which is consistent with studies demonstrating a negative relationship between higher educational attainment and poverty (Eshetu et al., 2022). Moreover, the greater educational inequality in energy poverty pockets compared to municipalities that have made significant progress in reducing energy poverty supports Eyasu's (2020) findings, which highlight the positive impact of higher educational attainment on household welfare, particularly in rural poverty contexts.

In terms of literacy rates, energy poverty pockets exhibit lower literacy rates compared to other municipalities. This suggests lower educational attainment in these areas, highlighting a negative relationship between energy poverty incidence and education levels. These findings are consistent with existing literature, which shows that households with higher educational attainment are less likely to experience energy poverty (Benson et al., 2005; Qurat-ul-Ann and Mirza, 2020; Eyasu, 2020).

Geographic factors also play an important role, as noted by Abbas et al. (2020). Mountainous terrain can obstruct infrastructure investment, adversely affecting the expansion of services such as electricity, roads, and educational and health facilities. Since many energy poverty pockets are located in the Andean and valley regions at elevations above 3,000 meters, their challenging geography likely contributes to these issues.

5. Final Remarks

Access to clean and affordable energy is essential for household well-being and broader economic development, playing a crucial role in reducing poverty. Electricity is now fundamental for basic needs, such as education and health. Recognizing this, the literature on energy poverty has expanded. Understanding the state and evolution of energy poverty is vital for effective policymaking, yet there are few rigorous studies focusing on Bolivia, the poorest country in South America. With this study, we seek to fill this knowledge gap by assessing energy poverty levels and trends at the municipal level, the smallest local government jurisdiction in the country. Our results are promising in that, overall, we find that the country has made progress towards eradicating energy poverty, and that this happens around a converging pattern: energy poverty is reducing and so are the poverty gaps across municipalities. However, we also find that there are some municipalities that are being left behind in this positive process; we term them pockets of energy poverty.

To measure energy poverty, we use three absolute poverty lines based on the Tarifa Dignidad, a universal public subsidy that reduces energy bills for households with very low consumption levels. Estimating the first three indices of the FGT class of decomposable poverty measures to ensure coherence between national and subnational poverty levels, we find that energy poverty is markedly concentrated in small municipalities (population-wise) located in the highlands.

Simply comparing the first and last periods of observation, we also find that the incidence of extreme energy poverty (consumption < 25 kWh/month) has decreased over time for 201 out of 327 municipalities. In a deeper assessment, we conducted a β-convergence analysis to compare expected and observed rates of energy poverty reduction across municipalities. We do find compelling evidence of convergence. Building on this analysis, we classified municipalities according to their starting positions—advantaged or disadvantaged—and their progress rates, whether rapid or slow. We thus identified 64 municipalities as pockets of energy poverty, which are home to around 806’000 people (7.3%) and characterized by both high initial levels of energy poverty and slow progress in reducing it. A closer examination of these municipalities revealed that their population had systematically lower levels of education and health outcomes compared to municipalities that started from a more advantaged situation. These municipalities also have lower urbanization and slower population growth compared to the rest of the country.

Projections for 2030 suggest an increase in energy poverty in 25 of the 64 identified pockets of energy poverty. Additionally, the energy poverty gap is expected to widen in 19 of these municipalities, with households already below the poverty line falling further behind in energy consumption levels. Moreover, 13 of these municipalities are projected to see greater severity of extreme energy poverty, with the poorest households consuming significantly less electricity than the rest of the poor households.

Our study shows that Bolivia, as a whole, has made significant progress in reducing energy poverty. We show, moreover, that this progress is actually widespread across the 327 municipalities – as we find compelling evidence of a convergence pattern of energy poverty reduction. However, our study focuses mainly on the lasting need to ensure that all municipalities are indeed part of this positive dynamics. Clearly, the 806’000 people living in the 64 municipalities that we identify as being pockets of energy poverty are at a very high risk of simply being left behind in the national development process.

