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Energy poverty and income inequality: An economic analysis of 37 countries

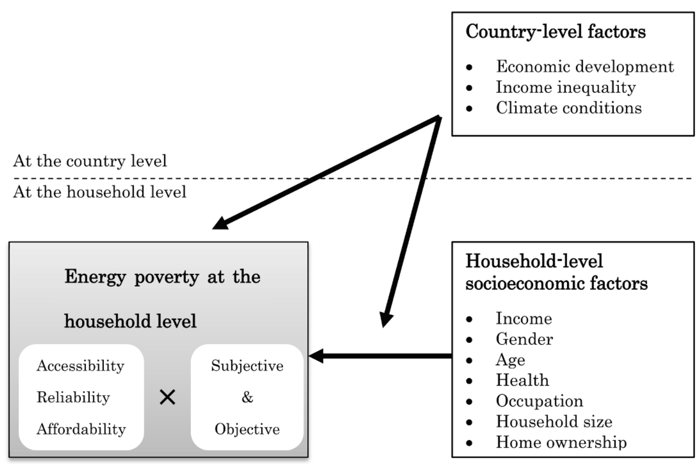
Moegi Igawa, Shunsuke Managi *

Urban Institute & Department of Civil Engineering, Kyushu University, 744 Motooka, Nishi-ku, Fukuoka 819-0395, Japan

HIGHLIGHTS

- We show the determinants of households' energy poverty from a global perspective.
- Affordability is the worst in middle-income countries with more income inequality.
- The negative effect of low income is heterogeneous across countries.
- Different criteria are necessary for defining energy poverty across countries.

GRAPHICAL ABSTRACT



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ABSTRACT

Identifying those who are vulnerable to energy poverty is important to sustainable development, for which vulnerability is known as the inability to access an adequate level of energy services in the home. Although many studies have investigated the determinants of energy poverty at the household level, none has examined how these determinants can change according to a country's economic situation. We use original survey data of 37 countries at various economic levels to address this issue by creating objective and subjective indicators in three dimensions: accessibility, reliability, and affordability. We employ a three-level hierarchical model to investigate how a country's economic development level and income inequality, as well as household-level socioeconomic factors, affect households' energy poverty. We find that energy poverty for country-average households shows an improving trend with economic development in the accessibility and reliability dimensions, while affordability is the worst in countries with a middle level of economic development and greater income inequality. Although it is well known that low household income is linked to worse energy poverty in affordability dimension, our findings add new insight that a higher economic development level and larger income inequality are the most relevant factors in the strong negative association, not climate conditions. We reveal that in addition to country-level factors, several household-level socioeconomic factors are associated with energy poverty in different ways

* Corresponding author.
E-mail address: managi@doc.kyushu-u.ac.jp (S. Managi).

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depending on the dimension, which implies that customized criteria are necessary to define vulnerable households in each dimension.

1. Introduction

When people cannot access domestic services for clean and affordable energy, they face a high risk of physical, mental, and social problems. A lack of energy services occurs in multiple dimensions around the world. The most fundamental one—a lack of access to clean energy (e.g., electricity and gas)—is commonly found in low-income countries in South and Southeast Asia and Africa. In 2019, a total of 840 million people lived without electricity, and 3 billion people relied on traditional fuels (e.g., firewood) to prepare food [1]. An annual 2.6 million deaths are associated with indoor air pollutants emitted by open cooking fires [3]. Collecting firewood also requires significant time and deprives those engaged in the activity—mainly women—of opportunities for education and employment [4]. In contrast, in high-income countries, the affordability of domestic indoor warmth is a serious problem leading to negative health effects, such as respiratory illness [5,6], excess winter deaths [7,8], and mental illness due to the psychological burden of making ends meet [9,10]. More generally, inadequate access to energy services undermines an individual's well-being and social life [11,12].

The problem of a lack of domestic energy services has been studied under the term energy poverty (or fuel poverty).[1] Although energy poverty has been investigated in both low- and high-income countries, a dichotomy between accessibility and affordability is evident in related studies [14]. The energy poverty in low-income countries drew attention in the late 2000s in the development field [15], and these studies focused on the absence of a connection to an electricity grid in developing countries [16]. In contrast, energy poverty in high-income countries started to be addressed earlier, with studies appearing in the United Kingdom in the 1970s [17]. The affordability dimension has been the subject of focus [18,19].

However, at the global scale, the question remains as to how precisely energy poverty can be depicted, given this dichotomy between accessibility problems in low-income countries and affordability problems in high-income countries. In fact, the boundary between accessibility and affordability is becoming blurred in both the real world and the literature in three respects. First, in the last two decades, electricity access has improved by 10 percent and reached 90 percent in 2018 [2]. Reflecting this trend, recent studies on energy poverty in low-income countries have underlined the importance of going beyond electricity connections, and more focus is being placed on reliability and affordability [20,21]. Second, the scope of energy poverty in high-income countries has changed with the expansion of academic attention from the United Kingdom to other high-income countries, including European countries [22–24], the United States [25,26], Australia [27], and Japan [28,29]. In this process, disconnections from an electricity grid, which were not observed in the initial UK studies, were found to exist in some Eastern and Central European countries [30,31]. Furthermore, other dimensions in addition to indoor warmth have been examined. Indoor cooling is another issue linked to the unaffordability of energy services in countries with a slightly warmer climate, such as Eastern and Central European countries and Japan [32,33]. Last, the rising interest in energy poverty in middle-income countries, such as South American countries and China, poses a new challenge. Because of the economic transition that these countries are undergoing, energy poverty is difficult to measure by the simple application of the same indicators used in studies of low- or high-income countries [34–36].

Although the binary between 'accessibility in low-income countries' and 'affordability in high-income countries' is no longer applicable from a global perspective, no study has attempted to examine energy poverty at the household level in a multicountry setting encompassing various development levels. As shown through the lens of energy justice, securing affordable energy has universal value, and there is an urgent need to recognize who is marginalized in energy systems on a global scale [37,38]. To this point, whether indicators for energy poverty can reflect lived experience is key to obtaining a deeper understanding of the plight of the energy poor [39]. Thus, we aim to first present a global picture of households' energy poverty by utilizing original survey data covering 37 countries in Europe, Asia, North and South America, Africa, and Australia from approximately 100,000 samples.

We contribute to the literature on energy poverty in two ways. First, we build on the literature measuring the prevalence and severity of energy poverty. Prior studies have used two main typologies to measure energy poverty: subjective and objective measures. While many studies have shown the prevalence of energy poverty using different indicators, they were based on either a single country or multiple countries with similar economic levels, such as EU member states, African countries or South Asian countries.[2] To present a global comparison of energy poverty, we create five original indicators with subjective and objective measures in three dimensions: accessibility, reliability, and affordability. To shed light on lived experience, using subjective measures is very important because it can uncover what objective measures cannot, such as cultural or individual preferences. Our study is the first attempt to compare energy poverty using subjective measures among countries of different development levels and can add new evidence to studies conducting global comparisons of energy poverty, such as Che et al. [47].

