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Energy poverty measures and the identification of the energy poor: A comparison between the utilitarian and multidimensional approaches in Chile

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Energy poverty measures and the identification of the energy poor: A comparison between the utilitarian and multidimensional approaches in Chile

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ABTRACT

This work explores the consequences that different energy poverty definitions might have in the energy policy debate. We estimate the ten percent rule index (TPRI) while proposing and measuring a multidimensional energy poverty index (PMEPI). Both indices uses the 2017 National Survey of Public Perception on Energy applied to a sample of 3,500 households in Chile. Although both measures find that the energy poor represents about 15% of the population, energy poverty levels vary differently across the population depending on the employed measure. Moreover, the indices produce different energy poverty rankings across the territory, and most energy poor households are either TPRI poor or PMEPI poor. We found that this discrepancy between both energy poverty measures is mostly explained by territory-linked factors such as public lighting, service quality, service reliability, and thermal comfort. Consequently, an energy poverty analysis based solely on income or energy expenditure information (TPRI) is likely to neglect supply side constraints that are captured by the PMEPI. When identifying and targeting the energy deprived, the conclusion is that both energy poverty measures should not be used as substitutes but as complements.

Keywords: Energy Poverty; Poverty; Multidimensional Energy Poverty Index, Ten Percent Rule Energy Poverty Index, Affordability, Reliability of Energy Services, Quality of Energy Services, Association of Energy Poverty Measures, Energy Poverty Classification.

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1. Introduction and Background

According to the United Nations, energy is an essential resource to face the challenges of today's society. The three first targets associated to Goal 7 of the Agenda for Sustainable Development require, by 2030, to ensure universal access to affordable, reliable and modern energy services (Target 7.1), to increase substantially the share of renewable energy in the global energy mix (Target 7.2), and to double the global rate of improvement in energy efficiency (Target 7.3). These targets could guide us in defining energy poverty since they introduce the energy-related welfare dimensions that can be considered at the core of any energy poverty measure. These dimensions should also be considered in any energy policy plan since they have important linkages to national development and poverty reduction strategies (Birol, 2018; Kuzemko et al., 2017; Smith, 2018; UN, 2018).

Traditionally, energy poverty has been defined by how it has been measured (Bazilian et al., 2008). However, it is not yet clear whether a consensus on its definition is going to be reached.[4] One can argue that the lack of consensus is advantageous since the circumstances determining energy-related wellbeing varies between and within societies and the definition of energy poverty depends strongly on the context of evaluation. In developing countries, current measures focus primarily on the access to modern forms of energy (Malla, 2013; Nussbaumer et al., 2012; Sadath and Acharya, 2017; Tang and Liao, 2014; Zhang et al., 2019). Contrarily, in developed countries the focus lies prominently on the issue of economic affordability (Boardman, 1991; Hills, 2012; Bouzarovski and Petrova, 2015; Moore, 2012; Robinson et al., 2018). In transition countries, energy poverty measures have been focused on tracking rural electrification as in Brazil (Giannini et al., 2011) or comparing household energy costs to household income to identify the energy poor as in Poland (Miazga and Owczarek, 2015).

In Chile, the government has neither adopted a definition of energy poverty nor conducted a systematic effort to measure it. The long-term policy focus lies on decarbonization (Ministerio de Energía, 2014) while the short-run effort has been devoted to achieving modernization of the electricity distribution service (Ministerio de Energía, 2018). Given this, UNDP (2018) recommends that Chile first defines energy poverty and, secondly, goes beyond the issues of generating and accessing electricity. According to this recommendation, energy poverty has to

[4] Nowadays, there is still no unanimously accepted energy poverty definition being measured in a standardized form at national and international levels. In contrast, there has been international consensus on how to measure income poverty and, more recently, on how to measure multidimensional poverty (see Alkire and Jahan, 2018).

be recognized as a multidimensional phenomenon including the availability of alternative sources of energy, their attributes such as quality, reliability, and its interaction with other contextual factors.

In this paper, we propose a perception-based multidimensional energy poverty index (PMEPI) and measure it for the case of Chile. We do so based on the capability approach advocated by Sen (1999) and using the Alkire and Foster method (Alkire and Foster, 2011). Our empirical effort uses a unique data set based on a survey applied to 3,500 households across the country during 2017. We also identify energy poor households according to the ten percent rule (TPRI) and monetarily poor households that allows to estimate the standard poverty headcount ratio (FTG_0, see Foster et al., 1984). The group of indices is then decomposed across population subgroups to assess their distributional patterns (by macrozones, socio-economic levels, indigenous status, formal schooling of the household head, and the urban-rural divide). Furthermore, we propose an energy poverty classification which is empirically evaluated throughout the use of measures of association between all welfare indices. Finally, we explore the role of households' socio-economic and demographic characteristics as determinants of the level of association between the different energy poverty measures.

This paper contributes to the existing literature on energy poverty in three different aspects. First, our work is the first one that is devoted to researching multidimensional energy poverty at the household level in a recently classified high-income country. The Chilean GDP per capita PPP rose from 10,438 in 1992 to 22,767 in 2017.[5] This is important since there are many low income and lower-middle income countries that are likely to follow a similar pattern of development in the years ahead. Providing estimates of energy poverty in this context as well as exploring its determinant factors could shed light on the design of interventions according to the needs of different societies and their level of development (Bazilian et al., 2008). Second, we explore the level of association between the mentioned measurements of poverty (PMEPI, TPRI and FTG_0). Finally, based on the redundancy level that the different energy poverty measures have, we propose a classification for energy poverty measures according to the impact that this condition may have on the household's overall wellbeing.

The paper is structured as follows. Section 2 briefly describes energy poverty definitions and the capability approach in which our proposed energy poverty assessment is embedded. Section

[5] Figures in 2011 international Dollars. Data from the World Development Indicators.

3 presents the literature review focusing on empirical measures of energy poverty. The methodology in section 4 briefly presents the datasets used in this work, the Alkire-Foster method, the imputation procedure to allow the estimation of TPRI, and the analytical description of a measure of redundancy between both poverty measures. In the same section, we formulate our 2017 Perception-based Multidimensional Energy Poverty Index (PMEPI) for Chile. Results are presented in section 5. Section 6 concludes.

2. Theoretical Framework: A Classification of Energy Poverty Definitions and the Capability Approach

2.1. First-order Energy Poverty Definitions

According to our classification, first-order definitions of energy poverty are those based on the direct impact that the energy underachievement has on the overall household's wellbeing. That is, energy poverty increases the likelihood of a household of being poor (income or multidimensionally). In this category, one can classify energy poverty definitions aiming to capture households unable to access energy services at the home up to a socially- and materially-necessitated level (Bouzarovski et al., 2012; Robinson et al., 2018). The empirical test consists of assessing the level of redundancy between the identification of an energy poverty measure and a poverty measure. If both measures are highly correlated, then energy poverty can be treated as a poverty determinant.

2.2. Second-order Energy Poverty Definitions

In this classification, we move from the overall well-being space to an energy-related subset of it. That is, we focus exclusively on energy-related achievements. From a sectoral policy perspective, this type of indicator should be more informative and useful as they provide information on deficits in energy dimensions that could be addressed by the design and implementation of specific public policies (Bazilian et al., 2008).

2.3. Energy and the Capability Approach

The capability approach advocated by Sen (1999) is a welfare evaluation framework that rejects the view that the commodity holdings (resources) are adequate for judging the freedom that individuals enjoy when pursuing their life purpose. The problem of assessing the quality of life consists in evaluating the functionings (doings and beings that are valuable for the individual) and the capability to function (Sen, 1985). Then, poverty is ultimately a matter of capability deprivation (Drèze and Sen, 1995). In this framework, we define energy poverty as the condition of a household experiencing systematic underachievements in energy-related dimensions that, because their simultaneity, have the potential to negatively affect different functionings (education, health, etc.) and the capability to function. The magnitude of this potential is what distinguishes first and second order energy poverty definitions.