References

Abbas, K., Li, S., Xu, D., Baz, K., & Rakhmetova, A. (2020). Do socioeconomic factors determine household multidimensional energy poverty? Empirical evidence from South Asia. Energy Policy, 146, 111754. https://doi.org/10.1016/j.enpol.2020.111754

Acharya, R. H., & Sadath, A. C. (2019). Energy poverty and economic development: Household-level evidence from India. Energy and Buildings, 183, 785-791. https://doi.org/10.1016/j.enbuild.2018.11.047

Anastasiou, A., & Zaroutieri, E. (2023). Energy poverty and the convergence hypothesis across EU member states. Energy Efficiency, 16(5), 38. https://doi.org/10.1007/s12053-023-10113-9

Aliaga, J., & Mansilla, S. (2023). Evolution of Multidimensional Energy Poverty Risk in Bolivia from 2005 to 2019 (No. 01/2023). Institute for Advanced Development Studies.

Alkire, S., & Foster, J. (2011). Counting and multidimensional poverty measurement. Journal of public economics, 95(7-8), 476-487. https://doi.org/10.1016/j.jpubeco.2010.11.006

Alkire, S., Kanagaratnam, U., & Vollmer, F. (2021). Interlinkages between multidimensional poverty and electricity. A study using the global Multidimensional Poverty Index (MPI). https://ophi.org.uk/interlinkages-2021/

Alkire, S., Nogales, R., Quinn, N. N., & Suppa, N. (2023). On track or not? projecting the global multidimensional poverty index. Journal of Development Economics, 165, 103150. https://doi.org/10.1016/j.jdeveco.2023.103150

Andersen, L. E., B. Branisa & F. Calderón (2019) "Estimaciones del PIB per cápita y de la actividad económica a nivel municipal en Bolivia en base a datos de consumo de electricidad." Investigación ganadora presentada al Centro de Investigaciones Sociales (CIS) de la Vicepresidencia del Estado Plurinacional de Bolivia. May.

Andersen, L. E., Canelas, S., Gonzales, A., Peñaranda, L. (2020). Atlas municipal de los Objetivos de Desarrollo Sostenible en Bolivia 2020. La Paz: Universidad Privada Boliviana, SDSN Bolivia

Andersen, L. E., Villarroel, A., Romecín Duarte, D. V., Cuadros Roca, P. A., Zeballos, C. A. & Calderón, F. (2023). ELBOL: An anonymized research database with monthly electricity consumption in Bolivia 2012 – 2016. Working Paper No. 2/2023. La Paz: Universidad Privada Boliviana, SDSN Bolivia.

Arias, O., & Robles, M. (2007). The Geography of Monetary Poverty in Bolivia: The Lessons of Poverty Maps. *More Than a Pretty Picture: Using Poverty Maps to Design Better Policies and Interventions, Washington, DC: World Bank*, 67-89.

Barnes, D. F., Khandker, S. R., & Samad, H. A. (2011). Energy poverty in rural Bangladesh. Energy policy, 39(2), 894-904. https://doi.org/10.1016/j.enpol.2010.11.014

Barro, R. J., Sala-i-Martin, X., Blanchard, O. J., & Hall, R. E. (1991). Convergence across states and regions. Brookings papers on economic activity, 107-182. https://doi.org/10.2307/2534639

Barro, R. J., & Sala-i-Martin, X. (1992). Convergence. Journal of political Economy, 100(2), 223-251. https://doi.org/10.1086/261816

Bartiaux, F., Day, R., & Lahaye, W. (2021). Energy poverty as a restriction of multiple capabilities: a systemic approach for Belgium. Journal of Human Development and Capabilities, 22(2), 270-291. https://doi.org/10.1080/19452829.2021.1887107

Benson, T., Chamberlin, J., & Rhinehart, I. (2005). An investigation of the spatial determinants of the local prevalence of poverty in rural Malawi. Food Policy, 30(5-6), 532-550. https://doi.org/10.1016/j.foodpol.2005.09.004

Birol, F. (2007). Energy economics: a place for energy poverty in the agenda? The energy journal, 28(3). 10.5547/ISSN0195-6574-EJ-Vol28-No3-1

Boardman, B. (1991). Fuel poverty: from cold homes to affordable warmth. Behalven Press. https://books.google.com.bo/books?id=HwYtAAAAMAAJ

Calvo, R., Álamos, N., Billi, M., Urquiza, A., & Contreras Lisperguer, R. (2021). Desarrollo de indicadores de pobreza energética en América Latina y el Caribe. https://repositorio.cepal.org/items/b6cf8253-f600-46c9-ae5d-6d9663091e15