Second, we contribute to the literature on the determinants of energy poverty at the household level. Many studies in sociology and relatively few in economics have investigated the factors that increase the possibility of falling into energy poverty.[3] Although several studies utilized multicountry analyses, they did not explain the country-level determinants of households' energy poverty because the employed methods were descriptive [55], a completely pooled estimation [7], or a completely separate estimation [37,24]. It is important to investigate country-level determinants from a more global point of view because such determinants are key elements that can support more efficient global cooperation for sustainable development. We fill this gap using a hierarchical model. The hierarchical model enables us to capture both country-level and household-level determinants of households' energy poverty. Importantly, it can also reveal how country-level factors change the determinants of energy poverty at the household level. Although it is well-recognized that low household income is a major determinant of energy poverty, how its effect varies depending on countries' heterogeneity is unknown. Specifically, we focus on two country-level factors, economic development level and income inequality, while paying attention to climate conditions. We investigate how they might change the possibility of households falling into energy poverty and whether they change the severity of the association between household income and energy poverty.

[1] Although the term "energy justice" is also used synonymously, it has a broader scope. See McCauley et al., [13] for details.

[2] For example, Healy [40], Doll and Pachauri [41], Nussbaumer et al. [42], Heindl [43], Lenz and Grgurev [44], Bouzarovski and Tirado Herrero [45], Bartiaux et al. [46], Deller [19], and Sambodo and Novandra [34].

[3] For example, Healy and Clinch (2002b), Fahmy et al. [48], Legendre and Ricci [22], Carvalho [49], Bouzarovski and Thomson [37], Muller and Yan [4], Castaño-Rosa et al. [50], Recalde et al. [51], Robinson et al. [52], Abbas et al. [53], Awaworyi Churchill and Smyth [54], and Tabata and Tsai [32].

The remainder of this paper is structured as follows. Section 2 presents a review of the literature on major existing indicators for energy poverty and key factors related to the indicators employed in this study. Section 3 explains the five indicators used in this study to identify households in energy poverty. Section 4 describes the methodology for the empirical analysis. Section 5 presents the results and discussion. Section 6 gives the conclusion.

2. Review of indicators for identifying energy poverty at the household level

This section reviews major existing indicators for energy poverty at the household level.[4] Because the number of existent indicators is vast, this section only highlights the well-known indicators among the scholars, including pioneering indicators or those implemented in international or national institutions. To provide a coherent understanding of these various energy-poverty indicators which have been developed from studies on both low- and high-income countries, we characterize the difference in these indicators by categorizing them into five types of approaches: the connection-based approach, the energy consumption-based approach, the energy service-based approach, the energy expenditure-based approach, and the consensual based approach. We discuss the weakness and strength of each measurement type, leading us to acknowledge the benefit of comparing different types of indicators, as done in Section 5.

The connection-based approach is the most dominant indicator in the context of low-income countries because the absence of a connection to an electricity grid has been the main concern. This binary metric is often employed for international comparisons because of its simplicity and the ease of data collection [57]. However, having a connection to an electricity grid does not always mean that a household benefits from electricity usage because this indicator does not describe the amount and quality of electricity services at the end-user level [58].

To overcome the shortfall of connection-based approach, the energy consumption-based approach was proposed by several studies [59–61]. In this approach, a certain amount of energy consumption is set as the minimum standard for satisfying basic human needs. This approach regards households as energy poor if their energy consumption is lower than the set threshold. One of the criticisms of the energy consumption-based approach is that it does not take into account fuel types but, instead, adopts an oil-equivalent unit to calculate the sum of all fuel types [62]. Another criticism is that this approach does not reflect the quality of energy services because the energy itself can play a role as it is converted into certain energy services (i.e., better energy efficiency can be used to produce more energy services with the same amount of energy). Additionally, the approach does not capture different aspects of the energy supply, such as reliability and affordability [42].

The energy service-based approach has several advantages over the energy-consumption approach. There are two well-known indicators based on this approach. The first is the multidimensional energy poverty index (MEPI) proposed by Nussbaumer et al. [42]. The MEPI has 5 dimensions (e.g., cooking, lighting, entertainment) and uses the ownership of a certain set of electric appliances (phones, fridges, radios, and televisions) as proxies to measure the level of energy services in each dimension. This approach also incorporates information on fuel types for cooking and a connection to an electricity grid. The use of electric appliance ownership in the MEPI enables the affordability aspect to be implicitly considered because households would not have electric appliances unless they assumed that they could pay the electricity bills for these energy services. The other well-known indicator is the Global Tracking Framework (GTF), which was introduced by the United Nations and the World Bank under the Sustainable Energy for All project [58]. The GTF combines many aspects proposed in previous works; it utilizes supply-side attributes, energy services on the demand side, and actual energy consumption. Additionally, the GTF clearly includes a reliability aspect within the supply-side attributes. The dimension of reliability (e.g., electric outages) has received more attention in recent development studies because it can hamper a business and reduce the quality of socioeconomic life [63,64].

The energy expenditure-based approach is mainly adopted for high-income countries, in which affordability dimension of energy poverty has been the main focus. The traditional indicator used is the 10 percent indicator proposed by Boardman [65]. It identifies households as energy poor if their expenditure on required energy is above 10 percent of their income. One of the main criticisms for the 10 percent indicator is that it cannot exclude households with high incomes and high preferences for energy services beyond the socially normal standard, such as households with pools. To overcome such a misspecification, another well-known indicator, Low Incomes and High Costs (LIHC) indicator [66], was adopted as the official definition in England and Wales. Under the LIHC indicator, households are defined as energy poor if their required fuel costs are above the national median and their residual incomes after these energy costs are lower than the national poverty line. The critical point of the energy expenditure-based approach is that it utilizes "required" energy expenditure instead of "actual" energy expenditure. Required energy expenditure is based on the level of energy consumption that household occupants are assumed to need to maintain their livelihood. In the UK's LIHC indicator, required energy consumption is calculated by modeling based on "standard" patterns of the use of domestic energy services (e.g., heating, cooling, lighting) [67].

The consensual approach utilizes self-report responses to survey questions [7]. A sample question, "*Can you afford to keep your home adequately warm?*" was adopted in the EU statistics on income and living conditions [68]. In the consensual approach, households are identified as energy poor if they answer "yes" to these questions.

So far, we have categorized the existent indicators into five approaches. Because the literature often classifies them by whether indicators are based on objective or subjective measures, we also relate these five approaches to objective or subjective measures and then discuss the weakness and strength of these measures. The consensual approach is unique compared with the other four approaches in that it is based on a subjective evaluation, whereas the other four approaches are based on objective measurements. Regarding the objective measures of these four approaches, there can be two weaknesses. The first is that the thresholds are set based on assumptions regarding the "standard" level of energy consumption or services. However, this "standard" is somewhat arbitrary and can vary depending on regional factors, such as social, cultural, or geographical conditions. The second weakness is the difficulty of the data collection. Although the newly proposed indicators, such as the GTF and the LIHC, are more sophisticated and less likely to misidentify the extent of energy poverty than the other previous indicators, they require detailed survey data. Indeed, in most studies and policies across the world, actual energy consumption is used instead [67]. With the consensual approach, these two weaknesses related to objective measures do not exist: the consensual approach does not need to set such a threshold in an arbitrary manner and collect detailed data. In addition, despite its simplicity, the consensual approach can incorporate a respondent's subjective evaluation of the mismatch between required and actual energy into the identification of those who are fuel-poor. In contrast, the weakness of the subjective measure is that households can fail to recognize that they are facing energy poverty even if they are regarded as energy poor according to objective criteria, such as being exposed to health risks [67].