Under the capability approach, first-order definitions of energy poverty should classify households as energy poor if, because energy-related underachievements, they are not capable to function in the unrestricted space of n-tuples of functionings (Sen 1985, 1999). Then, first-order energy poor households are in a high degree a subset of the multidimensionally poor ones. Contrarily, second-order definitions of energy poverty should classify households as energy poor if they are sufficiently and simultaneously deprived across energy welfare dimensions. However, since energy is a resource but not a decisive welfare determinant in the functionings space, energy poor households are not necessarily incapable to function. Here, the level of association between energy poverty and poverty will depend on the capacity of adaptation, substitution, and use of the other available resources and endowments by the household. Consequently, not all energy poor households will be multidimensionally or monetarily poor and not all energy non-poor households will be multidimensionally or monetarily non-poor.

The advantage of second-order measures of energy poverty is that they can provide energy underachievement profiles that are more likely to go hand-in-hand with poverty (income/multidimensional).

3. **Energy poverty: empirical evidence**

3.1. First-order energy poverty measures

First in this category and relevant to this work is the "Ten Percent Rule Index" (TPRI) proposed by Boardman (1991) who took the concept of fuel poverty to cover those households in the United Kingdom whose financial expenditure exceeds 10% of their net income.[6] Other first-order measures are the Low Income-High Costs index (LIHC) proposed by Hills (2012), and the Minimum Income Standard (MIS) indicator by Moore (2012).

Despite their limitations, these first-order definitions of energy poverty have inspired several studies overseas: Bouzarovski et al. (2012) in Bulgaria, Boltz and Pichler (2014) in Austria, Miniaci et al. (2014) and Miazga and Owczarek (2015) in Poland, Legendre and Ricci (2014) and Imbert et al. (2016) in France, and Papada and Kaliampakos (2016) in Greece, Heindl and Schuessler (2015) in Germany, and Mbewe (2018) in South Africa.

Fewer studies have looked at the association level between different energy poverty measures. Romero et al. (2018) finds divergence when identifying who is energy poor between the TPRI, LIHC and MIS measures in Spain. In the same vein, Robinson et al. (2018) finds spatial divergence in the distribution of fuel poverty in England using TPRI and LIHC indicators.

3.2. Second-order energy poverty measures

Since energy-related achievements go beyond the income-expenditure relation, measures in this category consider broader sets of information when assessing the energy poverty status of a household. Nussbaumer et al. (2012) measures energy poverty using the Alkire and Foster method (Alkire and Foster, 2011) throughout the Multidimensional Energy Poverty Index (MEPI). This multidimensional index focuses on the joint deprivation in accessing modern energy services.[7]

[6] Although one can claim that there are differences between fuel poverty and energy poverty, under this utilitarian framework, both concepts have been used interchangeably as they rely on the relationship between income and energy/fuel expenditure.

[7] MEPI is part of the family of multidimensional measures. They are different from the composite indices since multidimensional measures capture the joint distribution of deprivations.

Several studies had been developed using multidimensional indices. Ogwumike and Ozughalu (2015) find that about 75% of the population is energy poor in Nigeria.[8] In the same country, Ozughalu and Ogwumike (2019) find that energy poverty it is more pronounced in the rural sector and in the northern regions of Nigeria. Bersisa (2019) using estimates of the MEPI for Ethiopia in 2011 and 2014 find that a large part of households living in rural and small towns are identified as energy poor. Crentsil et al. (2019) study the dynamics of multidimensional energy poverty in Ghana between 2008 and 2014 and find that even though multidimensional energy poverty was reduced in Ghana from a MEPI value of 0.505 to 0.363 between 2008 and 2014, energy poverty is biased against female-headed and rural households. Finally, Mbewe (2018) estimates the MEPI for South Africa and finds declining levels of energy poverty. In Pakistan, Sher et al. (2014) find that more than the half of the population lives in an energy poverty condition, being the situation much worse in rural areas. Olang et al. (2018) using a MEPI explores the interaction between energy poverty and the determinants of household energy choice in Kisumu City, Kenya.

Although indigenous people might face different state regimes and laws around the world, they can share some energy-related disadvantages in accessing energy services. To the best of our knowledge, there is no study devoted to detecting and explaining the causes of energy underachievement in indigenous communities.

In the developed world, Okushima (2017) uses the MEPI approach considering three dimensions: energy costs, income, and energy efficiency of housing revealing the consequences of the Fukushima accident on the energy poverty level in Japan. Delugas and Brau (2018) measure multidimensional energy poverty using data from dwelling conditions and sources of energy inefficiency in Italy. Their results show negative effects of energy poverty on subjective wellbeing. Finally, Gouveia et al. (2019) estimate the Energy Poverty Vulnerability Index (EPVI) in Portugal by combining socio-economic indicators of the population with buildings' characteristics and energy performance. As a result, the authors show higher energy poverty vulnerability in the inland region and the islands, especially in rural areas.

[8] Sanusi and Owoyele (2016) employ a complementary approach. The authors developed an Energy Development Index (EDI) ranging between 0 and 1, where 1 means maximum energy wellbeing and 0 the lowest energy wellbeing.

3.3. *Association between welfare indicators*

We now turn our attention to the relationship between measures of energy poverty and poverty.

Using the MEPI in developing countries, some studies have found significant correlation between energy poverty and other income and non-income indicators. Olawumi Israel-Akinbo et al. (2018) find that low-income households in rural areas are more multidimensionally energy deprived than those in South African urban areas. In India, Sadath and Acharya (2017) find that energy poverty comes hand-in-hand with income poverty and gender gap, since women manage the domestic activities such as the collecting firewood and cooking. Moreover, they also find a significant associaton between energy poverty and health issues due to the incomplete combustion of fuels. Mendoza et al. (2019) find that income poverty and other socio-economic indicators are strongly correlated with multidimensional energy poverty in Philippines.

Contrarily, in the developed world, Charlier and Legendre (2019) find that a multidimensional fuel poverty index (FPI), considering the dimensions of income, residential energy efficiency, and heating, has a low level of association with the TPRI and LICH indices in France.

3.4. *Energy Poverty in Chile*

Only a few measures of energy poverty are available in the case of Chile. To the extent of our knowledge, only Cerda and González (2017) provide empirical measures of energy poverty at the household level, all of them based on energy-income-expenditure-related metrics (first-order measures). By using data from the 2013 Chilean Expenditure Survey (EPF2013), they found an energy poverty rate of about 5.2% under the Low Income and High Cost (LIHC) measure. The energy poverty rate could go up to 15.7% under the Minimum Income Standard measure (MIS).[9]

The issue of energy poverty has also recently been explored due to the severe air pollution problems caused by households burning wood for heating in urban areas of central-southern regions of Chile. Reyes et al. (2018; 2015) have examined the effects of air pollution control

[9] Cerda and González (2017) also explored the impacts of a tax on CO_2 emissions on energy poverty in Chile and found that, because of the relevance of energy expenditure, any policy that targets emissions but increases the price of energy will increase energy poverty in the country.

policies on energy poverty. Based on case studies in the city of Valdivia, a medium size city located in southern Chile, they found that due to the relevance of households' expenditure on energy for heating and the poor thermal insulation of the current stock of households' dwellings, policies intended to reduce emissions from households should focus on improving thermal efficiency.

4. Methodology

4.1. Data

The information used to implement our energy poverty measures comes from the 2017 National Energy Survey (ENE2017) designed by the Ministry of Energy. The survey considers a total sample of 3,500 households distributed in statistically representative macrozones. A thousand households were surveyed in the metropolitan region (MET) and 500 households in each of the following macrozones: NGR (the northernmost region), NCH (northern region), CEN (central region), CES (central southern region), SUR (the southernmost region). The survey is also representative by socioeconomic level as defined by the National Readership Survey social grades system of demographic classification for Chile (high-middle-class families (ABC1), middle-class families (C2), low-middle-class families (C3), and poor and working-class families (D+E).