CEPAL (2009). Contribución de los servicios energéticos a los objetivos de desarrollo del milenio y a la mitigación de la pobreza en América Latina y el Caribe. https://repositorio.cepal.org/items/2d79a170-71b6-4aef-b289-897c9f8814d1

Crentsil, A. O., Asuman, D., & Fenny, A. P. (2019). Assessing the determinants and drivers of multidimensional energy poverty in Ghana. Energy Policy, 133, 110884. https://doi.org/10.1016/j.enpol.2019.110884

Day, R., Walker, G., & Simcock, N. (2016). Conceptualizing energy use and energy poverty using a capabilities framework. Energy Policy, 93, 255-264. https://doi.org/10.1016/j.enpol.2016.03.019

Eshetu, F., Haji, J., Ketema, M., & Mehare, A. (2022). Determinants of rural multidimensional poverty of households in Southern Ethiopia. Cogent Social Sciences, 8(1), 2123084. https://doi.org/10.1080/23311886.2022.2123084

Espinoza Vásquez, L., & Jiménez Pozo, W. (2012). Equidad en la prestación de servicios en Bolivia: tarifa dignidad en electricidad. Revista Latinoamericana de Desarrollo Económico, (17), 135-168.

Eyasu, A. M. (2020). Determinants of poverty in rural households: Evidence from North-Western Ethiopia. Cogent food & agriculture, 6(1), 1823652. https://doi.org/10.1080/23311932.2020.1823652

Foster, J., Greer, J., & Thorbecke, E. (1984). A class of decomposable poverty measures. Econometrica: journal of the econometric society, 761-766.https://doi.org/10.2307/1913475

Foster, V., Tre, J. P., & Wodon, Q. (2000). Energy prices, energy efficiency, and fuel poverty. Latin America and Caribbean Regional Studies Programme. 131(42), 1-7.

Han, L., Han, B., Shi, X., Su, B., Lv, X., & Lei, X. (2018). Energy efficiency convergence across countries in the context of China's Belt and Road initiative. Applied Energy, 213, 112-122. https://doi.org/10.1016/j.apenergy.2018.01.030

Hills, J., (2011) Fuel poverty: the problem and its measurement. CASEreports (69). Department for Energy and Climate Change. http://sticerd.lse.ac.uk/case/

Huang, Z., Ming, X., & Duan, H. (2022). Heterogeneous effects of energy poverty convergence in Europe. Energy Strategy Reviews, 41, 100822. https://doi.org/10.1016/j.esr.2022.100822

IEA (2010) Energy Poverty. How to make modern energy access universal. *Special early excerpt of the World Energy Outlook*. https://iea.blob.core.windows.net/assets/fdbdd604-de2c-4977-8a3f-20f93e68e738/HowtoMakeModernEnergyAccessUniversal.pdf

Janekalne, S. (2016). Beta and sigma convergence in EU28 (Doctoral dissertation, Karl-Franzens-Universität Graz).

Lewis, P. (1982). Fuel poverty can be stopped. National Right to Fuel Campaign. https://books.google.com.bo/books?id=FBQktwAACAAJ

Li, K., Lloyd, B., Liang, X. J., & Wei, Y. M. (2014). Energy poor or fuel poor: What are the differences? Energy Policy, 68, 476-481. https://doi.org/10.1016/j.enpol.2013.11.012

Li, K., & Lin, B. (2015). Metafroniter energy efficiency with CO2 emissions and its convergence analysis for China. Energy Economics, 48, 230-241. https://doi.org/10.1016/j.eneco.2015.01.006

Liddle, B. (2010). Revisiting world energy intensity convergence for regional differences. Applied energy, 87(10), 3218-3225. https://doi.org/10.1016/j.apenergy.2010.03.030

Mashhoodi, B., Stead, D., & van Timmeren, A. (2019). Spatial homogeneity and heterogeneity of energy poverty: a neglected dimension. Annals of GIS, 25(1), 19-31. https://doi.org/10.1080/19475683.2018.1557253

Mahoney, K., Gouveia, J. P., & Palma, P. (2020). (Dis) United Kingdom? Potential for a common approach to energy poverty assessment. Energy Research & Social Science, 70, 101671.
https://doi.org/10.1016/j.erss.2020.101671

Middlemiss, L., Ambrosio-Albalá, P., Emmel, N., Gillard, R., Gilbertson, J., Hargreaves, T., ... & Tod, A. (2019). Energy poverty and social relations: A capabilities approach. Energy research & social science, 55, 227-235. https://doi.org/10.1016/j.erss.2019.05.002