As such, each approach has strengths and weaknesses. Scholars seem to agree that there is no one-size-fits-all measure. Employing a combination of indicators can capture different aspects of energy poverty and

[4] For an exhaustive review of energy poverty indicators in European countries, see Trinomics [56]. Because the number of energy poverty indicators in low-income countries is relatively limited, our paper covers most major existent indicators.

Table 1
The indicators for energy poverty in this study.

Dimensions	Subjective or Objective	Approach	Measures
Accessibility	Objective	Energy services	The first principal component scores multiplied by minus one from PCA with eleven electric appliances: lamps, fans, televisions, radios, landline phones, mobile phones, fridges, microwaves, personal computers, washing machines, and air conditioners. The value is larger when energy poverty is more intense.
	Subjective	Consensual	Takes the value 1 if respondents are dissatisfied with the electricity supply condition.
Reliability	Subjective	Consensual	Takes the value 1 if respondents report that they experience electric outages in their daily life.
Affordability	Objective	Energy expenditure	The average share of the household income spent on energy and water. Energy includes electricity, gas, kerosene, and gasoline. Options were available only for discrete values ("*10–19%*," "*20–29%*," "*30–39%*," "*40–49%*," and "*50% and above*").
	Subjective	Consensual	Takes the value 1 if households consider their electricity bills to be very expensive.

thus provide a better overall picture for policymaking [69]. Based on this background, this paper uses both objective and subjective measures to identify energy poverty at the household level, which we explain in the next section.

3. Energy-poverty indicators and the survey design in this study

This section explains the indicators employed in this study for identifying energy poverty at the household level by relating them with the existent approaches introduced in Section 2. Based on the three approaches (the energy-service approach, the energy-expenditure approach, and the consensual approach), we constructed five indicators for energy poverty in the three dimensions of accessibility, reliability, and affordability (Table 1). All of them are categorized into either objective or subjective indicators based on the selected approach. We then explain our original survey data for these indicators. Although our survey was not specifically designed to examine energy poverty, it includes many questions analogous to the well-used indicators in the literature.

3.1. Energy-poverty indicators in this study

3.1.1. Accessibility

For objective accessibility, we utilized the energy service-based approach, which is recommended for quantifying the electricity accessibility in developing countries. We used information on the ownership of eleven electric appliances: lamps, fans, televisions, radios, mobile phones, landline phones, fridges, microwaves, personal computers, washing machines, and air conditioners. While some of these, such as lamps, are universally regarded as life necessities, the degree of necessity of others is situation dependent. For instance, having a television or radio can have a large impact on daily entertainment for households in low-income countries. On the other hand, both appliances are less important for those in high-income countries who can access Internet services with personal computers. Thus, rather than creating binary variables for the ownership of each appliance as was done in previous studies, we aggregate all information to create a single index with principal component analysis (PCA). Because the correlations among the eleven appliances are all positive, the index is larger when households have less appliances (see Appendix A, Table A.1 for summary statistics for electric appliances and Table A.2 for the results of our PCA).

For subjective accessibility, we used the question, "*Please select all items that you are dissatisfied with*," with the option of "electricity supply conditions". Although satisfaction with supply conditions can be linked to the accessibility dimension, both reliability and affordability can also be issues depending on the respondent. Indeed, it is inappropriate to consider these dimensions separately because several studies imply that households may choose whether to pay connection fees based on the affordability of electricity and appliances [70,16,21,71]. Thus, it is plausible to assume that accessibility can include the reliability and affordability dimensions depending on respondents' situations.

3.1.2. Reliability

Reliability generally includes various characteristics of the electricity grid, such as the frequency and duration of outages and voltage stability (Aklin et al., 2016b). Our indicator is related to outages. We used the question of whether the respondents experienced electric outages in their daily lives, which is in line with the consensual approach. Thus, our indicator captures subjective reliability. Whereas the World Bank offers a database of reliability with objective measures (average duration and frequency of outages at the country level) [72], our indicator is the first to quantify subjective reliability on a global scale.

3.1.3. Affordability

For objective affordability, we used the energy expenditure approach. The question is, "*What is the average share of energy billings (including charges for electricity/gas/water/kerosene/gasoline) out of your monthly household income?*" The options include "*10–19%*," "*20–29%*," "*30–39%*," "*40–49%*," "*50% and higher*," "*do not use at all*," and "*do not know*." We used the median value for each of the first four options and 55 percent for the last option. We assigned a value of 0 for "do not use at all." We excluded households that selected "*do not know*."

Importantly, this question does not have separate options for each fuel type, unlike the other indicators. Among the fuel types referred to in the question, gasoline and water are generally excluded in the literature. In contrast, the question excludes the other more traditional types of fuels, which are included in the studies on low-income countries. Thus, the results obtained from our objective affordability indicator might indicate a higher prevalence of energy poverty for transportation-intensive countries and a lower prevalence for low-income countries than indicated in the literature.

However, this does not mean that our indicator captures energy poverty in a less meaningful way. In fact, these differences allow us to highlight aspects that are less explored in the literature. Energy for transportation has received attention in recent studies, and several studies insist on the importance of including it in the research scope [22,73]. This research area will become more important with the growing trend of rising gasoline prices. The exclusion of traditional fuels is reasonable in that the use of traditional fuels has serious health effects. Although the inclusion of water might be inappropriate for energy studies, water is another basic commodity and might be relevant to the use of household energy because households determine the energy consumption level by considering the use of necessary water.

For subjective affordability, we used a question asking how the respondents feel about their electricity costs. The options include "*very expensive*," "*slightly expensive*," "*just right*," "*slightly inexpensive*," "*very inexpensive*," "*do not care*," and "*do not use at all*." We created a binary variable that takes the value 1 only if households selected "*very expensive*" because the inclusion of "*slightly expensive*" yielded a large proportion of households experiencing energy poverty.

3.2. Survey design and data collection process

The survey includes 37 countries and was conducted in 2015, 2016, or 2017 for each country (see Table B.1 in Appendix B for the corresponding sample size and the year in which the survey was conducted for each country). The selection of 37 countries was based on the representativeness of the global population and the financial and technical feasibility of the survey. To cover households at various economic levels and all six continents (Europe, Asia, North and South America, Africa, and Australia), we also paid attention to selecting countries that are geographically dispersed (e.g., from North European countries, we only selected Sweden and did not select Denmark or Finland) because adjacent countries are more likely to have a similar culture and climate condition. Within each country, we set the goals of the sample sizes according to each country's population age and gender categories. The survey was conducted by the Nikkei Research Company, which has provided many web-based survey services and has a reliable panel of the samples that match the specified gender and age distributions [86]. A questionnaire is distributed to the randomly sampled registered panel that met the targeted conditions. To reach those who cannot access the Internet, we conducted face-to-face interviews in low-income countries, including Egypt, India, Indonesia, Kazakhstan, Mongolia, Myanmar, Sri Lanka, and Vietnam. Because of these procedures and the financial constraints, the sample sizes of each country are not necessarily proportionate to the actual population sizes. The translated questionnaire is subjected to multiple checks to ensure accuracy.

Although one might question the validity of the unbalanced sample sizes for each country, this concern can be addressed to some extent by applying the hierarchical model with random coefficients, as explained in Section 4.