The ENE2017 considers the demographic, socio-economic, and geographic information of its respondents as well as plenty of energy-related information from objective questions, quizzes, and perceptions. It also includes income information that can be used to estimate the monetary poverty status of a household and the monetary poverty headcount ratio (FTG_0).[10]

As the ENE2017 does not contain any information on energy expenditure, we rely on the 2017 Chilean Expenditure Survey (EPF2017) to impute the energy expenditure status of the households surveyed in the ENE2017. This procedure is feasible since similarly to ENE2017, the EPF2017 contains equivalent household level demographic information, socio-economic characteristics, and geographic information.

[10] The FTG_0 measure relies on the official poverty line set at 155,443 Chilean pesos in 2017. Following the official procedures, we set the parameter of the household economies of scales at 0.7 used to adjust total per capita income figures.

4.2. The Alkire-Foster Method

The Alkire-Foster (AF) method is a straightforward multidimensional extension of the Foster-Greer-Thorbecke (FGT) poverty measures (Foster et al. 1984). Consider a population of interest of n individuals measured across d indicators of achievement. Then, the n x d dimensional achievement matrix X might have cardinal, ordinal and dichotomous information of the achievement of individual i in indicator j (x_{ij}). Each indicator j has a corresponding deprivation cutoff z_j. Then, an individual is deprived in indicator j if its achievement in that indicator is below z_j.[11] The entries g^0_{ij} of the deprivation matrix g^0 takes the value of 1 if $x_{ij} < z_j$ and 0 otherwise. Normalized weights (w_j) can be used to represent the relative importance of each dimensional deprivation. The weighted sum of deprivations $c_i = \sum_{j=1}^{d} w_j g_{ij}^0$ can take a value between zero (representing an individual with no deprivation) and the unity (representing an individual simultaneously deprived in all dimensions). An individual (or household) is identified as poor if its sum of weighted deprivations c_i is higher than a poverty cutoff denoted by k.

An AF Multidimensional Poverty Index requires aggregating deprivations across dimensions of those already identified as multidimensionally poor while neglecting deprivations of those non-poor (with $c_i < k$). The censoring of the deprivation score vector originates the censored deprivation score vector $c_i(k)$, which preserves the entries of $c_i(k)$ when $c_i > k$ and takes the values of zero for all individuals when $ci < k$. Being q the number of individuals identified as poor, and n the total number of individuals, one possible analytic definition of the AF Multidimensional Poverty Index is $M_0 = \frac{q}{n} \times \frac{1}{q} \sum_i^q c_i(k)$. This is a convenient way to decompose the index in a (multidimensional) poverty headcount ratio ($H=q/n$) and in an intensity factor (A), which is the mean deprivation of those multidimensionally poor. Consequently, the Multidimensional Poverty Index M_0 is a multidimensional headcount ratio (H) adjusted by the deprivation intensity (A) suffered by the poor ($M_0 = H \times A$). These partial indices are of interest to policymakers.

The AF Multidimensional Poverty Index can be decomposed by population sub-groups using population shares as weights and it is possible, using the censored headcount ratios, to assess the contribution of dimensional deprivations to overall poverty (dimensional breakdown). The censored headcount ratio of an indicator corresponds to the population share who are

[11] The individual refers to the unit of analysis. It can be people or households, in which case, the deprivations suffered by the household members are aggregated at the household level.

energy poor and simultaneously deprived in that indicator. Formally, if j is a given welfare indicator, then the censored headcount ratio is defined as $h_j(k) = \frac{1}{n}\sum_{i=1}^{n} g_{ij}^{0}(k)$, being $g_{ij}^{0}(k)$ the censored deprivation matrix.

4.3. Perception-based Multidimensional Energy Poverty Index (PMEPI)

Our proposed energy poverty measure follows the AF method and considers five energy-related achievement dimensions supported by the ENE2017. In the adoption of the normative decision for the PMEPI (dimensions, weights, dimensional cutoffs and an energy poverty cutoff) expressed in Table 1, we consider first the issues mentioned by UNDP (2018). In this report devoted to Chile, any energy poverty measure should not be restricted exclusively to the assessment of the affordability of energy services.[12] The measure should also include an assessment of the access to other energy sources, their qualitative attributes as well as their sustainability. The key role that UNDP (2018) attaches to affordability justifies to put this dimension first in the weighting hierarchy. However, the implicit message is that energy poverty is more than only an affordability problem. This led us to set the energy poverty line k above 1/3 at 0.44.[13]

The dimensions considered in the PMEPI maximize the use of information from the ENE2017 household survey. They are weighted following a discussed hierarchy: (i) affordability (1/3), (ii) energy-related households and neighborhood characteristics: thermal comfort (1/6) and public lighting (1/6), (iii) energy demand behavior (1/9) (iv) quality of energy services: service quality (1/18) and service reliability (1/18), and (v) Information: energy-saving information (2/45), information for a well-informed consumer (2/45), and energy education (1/45).

Finally, PMEPI is Sustainable Development Goals sensitive. It means that progress in each indicator translates into a reduction in the gap between the current situation and the achievement of Targets 7.1, 7.2 and 7.3 (see Table 1).

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[12] According to the Chilean household survey ('Encuesta Nacional de Caracterización Socio Económica' – CASEN), in 2017, electrical coverage reached 99.47% in the country (99.7% and 97.6% in urban and rural areas, respectively). In the ENE2017 household survey, 100% of households reported having access to electrical services.

[13] The assumptions used in this study for the definition of dimensions and weights were discussed in a working session held with members of the Division of Prospective and Regulatory Impact Analysis of the Ministry of Energy, January 2019. Additionally, an equal-weights estimation was performed to test the robustness of our results. The conclusion is that our results are not affected by the weighting structure of the PMEPI.

Table 1. Perception-based Multidimensional Energy Poverty Index (PMEPI) for Chile 2017. Deprivation indicators, cutoffs and weights.

Dimensions	Deprivation indicators (People who live in households with the following characteristics)	Weights	Related SDG Target
	Energy Spending (Affordability)	**1/3**	
Affordability	Households where their adjusted household per capita income is less than two times the poverty line and perceive that, in relation with the quality of services, BOTH services, electricity and natural gas, are found to be expensive.	1/3	Target 7.1
	Energy-related House and Neighborhood Characteristics	**1/3**	
Thermal Comfort	Households where their members perceive that they cannot maintain an adequate temperature during winter.	1/6	Target 7.3
Public Lighting	Households where their members are not satisfied with the Public Lighting in their neighborhood (less than four in the 1-7 scale).	1/6	Target 7.1
	Behavior	**1/9**	Target 7.3
Behavior	Households where their members have adopted up to five (out of 11) of the energy saving measures listed in question P42 of the ENE2017 questionnaire.	1/9	Target 7.3
	Quality of Energy Services	**1/9**	
Service Quality	Households where their members are generally not satisfied with the electricity service OR the natural gas service (from 1 to 3 in the satisfaction scale out of 7). If they are satisfied, they are still deprived if their assessment of the quality of the electricity service is bad AND it is also bad for the natural gas service.	1/18	Target 7.1
Service Reliability	Households where their members are not confident that, in the case of an earthquake, fire, alluvium, volcanic eruption, etc., the fuel supply will be enough to satisfy the needs of the population AND that the electricity service will be restored shortly AND that the natural gas supply will be enough to satisfy the needs of the population.	1/18	Target 7.1
	Information	**1/9**	
Energy-Saving Information	Households where their members know up to five (out of 11) of the mentioned possible domestic actions to save energy listed in question P41 of the ENE2017 questionnaire.	2/45	Target 7.2 & 7.3
Information for a Well-informed Consumer	Households where their members know up to two (out of 5) key energy-related information listed in questions P7 and P29 (price, saving measures, electricity bill, electricity consumption of an electronic device) of the ENE2017 questionnaire.	2/45	Target 7.2 & 7.3
General Energy Knowledge (Energy Education)	Households where their members know up to five (out of 11) of the non-key energy-related concepts listed in questions P17, P7, P5 and P22 of the ENE2017 questionnaire.	1/45	Target 7.3

Source: Own elaboration based on ENE2017.