Mishra, V., & Smyth, R. (2014). Convergence in energy consumption per capita among ASEAN countries. Energy policy, 73, 180-185. https://doi.org/10.1016/j.enpol.2014.06.006

Mishra, V., & Smyth, R. (2017). Conditional convergence in Australia's energy consumption at the sector level. Energy Economics, 62, 396-403. https://doi.org/10.1016/j.eneco.2016.07.009

Nussbaumer, P., Bazilian, M., & Modi, V. (2012). Measuring energy poverty: Focusing on what matters. Renewable and Sustainable Energy Reviews, 16(1), 231-243. https://doi.org/10.1016/j.rser.2011.07.150

Nguyen, C. P., & Nasir, M. A. (2021). An inquiry into the nexus between energy poverty and income inequality in the light of global evidence. Energy Economics, 99, 105289. https://doi.org/10.1016/j.eneco.2021.105289

Pachauri, S., Mueller, A., Kemmler, A., & Spreng, D. (2004). On measuring energy poverty in Indian households. World development, 32(12), 2083-2104. https://doi.org/10.1016/j.worlddev.2004.08.005

Peng, H. R., Tan, X., Managi, S., & Taghizadeh-Hesary, F. (2022). Club convergence in energy efficiency of Belt and Road Initiative countries: The role of China's outward foreign direct investment. Energy Policy, 168, 113139. https://doi.org/10.1016/j.enpol.2022.113139

Pereira, M. G., Freitas, M. A. V., & da Silva, N. F. (2011). The challenge of energy poverty: Brazilian case study. Energy Policy, 39(1), 167-175. https://doi.org/10.1016/j.enpol.2010.09.025

Qurat-ul-Ann, A. R., & Mirza, F. M. (2021). Determinants of multidimensional energy poverty in Pakistan: a household level analysis. Environment, Development and Sustainability, 23, 12366-12410. https://doi.org/10.1007/s10668-020-01174-2

Rafi, M., Naseef, M., & Prasad, S. (2021). Multidimensional energy poverty and human capital development: Empirical evidence from India. Energy Economics, 101, 105427. https://doi.org/10.1016/j.eneco.2021.105427

Ren, Z., Ge, Y., Wang, J., Mao, J., & Zhang, Q. (2017). Understanding the inconsistent relationships between socioeconomic factors and poverty incidence across contiguous poverty-stricken regions in China: Multilevel modelling. Spatial Statistics, 21, 406-420. https://doi.org/10.1016/j.spasta.2017.02.009

Salman, M., Zha, D., & Wang, G. (2022). Assessment of energy poverty convergence: A global analysis. Energy, 255, 124579. https://doi.org/10.1016/j.energy.2022.124579

Salvacion, A. R. (2020). Spatial pattern and determinants of village level poverty in Marinduque Island, Philippines. GeoJournal, 85(1), 257-267. https://doi.org/10.1007/s10708-018-9944-6

Sambodo, M. T., & Novandra, R. (2019). The state of energy poverty in Indonesia and its impact on welfare. Energy Policy, 132, 113-121. https://doi.org/10.1016/j.enpol.2019.05.029

Sen, A. (1993). Capability and well-being. The quality of life, 30, 270-293. https://doi.org/10.1093/0198287976.003.0003

Sen, A. (1999). Development as Freedom Oxford University Press Oxford.

Siksnelyte-Butkiene, I., Streimikiene, D., Lekavicius, V., & Balezentis, T. (2021). Energy poverty indicators: A systematic literature review and comprehensive analysis of integrity. Sustainable Cities and Society, 67, 102756. https://doi.org/10.1016/j.scs.2021.102756

Sovacool, B. K., Sidortsov, R. V., & Jones, B. R. (2013). Energy security, equality and justice. Routledge.