4. Methodology and data

4.1. A hierarchical model in this study

Our main interests are summarized in two points: (1) how macrolevel factors affect energy poverty at the household level and (2) how macrolevel factors change the relationship between energy poverty and household characteristics, especially household income. Such macrolevel factors are understood in this study in terms of contextual effects, namely, the effects of national and regional conditions that—in addition to household characteristics—determine households' energy poverty [74]. Such conditions can include the quality of the energy infrastructure, energy policies, energy markets, climate conditions, and culture. These macrolevel factors generally cannot be changed by a household's actions. Rather, they condition the probability of households falling into energy poverty irrespective of their attributes. For instance, in countries with low-quality electricity grids, households face difficulty obtaining reliable electricity even if their income is among the highest in the country. In European multicountry studies, such contextual effects have been overlooked because the authors estimated the relationship by combining (pooling) data for several countries or by conducting separate estimations for each country [12,24].

This study considers two types of contextual effects. The first is macrolevel factors that condition the probability of households falling into energy poverty, irrespective of household characteristics. The second is macrolevel factors that change the relationship between energy poverty and household characteristics. In econometric models, the former is captured by the intercept, and the latter is captured by the slope of household income. Both the intercept and the slope vary across countries and regions when they are assumed to be randomly distributed. This assumption allows us to analyze countries with different cultures in one estimation process. In addition, both the intercept and the slope are further predicted by country-level factors in this study. Hierarchical models are widely used in many fields, including sociology and economics [75–77]. Hierarchical models seem suitable for studies with subjective dependent variables because they are considered to be largely influenced by cultural factors.

We treat our survey data set as a global sample. For the hierarchical structure, we consider three levels: the household represents level 1, the administrative division represents level 2 (we call this the "region" in the rest of the paper), and the country represents level 3. In this hierarchy, survey respondents are nested within regions, which are further nested within countries. We consider the following equations:

$$EP_{ijk} = \beta_{jk}^{0} + \beta_{jk}^{1}(I_{ijk} - \overline{I_k}) + \sum_{h=2}^{H}\beta^{h}(x_{ijk}^{h} - \overline{x_k^h}) + R_{ijk} \tag{1}$$

$$\beta_{jk}^{0} = \gamma^{0} + \sum_{l=1}^{L}\gamma^{0,l}(z_k^l - \overline{z^l}) + V_k^0 + U_{jk}^0 \tag{2}$$

$$\beta_{jk}^{1} = \gamma^{1} + \sum_{l=1}^{L}\gamma^{1,l}(z_k^l - \overline{z^l}) + V_k^1 + U_{jk}^1 \tag{3}$$

where subscript i denotes the survey respondent ($i = 1, 2 \ldots, N$), j the region ($j = 1, 2 \ldots, J$), and k the country ($k = 1, 2 \ldots, K$). $N, J,$ and K differ depending on the selected energy poverty indicator due to the availability of data. EP_{ijk}, I_{ijk}, and x_{ijk}^h denote energy poverty, household income, and the other household characteristics, respectively, for household i in region j in country k. $\overline{I_k}$ and $\overline{x_k^h}$ are the country means of I_{ijk} and x_{ijk}^h. z_k^l and $\overline{z^l}$are country-level predictors and their grand means, respectively. β_{jk}^0 and β_{jk}^1 are the coefficient of the intercept and the slope for income, respectively, for region j in country k. β^h is the coefficient for the other household-level predictors. γ^0 and γ^1 denote the common part of the intercept and slope for income, respectively, for all countries. $\gamma^{0,l}$ and $\gamma^{1,l}$ are the coefficients of the country-level predictors for the country-level intercepts and slopes, respectively. R_{ijk}, U_{jk}^0, and V_k^0 are the random terms at the household level and the random terms of the intercept at the region level and country level, respectively. For each residual, the variance parameters, σ^2, τ_0^2, and φ_0^2, are estimated. U_{jk}^1 and V_k^1 are the random terms for the income slope at the region level and country level, respectively. For each residual, the variance parameters τ_1^2 and φ_1^2 are estimated. These random terms are assumed to be normally distributed with mean 0. By substituting Eqs. (2) and (3) into Eq. (1) and reordering, the estimation equation is also expressed as follows.

$$EP_{ijk} = \gamma^{0} + \sum_{l=1}^{L}\gamma^{0,l}(z_k^l - \overline{z^l}) + \{\gamma^{1} + \sum_{l=1}^{L}\gamma^{1,l}(z_k^l - \overline{z^l})\}(I_{ijk} - \overline{I_k}) + \sum_{h=2}^{H}\beta^{h}\left(x_{ijk}^{h} - \overline{x_k^h}\right) + (V_k^1 + U_{jk}^1)(I_{ijk} - \overline{I_k}) + V_k^0 + U_{jk}^0 + R_{ijk} \tag{4}$$

For the household-level predictors, we include twelve variables based on the literature [78,52]: household income (*income*: household income in natural logarithm evaluated at US dollar purchasing power

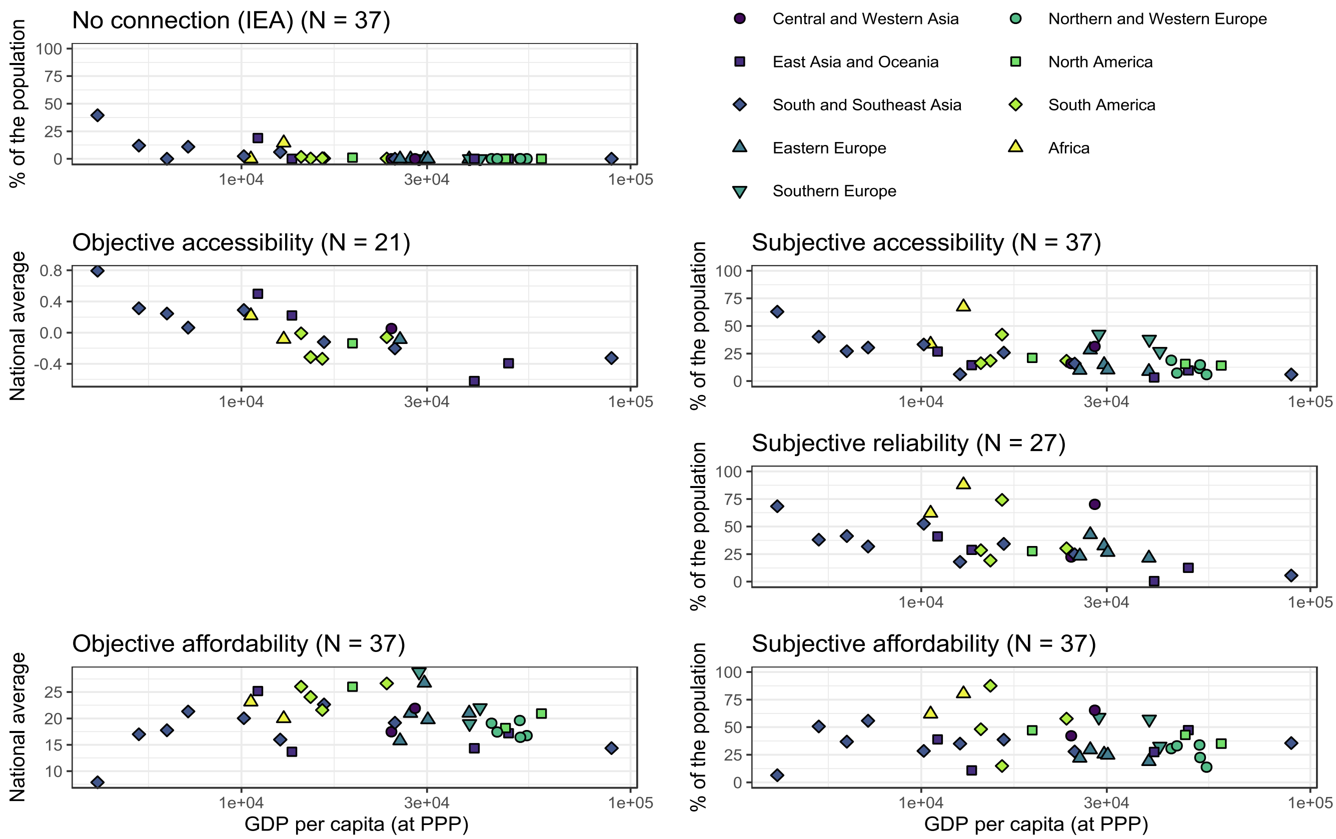

Fig. 1. Energy poverty and economic development.