4.4. *Estimation of TPRI Energy Poverty in the ENE 2017 Dataset*

Measuring TPRI requires information on energy expenditure and income. Although the ENE2017 contains information on households' income, the dataset does not contain any information regarding energy expenditure. Therefore, we rely on regression imputation to predict the point estimates of the household energy expenditure in the ENE2017. If the regression equation in EPF2017 is well specified, estimates are unbiased since the relevant data in ENE2017 is missing completely at random. For predictive purposes, the regression equation in EPF2017 maximizes the use of information that is available in both surveys (ENE2017 and EPF2017). The set of explanatory variables considered for the imputation model are: the household's total disposable income, occupation of the household head, level of education of the household head, type of dwelling, household size, and locality.

4.5. *Redundancy Between Energy Poverty Measures*

To assess the matches and mismatches between PMEPI and TPRI, we use the overlap R^0 (Alkire et al., 2015). Entries $\mathbb{P}_{00}^{jj'}$ and $\mathbb{P}_{11}^{jj'}$ in Table 2 show the percentages of people being classified simultaneously as PMEPI non-poor and TPRI non-poor, and PMEPI poor and TPRI poor, respectively. $\mathbb{P}_{10}^{jj'}$ and $\mathbb{P}_{01}^{jj'}$ show the population shares classified as TPRI poor but not PMEPI poor and vice versa, respectively. The marginal distributions are $\mathbb{P}_{1+}^{\cdot j}$ for the TPRI poor, $\mathbb{P}_{0+}^{\cdot j}$ for the TPRI non-poor, $\mathbb{P}_{+1}^{\cdot j'}$ for the PMEPI poor and $\mathbb{P}_{+0}^{\cdot j'}$ for the PMEPI non-poor.

Table 2. Two-way contingency table for TPRI and PMEPI energy poverty

		PMEPI energy poverty (j')		
		Non-poor	**Poor**	**Total**
TPRI energy poverty (j)	Non-poor	$\mathbb{P}_{00}^{jj'}$	$\mathbb{P}_{01}^{jj'}$	$\mathbb{P}_{0+}^{\cdot j}$
	Poor	$\mathbb{P}_{10}^{jj'}$	$\mathbb{P}_{11}^{jj'}$	$\mathbb{P}_{1+}^{\cdot j}$
	Total	$\mathbb{P}_{+0}^{\cdot j'}$	$\mathbb{P}_{+1}^{\cdot j'}$	**1**

Source: Own elaboration based on Alkire et al. (2015).

If both poverty measures are correlated, and at least one of the headcount ratios is higher than zero, this measure shows the poverty identification matches as a proportion of the minimum of the marginal poverty rates. By construction, R^0 ranges between zero to one and it is defined as follows:[14]

$$R^0 = \frac{\mathbb{P}_{11}^{jj'}}{min\,[\mathbb{P}_{+1}^{\cdot j'}, \mathbb{P}_{1+}^{\cdot j}]}$$

A low redundancy level is an indication of a low degree of substitution between both TPRI and PMEPI. Since TPRI is an income-related measure, a low level of substitution implies that a reduction of energy prices and/or increasing household income will not translate into a proportional PMEPI reduction.

Aiming to investigate the factors behind the R^0 level between both energy poverty measures, we estimate a probit model. In the selection of explanatory variables, we follow Klasen and Villalobos (2019) who investigate the level of association between multidimensional and income poverty in Chile. They find that household education, rurality and household size explain the divergent identification pattern between both poverty measures to a great extent. Consequently, our model specification includes the education level of the household head, macrozones, the indigenous status of a household, household size, and rurality.

5. Results

5.1. Energy Poverty in Chile

Our results in Table 3 show that 15.5% of the population lives in a household classified as multidimensionally energy poor (PMEPI-H) with an average deprivation of 56.3% (PMEPI-A), which results in a Perception-based Multidimensional Energy Poverty Index (PMEPI) of 0.087. Coincidentally, our estimate of TPRI classifies 15.5% of the population as energy deprived while 16.9% of the population is found to be monetarily poor.

By construction, if deprivations were randomly allocated across households, the dimensional contribution to the level of PMEPI would reflect the structure of the weighting

[14] As an example, if the monetary poverty headcount ratio is 10% and the energy poverty headcount ratio is 15%, then R^0= 0.5 implies that 50% of the income poor population is simultaneously energy poor. For robustness purposes, we additionally use the Cramer's V coefficient of association. It is defined as the product of the matches minus the product of the mismatches divided by the square root of the product of the marginal distributions or: $\frac{(\mathbb{P}_{00}^{jj'} \times \mathbb{P}_{11}^{jj'}) - (\mathbb{P}_{10}^{jj'} \times \mathbb{P}_{01}^{jj'})}{(\mathbb{P}_{+1}^{\cdot j'} \times \mathbb{P}_{1+}^{\cdot j} \times \mathbb{P}_{+0}^{\cdot j'} \times \mathbb{P}_{0+}^{\cdot j})^{1/2}}$.

vector. At the country level, the dimension of affordability is by far the most important contributing dimension to energy poverty, explaining 57.6% of its level (see the Dimensional contribution to PMEPI section in Table 3).[15]

Our results in Table 3 also support our expectations about the level of association between first and second-order energy poverty measures with an overall household's wellbeing index. On the one hand, the level of association between TPRI (a first-order energy poverty measure) and the income poverty headcount (FTG_0) is high (R^0=0.94 and Cramer's V=0.81). On the other hand, the level of association between PMEPI (our second-order energy poverty measure) and FTG_0 is low (R^0=0.37 and Cramer's V=0.23). Moreover, the redundancy between TPRI and PMEPI is also low (R^0=0.35 and Cramer's V=0.21). These results are congruent with the findings by Charlier and Legendre (2019) in the case of France. The conclusion is that TPRI and PMEPI are complementary welfare indicators while TPRI can be proxied by the standard monetary poverty measure. Moreover, as Table 3 also shows, our expectations about the level of association between first and second-order energy poverty measures are confirmed across macrozones.

Table 3: Welfare indices, dimensional contribution and measures of association by country level and macrozones.