Thomson, H., Day, R., Ricalde, K., Brand-Correa, L. I., Cedano, K., Martinez, M., ... & Pereira, M. G. (2022). Understanding, recognizing, and sharing energy poverty knowledge and gaps in Latin America and the Caribbean–because conocer es resolver. Energy Research & Social Science, 87, 102475. https://doi.org/10.1016/j.erss.2021.102475

World Health Organization. (2006). Fuel for life: household energy and health. https://iris.who.int/bitstream/handle/10665/43421/9241563168_eng.pdf

World Health Organization. (2016). Burning opportunity: clean household energy for health, sustainable development, and wellbeing of women and children. https://iris.who.int/bitstream/handle/10665/204717/9789241565233_eng.pdf

Ye, Y., & Koch, S. F. (2021). Measuring energy poverty in South Africa based on household required energy consumption. *Energy economics*, *103*, 105553. https://doi.org/10.1016/j.eneco.2021.105553

Young, A. T., Higgins, M. J., & Levy, D. (2008). Sigma convergence versus beta convergence: Evidence from US county-level data. Journal of Money, Credit and Banking, 40(5), 1083-1093. https://doi.org/10.1111/j.1538-4616.2008.00148.x

Appendix

Table A1: Unconditional Beta Convergence - Conditional Poverty Incidence FGT0 with 50% Tarifa Dignidad

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	ΔFGT_0	ΔFGT_0	ΔFGT_0	ΔFGT_0	ΔFGT_0	ΔFGT_0	ΔFGT_0
FGT_0P1	-0.0013***	-0.0017**	-0.0019***	-0.0043***	-0.0055***	-0.0041***	-0.0052***
	(-2.93)	(-2.52)	(-2.83)	(-6.07)	(-6.13)	(-5.25)	(-6.30)
Δ Pob		-0.0001				0.0000	0.0001
		(-0.50)				(0.35)	(0.57)
B			-0.0007		-0.0003		-0.0004
			(-0.80)		(-0.41)		(-0.48)
C			-0.0015		-0.0012		-0.0014
			(-1.36)		(-1.25)		(-1.22)
D			-0.0027*		-0.0043***		-0.0046**
			(-1.81)		(-2.84)		(-2.59)
Valles				-0.0019***	-0.0020***	-0.0020***	-0.0021***
				(-3.77)	(-4.13)	(-3.50)	(-3.91)

Llanos				-0.0067***	-0.0072***	-0.0068***	-0.0075***
				(-6.22)	(-6.75)	(-6.13)	(-6.52)
Constante	-0.0023***	-0.0024***	-0.0017**	-0.0017***	-0.0015**	-0.0016***	-0.0013
	(-6.53)	(-5.91)	(-2.42)	(-5.46)	(-2.40)	(-3.88)	(-1.35)
N	320	320	320	320	320	320	320
R^2	0.030	0.034	0.047	0.221	0.262	0.223	0.267

t statistics in parentheses
* p<0.10, ** p<0.05, *** p<0.010

Table A2: Unconditional Beta Convergence - Conditional Poverty Incidence FGT0 with 25% Tarifa Dignidad

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Δ FGT_0	Δ FGT_0	Δ FGT_0	Δ FGT_0	Δ FGT_0	Δ FGT_0	Δ FGT_0
FGT_0P1	-0.0052**	-0.0069**	-0.0065***	-0.0094***	-0.0112***	-0.0098***	-0.0114***
	(-2.51)	(-2.33)	(-2.66)	(-3.31)	(-3.69)	(-3.11)	(-3.52)
Δ Pob		-0.0004				-0.0001	-0.0001
		(-1.29)				(-0.63)	(-0.30)
B			-0.0014		-0.0006		-0.0005

			(-0.92)		(-0.52)		(-0.38)
C			-0.0029*		-0.0024*		-0.0023
			(-1.83)		(-1.72)		(-1.36)
D			-0.0094**		-0.0110***		-0.0107***
			(-2.27)		(-2.90)		(-2.82)
Valles				-0.0053***	-0.0052***	-0.0050***	-0.0050***
				(-3.03)	(-3.32)	(-3.23)	(-3.53)
Llanos				-0.0140***	-0.0148***	-0.0133***	-0.0145***
				(-3.26)	(-3.60)	(-3.60)	(-3.92)
Constante	-0.0069***	-0.0081***	-0.0062***	-0.0060***	-0.0060***	-0.0065***	-0.0063***
	(-3.25)	(-3.02)	(-3.01)	(-4.21)	(-3.96)	(-3.49)	(-2.90)
N	320	320	320	320	320	320	320
R^2	0.191	0.238	0.235	0.416	0.478	0.421	0.479

t statistics in parentheses
* p<0.10, ** p<0.05, *** p<0.010