parity (PPP) after division by the square root of the household size[5]), female (*female*: takes the value 1 for women and 0 for men), household size (*household size*), an elderly person (*old*: takes the value 1 if the respondent's age is 65 or older), having small children (*children*: takes the value 1 if the respondent has children aged 6 or younger), unemployment (*unemployed*: takes the value 1 if the respondent is unemployed or a homemaker), self-employed (*self-employed*: takes the value 1 if the respondent is self-employed), student (*student*: takes the value 1 if the respondent is a student), education (*education*: if the respondent (or his/her partner) has a university or higher degree), self-reported health status (*health*: takes a value between 5 and 1 for the question "*How would you describe your overall health condition?*", 1 = "*very good,*" 2 = "*good,*" 3 = "*neither,*" 4 = "*poor,*" 5 = "*very poor*"), mental health status[6] (*mental*: takes a value between 4, for the worst, and 1, for the best), and housing occupation status (*rent*: takes the value 1 if the respondent lives in a rented apartment or a rented single family home).

β^0_{jk} in Eq. (1) captures the contextual effects, and Eq. (2) explains how the contextual effects are predicted. Eq. (2) includes $z^l_k - \overline{z^l}$, which are differences in the country-level predictors between countries (grand mean-centered values) and random terms that are different across regions and countries. This means that the average risk of households falling into energy poverty is partly determined by country-level and region-level factors in addition to household characteristics. The same applies to β^1_{jk} in Eqs. (1) and (3).

For the country-level predictors (z^l_k), we use GDP per capita (*GDP*) and GINI coefficients (*GINI*) from the World Bank database. We hypothesize that they are the most representative and interesting factors for global comparison. A higher GDP can imply a higher development level of energy infrastructure and energy efficiency and thus can lower energy poverty, especially regarding accessibility and reliability. GINI coefficients represent the degree of income inequality within a country and thus can be a proxy for social protection policies. Additionally, the GDP and GINI coefficients can reflect some cultural aspects of the countries. For instance, the 'required energy' for livelihood maintenance is affected by the country's development level (e.g., having air conditioners is regarded as standard in Japan, while it is not in low-income countries in South Asia). In addition, the size of the income disparity within a country can affect individuals' view of their living standards. In a country with high income inequality, low-income households can have high expectations for energy services as they compare their lifestyle to that of wealthier households [79]. For the analysis, we used GDP per capita in natural logarithm and GINI coefficients divided by 10.

Because the level 1 predictors were centered at the country mean, as shown in Eq. (1), the coefficients β^1_{jk} and β^h capture the effect of the relative position of household *i* within the country. The literature agrees that lower income exacerbates energy poverty because it increases the energy burden and deprives households of opportunities to invest in improving energy efficiency. However, how such negative effects vary across countries and regions has not been explored. Our model reveals this point. In Eq. (3), we model how the slope for household income, β^1_{jk}, is predicted. It is determined in a similar way as the intercept. The income slope captures how the difference in relative incomes within a country can affect households' energy poverty. In other words, how households experience relative income poverty is associated with their likelihood of falling into energy poverty. For instance, consider the situation where a household experiences a drop in income because of the

[5] The reason for dividing by the square root of the household size is to account for economies of scale, as implemented in the poverty literature. Additionally, studies have suggested the use of household income after housing costs. However, we did not consider this because of the lack of available data.

[6] This is calculated as the average value of the answers to 12 questions on the 12-Item General Health Questionnaire [79].

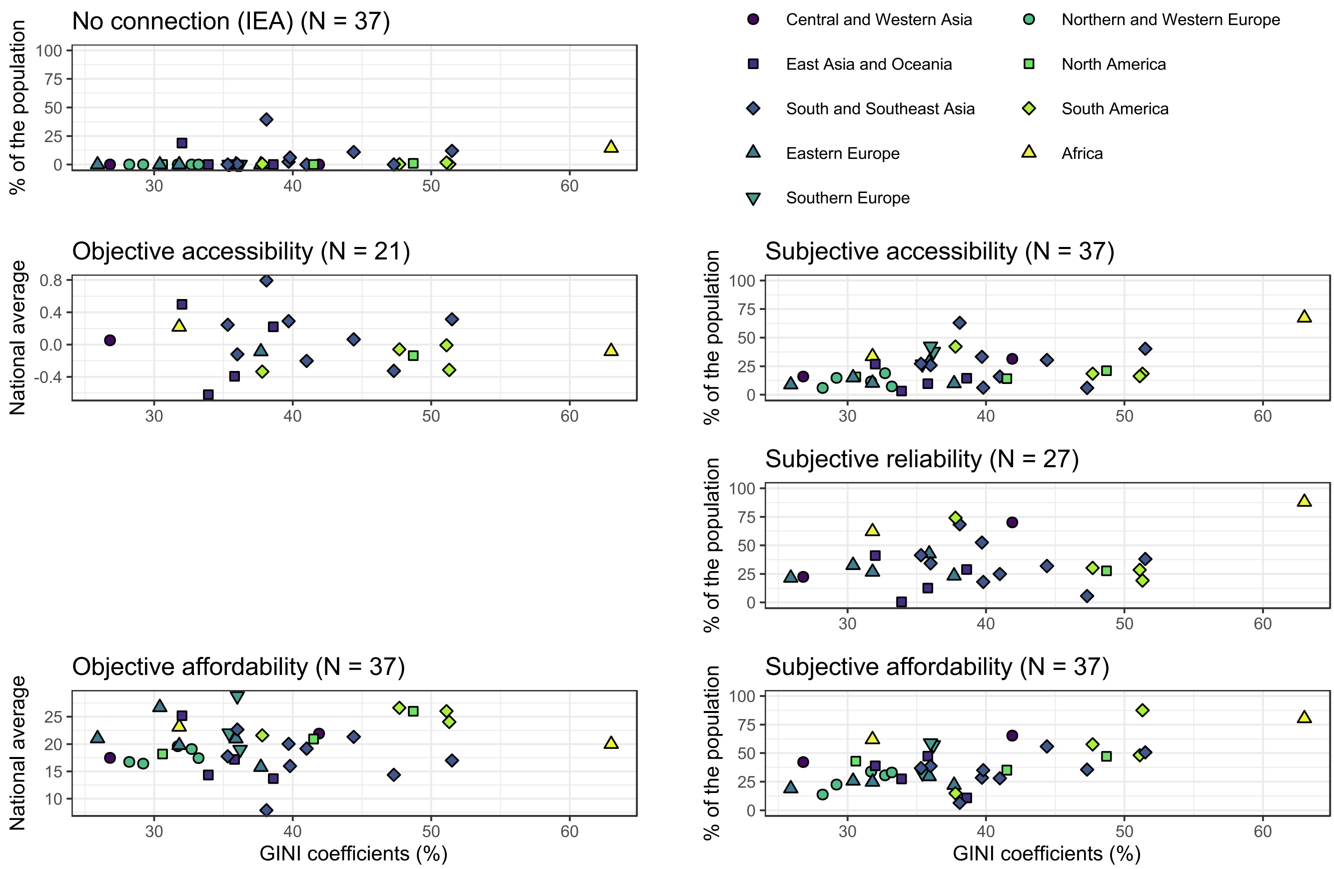

Fig. 2. Energy poverty and income inequality.