Indices	Country	Macrozones					
		NGR	NCH	CEN	CES	SUR	MET
PMEPI	0.087	0.070	0.140	0.067	0.090	0.136	0.074
s.e. PMEPI	0.006	0.019	0.033	0.012	0.013	0.024	0.011
Headcount (H)	0.155	0.124	0.251	0.123	0.160	0.245	0.130
s.e. H	0.011	0.032	0.059	0.022	0.023	0.042	0.018
Intensity (A)	0.563	0.568	0.559	0.548	0.560	0.555	0.575
s.e. A	0.005	0.009	0.012	0.014	0.013	0.008	0.007
Dimensional contribution to PMEPI (%)							
Quality	5.62	4.94	7.54	4.53	6.16	6.56	4.65
Spending	57.63	52.86	58.38	57.62	59.01	57.71	57.04
House	29.72	32.23	28.04	28.30	28.75	28.30	31.84
Information	6.60	8.29	5.62	8.48	5.91	7.17	6.15
Behavior	0.44	1.68	0.43	1.07	0.17	0.26	0.32
Ten Percent Rule Index (TPRI) and Monetary Poverty (FTG-0)							
TPRI	0.155	0.149	0.172	0.249	0.190	0.196	0.081
s.e. (TPRI)	0.012	0.065	0.049	0.042	0.032	0.053	0.010
FTG-0	0.169	0.158	0.199	0.264	0.214	0.233	0.082

[15] The affordability dimension is the only one whose contribution to energy poverty exceeds its random expectation of 33.3%. Household and neighborhood's characteristics contribute with 29.72% (expectation of 33.3%), quality of service with 5.62% (expectation of 11.1%), information with 6.6% (expectation of 11.1%), and behavior with 0.44% (expectation of 11.1%).

s.e. (FTG-0)	0.014	0.070	0.064	0.053	0.036	0.061	0.014
Overlap R^0 Measure							
TPRI & FTG0	0.940	0.956	0.927	0.969	0.899	0.985	0.935
s.e. (TPRI-FTG0)	0.018	0.039	0.036	0.029	0.044	0.012	0.041
PMEPI-H & TPRI	0.347	0.295	0.593	0.450	0.358	0.515	0.358
s.e. (PMEPI-H & TPRI)	0.033	0.119	0.072	0.081	0.088	0.085	0.088
PMEPI-H & FTG0	0.374	0.365	0.607	0.476	0.407	0.510	0.323
s.e. (PMEPI-H & FTG0)	0.031	0.128	0.065	0.103	0.086	0.095	0.062
Cramer's V Coeffcient							
TPRI & FTG0	0.807	0.853	0.819	0.843	0.786	0.839	0.720
PMEPI-H & TPRI	0.212	0.172	0.357	0.196	0.192	0.300	0.160
PMEPI-H & FTG0	0.225	0.203	0.413	0.166	0.198	0.344	0.175

Source: Own Elaboration based on ENE2017 and EPF2017 household surveys.
Note: s.e. = Standard errors.

5.2. Spatial Patterns of Energy Poverty in Chile

Figure 1 displays the spatial distribution of the welfare measures. From left to right, it shows the distribution of the PMEPI, its PMEPI-H, TPRI and FTG_0.[16]

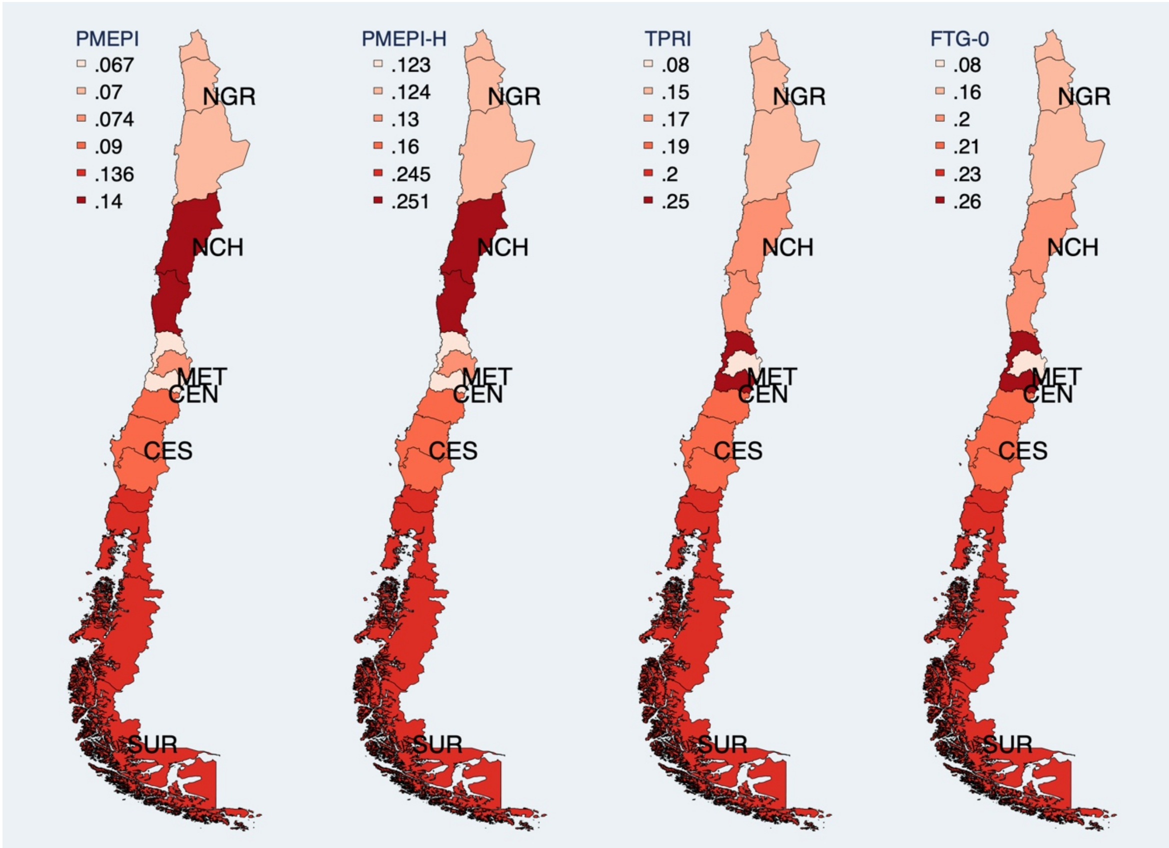
FTG_0 and TPRI produce exactly the same deprivation ranking across macrozones.[17] From the most to the least deprived macrozones, we find: CEN, SUR, CES, NCH, NGR, and MET. Contrarily, PMEPI-H and PMEPI rank from the most to the least energy deprived macrozones as follows: NCH, SUR, CES, MET, NGR, and CEN.

The least deprived macrozone by PMEPI-H and PMEPI is ranked as the most deprived one following the TPRI and FTG_0 poverty measures. Similarly, while NCH is the macrozone with the second lowest monetary poverty prevalence, it ranks as the most deprived one based on our second-order energy poverty measure.

By macrozone, affordability is still the most important contributing dimension to PMEPI, ranging from 52.9% in NGR to 59.0% in the CES macrozone. In this macrozone, although it has the lowest level of multidimensional energy poverty, affordability contributes the most to PMEPI. These results confirm that our measure goes beyond affordability, and therefore, other dimensions related to sustainability, quality, and comfort play a significant role in shaping energy-related wellbeing across the country.

[16] In general, intensity (PMEPI-A) does not explain the variation of PMEPI across the different population sub-groups including macrozones (see Table 3 and Figure 1.A in the appendix). Consequently, differences in energy poverty headcounts reported in Table 3 and in Figure 2.A in the appendix are behind the PMEPI divergence across the different macrozones as displayed in Figure 1.
[17] This is expected as both are income related welfare measures.

Figure 1. Energy Poverty and Poverty Indicators, Chile, 2017



Source: Own elaboration based on ENE2017 household survey.

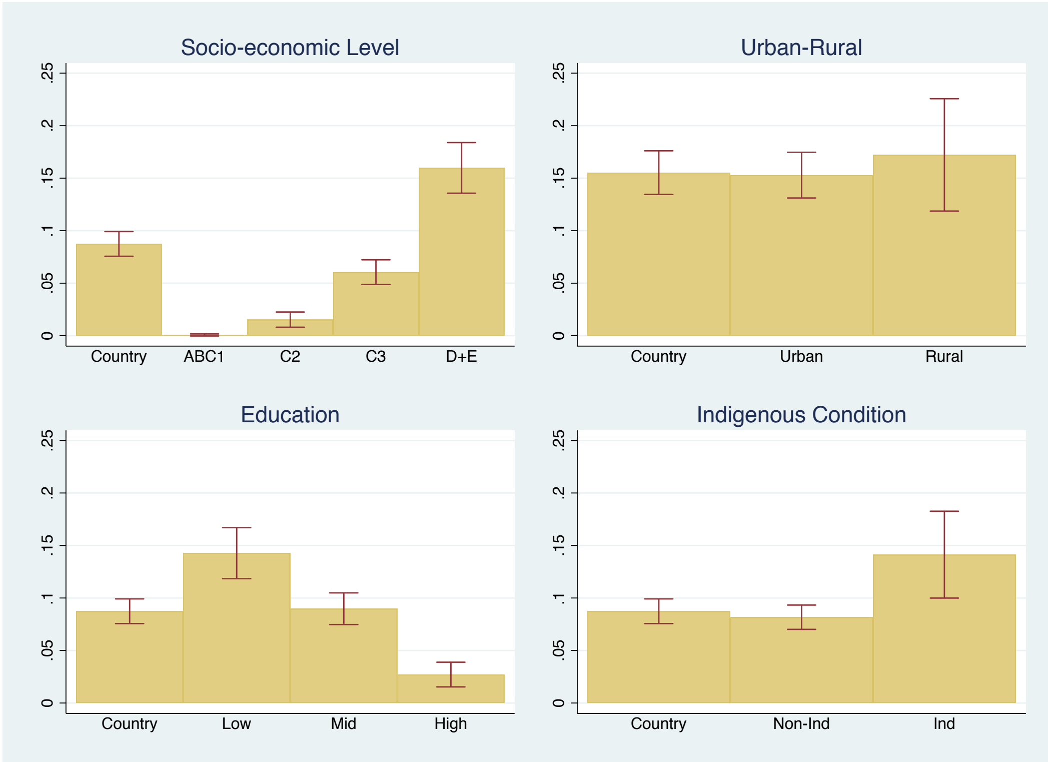
5.3. Energy Poverty in Chile by Population Subgroups

Figure 2 presents our results by the other subpopulations, including socio-economic level, rural-urban divide, education, and indigenous status of the households.

We find statistically significant gaps for most subgroups of the population. The higher the socio-economic classification and education level of the household head is, the lower the PMEPI. A similar pattern is reported by Olawumi Israel-Akinbo et al. (2018), Sadath and Acharya (2017), and Mendoza et al. (2019). Contrarily to the findings by Ozughalu and Ogwumike (2019), Bersisa (2019), Crentsil et al. (2019), Sher et al. (2014), and Gouveia et al. (2019), the urban-rural energy poverty divide is found to be non-existent in Chile.

Figure 2 also shows that the indigenous households experience significantly higher levels of energy poverty. This finding is consistent with the scarce literature on energy poverty and indigenous populations (see Carpenter and Jampolsky, 2015). Moreover, the gap is of interest since the indigenous gap is not connected with the rural condition of indigenous communities.

Figure 2. PMEPI – Energy Poverty Index (PMEPI), Chile, 2017



Source: Own elaboration based on ENE2017 household survey. 95% confidence intervals.

5.4. Explaining the PMEPI Differences Across Population Subgroups

PMEPI differences across population subgroups are mainly caused by differences in PMEPI-H across them. These differences are explained by the level and distribution of the censored headcount ratios (the average deprivation by indicator of those multidimensionally energy poor) presented in Table 4.

Compared against the macrozone with the lowest energy poverty (CEN macrozone), NCH has significantly higher censored headcount ratios for the dimensions of service reliability, affordability, thermal comfort, and energy education (10, 13, 12, and 5 more percentage points than CEN, respectively). Similarly, the SUR macrozone has significantly higher censored headcount ratios for the dimensions of service reliability, affordability, thermal comfort, information for efficiency, and energy education (8, 12, 9, 6, and 7 more percentage points than CEN, respectively). Thus, the gap is not only an issue of affordability; service reliability and thermal comfort, in this order, also play an important role in explaining this discrepancy.

PMEPI gaps by socio-economic and education levels are explained by higher deprivation levels among all indicators. Furthermore, although our results show no evidence that a PMEPI urban-rural gap exists, Table 4 reveals that the gap in service reliability amongst the energy poor is still statistically significant. Finally, Table 4 shows that the indigenous energy poverty gap is because of higher levels of deprivations in almost all indicators with the exception of behavior and service reliability. The largest contributor to the gap (about 11 percentage points) are underachievements in the affordability dimension.

5.5. Overlap Between Energy Poverty Measures and its Determinants

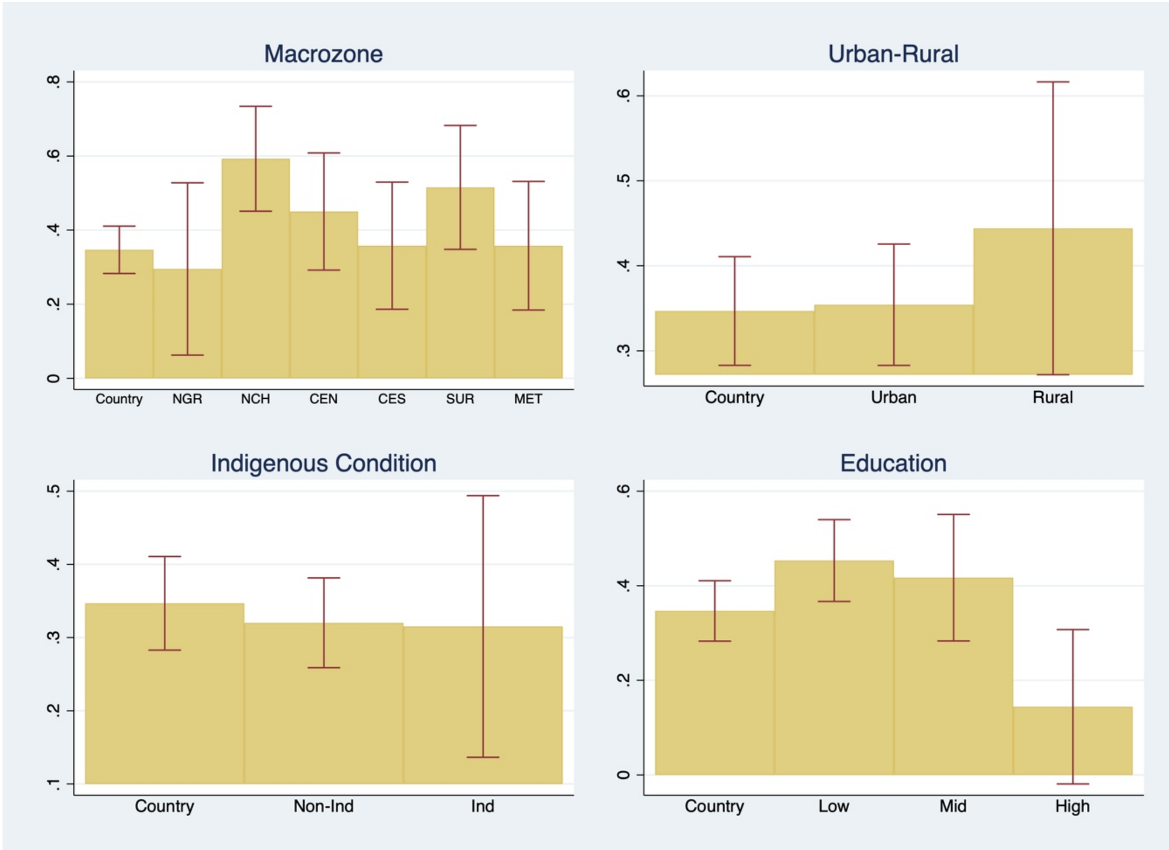
We now explore the overlap between energy poverty measures and its determinants. Figure 3 shows significantly lower R^0 levels among household heads with tertiary education. Klasen and Villalobos (2019) find the same when assessing the association level between income and multidimensional poverty between 1992 and 2017 in Chile. Our results also suggest higher overlap levels in NCH and SUR macrozones as well in rural areas. On the contrary, the indigenous status of a household seems be uncorrelated with the association measure.