need to care for aged parents. This puts the household in a situation of relative income poverty. If households are located in a country where the income slope is close to zero, such a decrease in income would not expose the household to energy poverty. On the other hand, in a country where the income slope is more sharply negative, such a situation would put the household in energy poverty. The factors that can potentially reduce the negative value of the slope are the same as those relevant to the intercept and include energy poverty policies, energy efficiency levels, and energy prices. Thus, we include the same country-level variables.

The exclusion of other country-level variables could generate a bias if these variables were correlated with the GDP and GINI coefficients and affected energy poverty at the same time. In this context, coldness would be critical because it is positively correlated with GDP and can also increase the energy required to ensure a certain domestic temperature level and, in turn, energy poverty. Thus, as a robustness check, we add heating degree days in natural logarithm (*HDD*) as a proxy of coldness.

Before estimating the three-level model as mentioned above, we estimated the two-level hierarchical model with the household level for level 1 and the country level for level 2 to confirm the validity of the hierarchical structure. We adopted the limited maximum likelihood method (implemented in *R*'s lme4 library). For a robustness check, we performed a logistic regression version of these hierarchical models for the binary indicators.

4.2. Data for predictor variables

Household-level predictors are derived from our survey data. As explained in Section 3, the sample sizes are unbalanced among countries. One concern in this unbalanced sample is the accuracy of the estimation for countries with small sample sizes. Intuitively, the estimated coefficients in regions with smaller sample sizes can cause larger bias if we estimate the coefficients for each country by separate estimation. By using random coefficient models in which the random coefficients of each region are assumed to follow a normal distribution, the model can adjust biases of the coefficients of regions with smaller sample sizes by adjusting them according to the global mean coefficient (γ^0 and γ^1 in the Eqs. (2) and (3)) [80].

For the macro variables, we used the World Bank database for macro variables, including GDP per capita, GINI coefficients, and PPP conversion factors [2]. For heating degree days, the KAPSARC database was utilized [81]. If the data for the corresponding year were not available, the data in the closest year was used.

Regarding the sample sizes, the final sample size for the analysis was 92,081 out of the original sample size of 100,956 after eliminating questionnaires with non-responses to the income question. For the summary statistics of the samples in the analysis, see Appendix B, Table B.2.

5. Results and discussion

5.1. Descriptive features

Before proceeding with the results of the hierarchical model, we present the country-level aggregation of energy poverty and its relationship with the GDP and GINI coefficients to outline the descriptive features and discuss the validity of our indicators (Figs. 1 and 2) (For the national average values, see Appendix B, Table B.3). As mentioned in Section 3, subjective accessibility in this study is based on households' dissatisfaction with electricity supply conditions. Thus, it can include reliability and affordability aspects because respondents can link energy prices with the term "supply condition." If the link is close,

Table 2
Parameter estimates in the three-level linear hierarchical models.

	Accessibility		Reliability	Affordability	
	Objective	Subjective	Subjective	Objective	Subjective
Intercept	-0.15^{**} (0.06)	0.22^{***} (0.03)	0.35^{***}	22.32^{***}	0.44^{***}
	(0.06)	(0.03)	(0.04)	(0.78)	(0.03)
GDP	-0.31^{***}	-0.11^{***}	-0.19^{**}	-0.86	-0.01
	(0.06)	(0.03)	(0.06)	(0.91)	(0.04)
GDP^2	0.09	0.02	-0.05	-4.30^{***}	-0.09*
	(0.06)	(0.03)	(0.05)	(0.99)	(0.04)
GINI	-0.08	0.04	0.04	0.93	0.14^{***}
	(0.05)	(0.03)	(0.04)	(0.78)	(0.03)
Income	-0.14^{***}	-0.02^{**}	-0.01	-1.60^{***}	-0.03^{***}
	(0.02)	(0.01)	(0.01)	(0.23)	(0.01)
Income*GDP	0.08^{***}	-0.00	-0.01	-1.10^{***}	-0.01
	(0.02)	(0.01)	(0.01)	(0.27)	(0.01)
Income*GDP^2	-0.01	0.00	0.00	0.25	0.00
	(0.02)	(0.01)	(0.01)	(0.30)	(0.01)
Income*GINI	0.00	-0.00	0.01	-0.58*	0.01
	(0.02)	(0.01)	(0.01)	(0.23)	(0.01)
Female	0.02*	-0.02^{***}	-0.01^{***}	0.82^{***}	0.03^{***}
	(0.01)	(0.00)	(0.00)	(0.08)	(0.00)
Old	-0.13^{***}	-0.01	-0.00	-1.36^{***}	-0.01
	(0.02)	(0.00)	(0.01)	(0.16)	(0.01)
Children	0.15^{***}	0.03^{***}	-0.01*	1.04^{***}	0.01^{***}
	(0.01)	(0.00)	(0.00)	(0.10)	(0.00)
Student	-0.08^{***}	-0.03^{***}	-0.00	0.16	-0.10^{***}
	(0.01)	(0.01)	(0.01)	(0.19)	(0.01)
Unemployed	-0.04^{***}	-0.01*	0.01*	0.32^{**}	0.01
	(0.01)	(0.00)	(0.00)	(0.12)	(0.00)
Self-employed	0.01	0.00	0.02^{**}	-0.12	0.02^{***}
	(0.01)	(0.00)	(0.01)	(0.15)	(0.01)
Education	-0.17^{***}	-0.00	0.02^{***}	-1.53^{***}	-0.03^{***}
	(0.01)	(0.00)	(0.00)	(0.09)	(0.00)
Household size	-0.06^{***}	0.01^{***}	0.01^{***}	0.62^{***}	0.02^{***}
	(0.00)	(0.00)	(0.00)	(0.03)	(0.00)
Health	-0.03^{***}	-0.01^{***}	0.01^{***}	-0.04	-0.00
	(0.00)	(0.00)	(0.00)	(0.05)	(0.00)
Mental	0.03^{***}	0.04^{***}	0.03^{***}	2.43^{***}	0.06^{***}
	(0.01)	(0.00)	(0.00)	(0.09)	(0.00)
Rent	0.24^{***}	0.01*	-0.01	-0.40^{***}	-0.00
	(0.01)	(0.00)	(0.00)	(0.10)	(0.00)
AIC	128897.64	76761.94	70332.74	658436.72	103560.84
BIC	129130.94	77007.13	70569.31	658679.80	103805.81
Log Likelihood	-64422.82	-38354.97	-35140.37	-329192.36	-51754.42
N	58,271	92,081	66,101	84,879	91,286
J	654	1054	832	1051	1052
K	21	37	27	37	37
τ_0^2	0.01	0.00	0.01	2.15	0.00
τ_1^2	0.00	0.00	0.00	1.51	0.00
Cov (U_{jk}^0, U_{jk}^1)	-0.00	-0.00	0.00	-0.62	0.00
φ_0^2	0.03	0.01	0.03	12.14	0.02
φ_1^2	0.00	0.00	0.00	0.74	0.00
Cov (V_k^0, V_k^1)	-0.00	-0.00	-0.00	0.30	-0.00
σ^2	0.53	0.13	0.17	135.00	0.18

Notes: $^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$. Standard errors in parentheses.

distinguishing the accessibility and affordability dimensions would be meaningless. However, the results in both dimensions are quite different: the former is linearly correlated with GDP, while the latter is not. Because subjective energy poverty from the perspective of accessibility shows a decreasing trend with an increase in GDP, it is assumed that the respondents recognized the term "supply condition" as denoting infrastructure-related factors rather than affordability aspects. In addition, because the reliability dimension of energy poverty shows a similar trend as subjective accessibility, it can be said that the term "supply condition" is a comprehensive term including the reliability aspect. Nevertheless, both dimensions position countries in a distinct way, and thus, it is helpful to separately quantify each dimension.

It is worth comparing energy poverty in this study with the electrification rate in the IEA database because this database is the only resource available for the global comparison of energy poverty. Fig. 1 shows that energy poverty in terms of electrification converges to zero as GDP per capita reaches the middle level ($13,500 at 2010 PPP). On the other hand, accessibility in this study shows a much larger heterogeneity than the electrification rate, which has been regarded as a measure of accessibility. Furthermore, heterogeneity exists among each of the three dimensions and between the objective and subjective indicators. This confirms the importance of quantifying energy poverty in different dimensions and with different measures beyond the single index of the electrification rate.

Due to these large heterogeneities, it is challenging to depict simple features for a global understanding of energy poverty. In terms of geographical classification, only Northern and Western European countries show similar trends in all dimensions, while the countries in the other continental groups are dispersed. When looking at specific countries, the differences in dimensions and measures can position

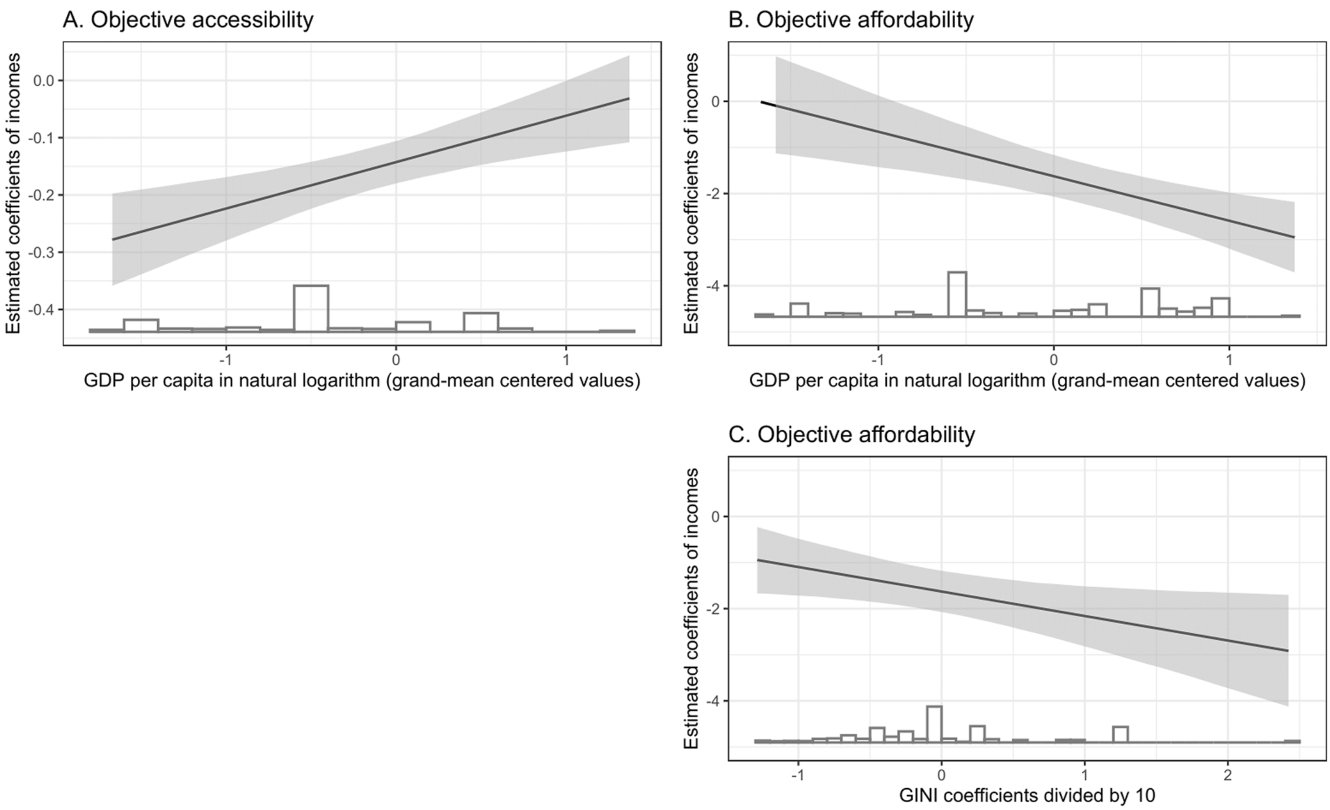

Fig. 3. The relationship between the estimated coefficients of household income and economic factors. Notes: The histograms in the bottom of the figures indicate the sample distribution in the analysis.

countries in quite different ways. For instance, Myanmar is among the countries with the worst energy poverty in terms of accessibility and reliability, while it is the best-performing country in terms of affordability. Although in the case of Myanmar, the difference between the objective and subjective measures does not affect its relative position with respect to energy poverty within the surveyed countries, it matters for other countries. For instance, South Africa presents the worst level of energy poverty in all dimensions when considering subjective indicators, while its objective energy poverty is at the middle level. The opposite trend is observed in Mongolia, which holds the lowest rank in terms of objective energy poverty but has an average level of subjective energy poverty. As we discuss later, the empirical results offer an explanation for the differences in the results between the objective and subjective indicators.

5.2. Estimation results

The level-three models show better fit than the level-two models, according to the AIC and BIC (See Appendix C, Table C.1). This implies that regionally specific factors that cannot be captured at the country level have a large impact on energy poverty. The estimation results of the linear regression and the logistic regression are mostly consistent (see Appendix C, Table C.2). Additionally, the consideration of heating degree days does not substantially change the estimated values for the coefficients (see Appendix C, Table C.3). Thus, this section explains only the results of the three-level linear hierarchical models (Table 2).

5.2.1. How GDP and GINI coefficients are associated with the country-level intercepts

For the association between the intercept and GDP, there seems to be a linear relationship in accessibility and reliability and an inverted U-shaped relationship in affordability (Fig. 1). Thus, we add the square term of GDP to the predictors at the country level. The results confirm that the intercepts in accessibility and reliability are significantly correlated with GDP in a negatively linear relationship, while the intercept in affordability is associated with an inverted U-shaped curve (Table 2). This implies that accessibility and reliability are the least achieved dimensions for households in countries with low development levels, while affordability is a more serious problem for households in middle-income countries than for those in low-income and high-income countries.