Table 4: Censored Headcount Ratios (PMEPI) by population subgroups

Indices	Country	Macrozones						Socio-Economic level				Ethnic group		Education			Zone	
		NGR	NCH	CEN	CES	SUR	MET	ABC1	C2	C3	D+E	Non-Indig.	Indig.	Low	Middle	High	Urban	Rural
Affordability	0.151	0.111	0.246	0.116	0.159	0.235	0.127	0.000	0.019	0.103	0.281	0.141	0.248	0.249	0.156	0.044	0.148	0.171
s.e	0.011	0.034	0.058	0.022	0.023	0.043	0.018	0.000	0.005	0.011	0.021	0.010	0.038	0.021	0.014	0.011	0.011	0.027
Thermal Comfort	0.099	0.051	0.192	0.071	0.096	0.162	0.088	0.001	0.023	0.068	0.179	0.093	0.161	0.160	0.107	0.027	0.096	0.121
s.e	0.008	0.013	0.052	0.016	0.020	0.030	0.012	0.001	0.006	0.008	0.018	0.008	0.030	0.018	0.011	0.007	0.008	0.024
Public Lighting	0.056	0.085	0.045	0.044	0.058	0.069	0.054	0.001	0.013	0.041	0.100	0.053	0.088	0.098	0.052	0.020	0.059	0.041
s.e	0.006	0.024	0.020	0.011	0.014	0.019	0.011	0.001	0.006	0.007	0.013	0.006	0.019	0.015	0.007	0.006	0.007	0.016
Behavior	0.003	0.011	0.005	0.006	0.001	0.003	0.002	0.001	0.007	0.006	0.001	0.004	0.000	0.001	0.003	0.006	0.004	0.001
s.e	0.001	0.004	0.004	0.004	0.001	0.003	0.001	0.001	0.003	0.002	0.001	0.001	0.000	0.001	0.002	0.002	0.001	0.001
Service Quality	0.047	0.033	0.066	0.036	0.052	0.060	0.043	0.000	0.012	0.025	0.090	0.041	0.100	0.066	0.055	0.015	0.047	0.044
s.e	0.006	0.013	0.025	0.016	0.012	0.015	0.011	0.000	0.005	0.005	0.013	0.006	0.023	0.012	0.009	0.006	0.006	0.015
Service Reliability	0.042	0.029	0.124	0.019	0.048	0.100	0.019	0.001	0.007	0.031	0.075	0.039	0.063	0.062	0.038	0.027	0.038	0.066
s.e	0.006	0.017	0.032	0.007	0.016	0.023	0.006	0.001	0.003	0.005	0.014	0.006	0.017	0.013	0.006	0.009	0.006	0.019
Energy-Saving Information	0.024	0.018	0.039	0.033	0.023	0.024	0.020	0.001	0.003	0.012	0.049	0.025	0.019	0.038	0.025	0.008	0.023	0.030
s.e	0.004	0.008	0.015	0.011	0.010	0.009	0.005	0.001	0.002	0.004	0.008	0.004	0.010	0.008	0.006	0.005	0.004	0.015
Information for a Well-informed Consumer	0.080	0.100	0.102	0.088	0.058	0.151	0.064	0.001	0.021	0.066	0.136	0.077	0.114	0.130	0.080	0.030	0.078	0.099
s.e	0.008	0.027	0.026	0.017	0.017	0.028	0.012	0.001	0.005	0.009	0.017	0.008	0.025	0.017	0.010	0.009	0.007	0.023
General Knowledge (Energy Education)	0.050	0.024	0.073	0.015	0.077	0.088	0.037	0.000	0.007	0.031	0.095	0.046	0.088	0.091	0.051	0.008	0.048	0.067
s.e	0.006	0.011	0.019	0.007	0.016	0.020	0.008	0.000	0.003	0.006	0.012	0.006	0.026	0.014	0.008	0.003	0.006	0.020

Source: Own Elaboration based on ENE2017.

Figure 3. Redundancy R^0 measure between PMEPI-H and TPRI, Chile, 2017



Source: Own elaboration based on ENE2017 household survey. 95% confidence intervals.

The results from the probit model investigating the factors behind the overlap between PMEPI and TPRI at the household level are presented in Table 5.[18] Among TPRI poor households, the dependent variable takes the value of 1 if the household is simultaneously PMEPI poor and 0 otherwise.

We find that low education is positively associated with the overlap between both energy poverty indices. The transmission channel works as follows: low education affects negatively the income generation capacity of the household, its energy behavior, and performance in the information dimension. Therefore, it increases the probability that PMEPI and TPRI go hand-in-hand in these households. However, neither household size nor rurality play a significant role in explaining the overlap level. A higher conditional overlap expectation is also found for the NCH and SUR macrozones.

[18] Table 5 also reports estimates for the overlap between PMEPI and FTG_0.

Table 5. Complex survey probit estimation and marginal effects at the mean for redundancy measures at the household level.

Explanatory Variables	PMEPI-H and TPRI		PMEPI-H and FTG_0	
	Probit Model	Marginal effects (at the mean)	Probit Model	Marginal effects (at the mean)
Basic Education	0.775*	0.169*	1.378*	0.295*
	(0.435)	(0.0921)	(0.757)	(0.169)
Secondary Education	1.063**	0.246**	0.00586	0.00115
	(0.494)	(0.116)	(0.759)	(0.149)
Tertiary Education	0.749	0.181	-0.387	-0.0730
	(1.009)	(0.251)	(0.987)	(0.175)
Indigenous Status	-0.358	-0.0769	-0.523	-0.0921
	(0.438)	(0.0885)	(0.344)	(0.0564)
Household Size	-0.00205	-0.000461	0.110	0.0216
	(0.115)	(0.0260)	(0.0985)	(0.0184)
Rural Area	-0.0494	-0.0111	0.388	0.0810
	(0.431)	(0.0962)	(0.437)	(0.0971)
NCH Macrozone	1.342***	0.323***	0.681**	0.150**
	(0.359)	(0.0813)	(0.325)	(0.0734)
SUR Macrozone	0.993**	0.239**	0.552	0.118
	(0.391)	(0.0943)	(0.393)	(0.0894)
Constant	-1.664***	-	-1.817**	-
	(0.587)	-	(0.882)	-
Number of observations	3,500		3,500	
Populaton size	12,754,999		12,754,999	
Subpopulation	260		394	
Subpopulation size	1,761,242		1,981,181	
F	2.33		4.96	
Prob > F	0.0242		0.0000	

Note: The probit models rely on the subpopulations to estimate coefficients. However, given the complex survey design, they rely on the full sample to estimate unbiased standard errors. Robust standard errors in parentheses. ***p<0.01, **p<0.05, *p<0.1.
Source: Own elaboration based on ENE2017 and EPF 2017 household surveys.

The strong impact of the macrozones on the overlap reveals that there are territory-linked factors that are beyond the control of TPRI poor families, affecting their probability of being PMEPI poor. In the NCH and SUR macrozones, high levels of TPRI poverty are followed by relative deficiencies in the quality of service, service reliability, and thermal comfort of dwellings, which results in a high energy poverty overlap. On the contrary, in the CEN macrozone, high levels of TPRI poverty are juxtaposed with high achievements in the same dimensions. This juxtaposition explains the apparent paradox between both energy poverty measures since the CEN macrozone ranks as the most deprived in TPRI poverty and the least poor according to PMEPI.

6. Conclusions and Policy Implications

We have proposed a perception-based multidimensional energy poverty index (PMEPI) and measured it using a unique data set for the case of Chile. Additionally, we identified the ten percent rule energy poor (TPRI) and monetarily poor households (FTG_0) using the standard poverty headcount ratio. Then, we decomposed these welfare indices by population subgroups to assess their distributional patterns. Furthermore, we provided association measures between PMEPI, TPRI, and FTG_0. Finally, we explored the role of households' socio-economic and demographic characteristics as determinants of the association level between the different measures.

We found that 15.5% of the population lives in PMEPI poor households. Coincidentally, the same percentage population is energy poor according to TPRI. The PMEPI differences across population subgroups is explained by the headcount poverty ratio rather than the energy poverty intensity suffered by the households. The PMEPI poverty is higher among those households with lower education levels living in the NCH and SUR macrozones. Interestingly, we do no observe the urban-rural divide, but do observe a gap based on the indigenous background of the household.

Although the affordability deprivation plays an important role explaining PMEPI poverty, the joint distribution of deprivations in other dimensions such as the quality of energy services, service reliability, public lighting, and thermal comfort shape the distribution of the PMEPI poor across different population subgroups. Contrarily to the high association between TPRI and FTG_0, we find a low degree of association between PMEPI and TPRI. These empirical analyses suggest that first and second-order energy poverty measures cannot be used as substitutes but as complements. Given the relatively higher correlation between TPRI and FTG_0 (which are widely available), the energy poverty analysis requires governments to first provide second-order energy poverty measures.

To the best of our knowledge, PMEPI is the first second-order energy poverty measure implemented in Chile, a recently classified high-income country. By discussing the drivers of the divergence between PMEPI and TPRI, we improve our understanding of the complementarity between both energy poverty measures. In fact, we show that energy poverty reduction strategies that only considered the TPRI can be misleading. For example, if the policy interventions prioritize CEN (the macrozone with the highest TPRI), it would do it in the macrozone with the lowest multidimensional energy poverty while neglecting macrozones with the highest PMEPI levels. This lesson can be relevant for other transition countries that are increasing their income levels and that are evaluating the implementation of energy poverty measures and subsequent policies.

The empirically testing for household-level determinants of the divergence between TPRI and PMEPI provides useful insights for policymakers. Among the variables under control of the families, we only find that education supports this divergence. However, the discrepancy is mostly explained by territory-linked factors. Consequently, energy-related wellbeing is not just about income or reducing energy cost, but more fundamentally about improving public lighting, service quality, service reliability, and the quality of building materials to foster thermal comfort.

Finally, there are several ways to extend our work. For example, further research should consider investigating the level of association between the family of multidimensional energy poverty indices (MEPI) and multidimensional poverty measures (MPI). This would improve our understanding of the transmission channels and consequences that energy poverty might have on the wellbeing of the population. The understanding of higher levels of energy poverty among indigenous populations is of interest as we show that the underachievement is not necessarily determined by the predominantly rural condition of these households. Additionally, more disaggregated spatial analysis could also help to improve identification and target of public policies intended to reduce energy poverty at local levels.

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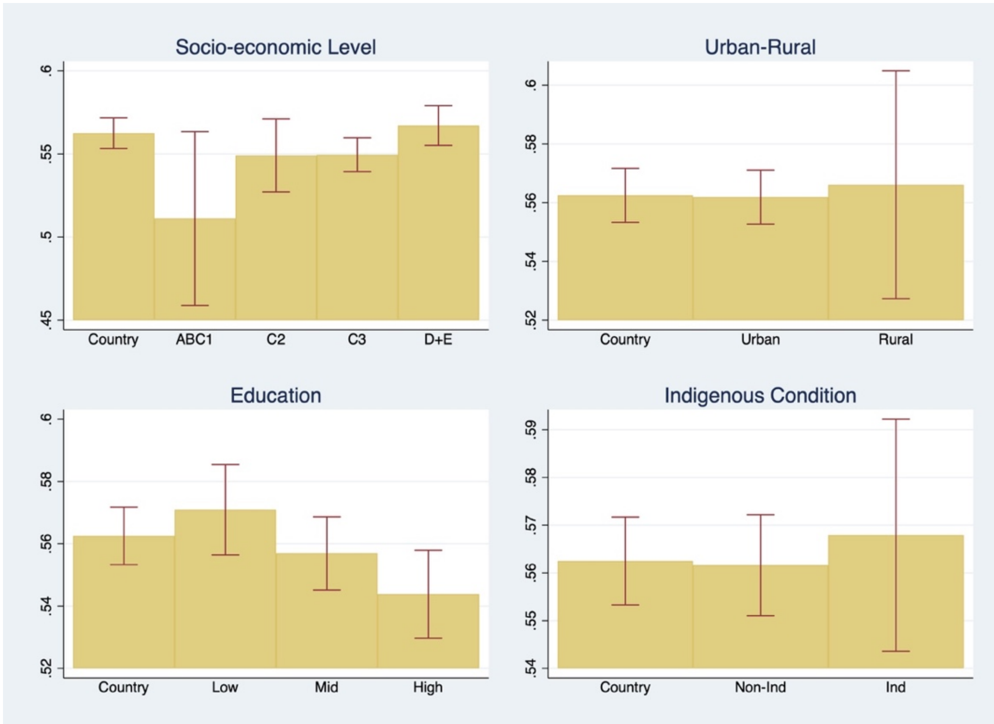
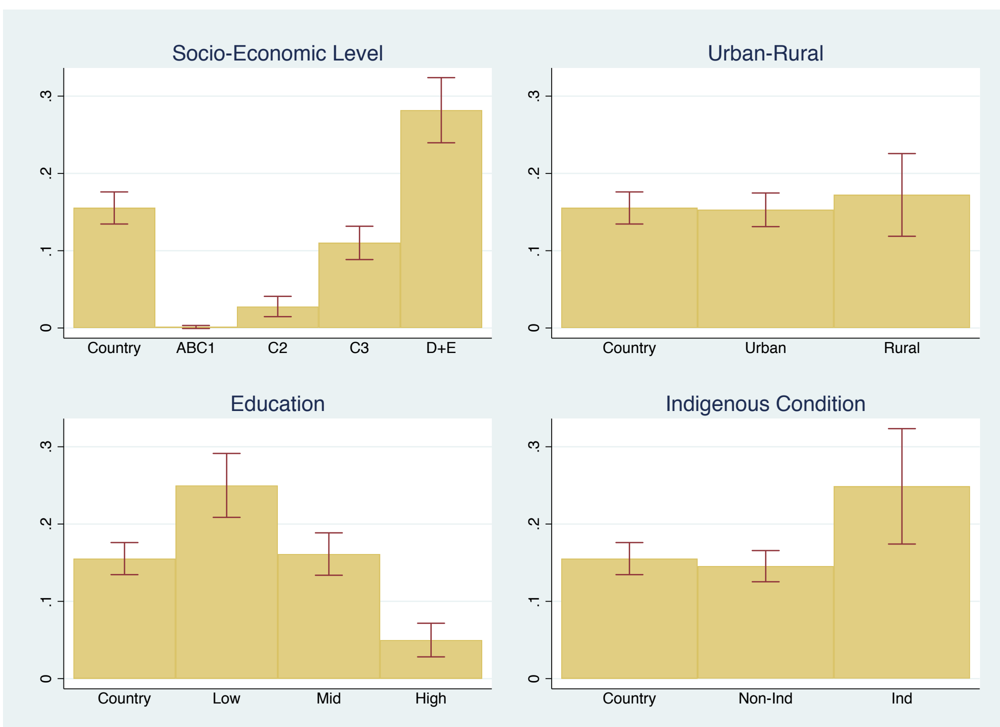
APPENDIX

Figure 1.A PMEPI – Intensity (A), Chile, 2017



Source: Own elaboration based on ENE2017 household survey. 95% confidence intervals.

Figure 2.A PMEPI – Headcount (H), Chile, 2017



Source: Own elaboration based on ENE2017 household survey. 95% confidence intervals.