We posit three possible explanations for this difference in the three dimensions. The first is that affordability plays a key role only after accessibility and reliability are ensured. In this study, higher energy poverty in terms of accessibility means that households own few electric appliances and are dissatisfied with the electricity supply conditions. However, the results show that this situation does not translate into worse affordability for electricity services. Although low-income countries have the lowest level of access to electricity, the probability that households feel their electricity costs to be “very expensive” is lower than in middle income countries. This implies that households in the initial stage of expansion of the electricity infrastructure do not expect the level of electricity services represented by the global standard. The second explanation is that low energy efficiency in middle-income countries exacerbates unaffordability. Better energy efficiency enables consumers to access more energy services with the same budget. Several studies show that residential energy efficiency is low in countries where this study finds energy poverty in terms of affordability to be high. Thomson and Snell [24] show that Eastern and Southern European countries suffer lower levels of energy efficiency than Northern and Western European countries. International Energy Agency [82] shows that the energy efficiency in the transportation sector is worse in South American countries than in countries such as Japan, the U.S., China, and Canada due to less use of electrified vehicles. The third reason is that policies specific to energy poverty might have mitigated energy poverty. Policies addressing energy poverty have been most discussed in EU member states and are stipulated among the targets in the EU policy framework [83].

Regarding the association with the intercept and GINI coefficients, the coefficient was significantly positive only for subjective affordability (Table 2), which is also confirmed in Fig. 2. This result implies that households living in a country with higher income inequality are more likely to experience higher energy poverty subjectively, irrespective of the household's characteristics. A possible reason for this is related to our explanation for the inclusion of the GINI coefficient. That is, in countries with larger income disparities, more households experience a larger gap between their expectations of standard energy costs and the actual costs because they can compare their living standards with those of wealthier households in the same country.

5.2.2. How GDP and GINI coefficients are associated with the marginal effect of household income on energy poverty

In addition to the effect on the intercepts, GDP also has a significant effect on the income coefficients for accessibility and affordability with the objective measures (Table 2). The way GDP changes the association between energy poverty and income differs between accessibility and affordability (Fig. 3). For objective accessibility, the coefficient of income approaches zero as GDP increases because the coefficients of income and the interaction term between GDP and income are significantly negative and positive, respectively (Table 2, Panel A of Fig. 3). On the other hand, for objective affordability, the coefficient becomes increasingly negative as GDP increases because the coefficient of the interaction term is significantly negative (Table 2, Panel B of Fig. 3). Remember that household income in the analysis is centered by the country mean, meaning that it captures a household's relative position within the country where it is located. Thus, these two contrasting results imply that a one percent drop in household income has different effects depending on the GDP level of a country and the dimension of energy poverty. In countries with low GDP, the differences in relative income within a country are critical to the objective accessibility dimension but not to the objective affordability dimension. Fig. 3 shows that as GDP increases, what matters shifts from accessibility to affordability. This finding is plausible because some of the electric appliances (e.g., washing machines, air conditioners, personal computers) in this study are not common goods in low-income countries, and household income is a crucial factor determining how many households can own these appliances. In high-income countries, on the other hand, these appliances are relatively easier to access for all households, but the share of expenditure on them can vary depending on the relative income level within a country. For middle-income countries, both objective accessibility and affordability matter.

Importantly, in the reliability dimension, the coefficient of household income is not statistically significant, and only the coefficient of GDP is significantly negative. However, the results for the two hierarchical linear models show a significantly negative effect of income (Appendix C, Table C.1). These results mean that subjective reliability (daily experience of outages) depends solely on countries' development level and regional heterogeneity, implying that regionally specific factors are more important than household income.

As for the effect of income inequality on the income coefficients, panel C in Fig. 3 shows that income coefficients become increasingly negative as GINI coefficients increase. Thus, considering the result of the negative effect of the GINI coefficients on the intercept in subjective affordability, it is found that income inequality affects affordability in both the subjective and objective measures but through different channels: in the subjective measure, income inequality is associated with more severe energy poverty for all households, while in the objective measure, it is linked to how strongly the difference in relative income within a country is associated with energy poverty.

5.2.3. Estimated coefficients of other household-level predictors

The other household-level variables, in addition to income, have different associations across dimensions and measures. Because our main concern is the effect of macrolevel predictors and household income, these variables are not randomly estimated across the countries. Although this might cause us to overlook country heterogeneity, the number of coefficients that can be treated as random is limited because of the computational load; thus, we do not address this point in this study. However, the overall results can provide a global benchmark of how the relative change in these characteristics within a country affects energy poverty at the household level. Identifying such societal factors can facilitate better targeting of the energy poor by policy supports [84].

For instance, being old is not in itself associated with worse energy poverty once income is controlled. Rather, it is associated with improved energy poverty in the accessibility and affordability dimensions. Having children is positively associated with worse energy poverty except in the reliability dimension, and mental illness is associated with worse energy poverty in all dimensions. These results imply that these are important characteristics for identifying vulnerable households on the global scale.

5.3. Discussions on policy implications

It is important to identify the determinants of energy poverty because this clarifies which households are more likely to experience energy poverty and thus should be better targeted by policy supports [84]. Although numerous studies have explored these factors at the household level, our study is the first to reveal the country-level factors and their effects on the association between income and energy poverty at the household level.

As stipulated in the United Nations Sustainable Development Goals (SDGs), securing the affordability of energy (SDG 7) and taking actions to address climate change (SDG 13) are globally important goals. Addressing energy poverty plays a key role in addressing both goals at the same time. When climate change actions are implemented with austerity policies, such as higher energy taxes, a disproportionately heavier burden is placed on households with low income, resulting in exacerbation of energy poverty. The findings in this study provide four policy implications. The first is related to indicators for identifying households in energy poverty. Several recent studies on middle-income countries have attempted to quantify energy poverty with the 10 percent indicator [34–36]. Although employing the same measure is important in terms of global comparison, its simple application as an indicator for tracking a country's progress over time is inappropriate because the 10 percent indicator was developed in the context of high-income countries. Our finding suggests that a threshold higher than 10 percent would be more appropriate for countries with a middle level of economic development and higher income inequality because their average energy burden is higher. In this sense, households in these countries are more vulnerable to a rise in energy prices. Thus, the second policy implication is that an improvement in energy efficiency is most critical in countries with a middle level of economic development and higher income inequality because this has been regarded as the sole strategy to reduce both energy consumption and the associated costs at the same time. Although energy efficiency in residential space heating has been well discussed in the context of energy poverty in European countries, the energy efficiency of transportation sectors has been less extensively addressed. However, the energy efficiency of passenger cars can have significant impacts on addressing energy poverty, considering that the International Energy Agency [57] shows that the passenger car sector consumes almost twice as much energy as residential space heating. Third, reducing income inequality can improve subjective affordability. Our results show that the existence of severe income inequality can aggravate subjective affordability for all households, not just for households with low income. Thus, in addition to protecting low-income households from energy poverty, reducing income disparity can reduce the energy poverty in a country. Last, in constructing suitable criteria for defining households vulnerable to energy poverty, considering the dimension of focus is important. On the global scale, household income, having children, and mental illness are the most important factors in all dimensions in policy making, while the other socioeconomic factors are differently associated with energy poverty depending on the dimension.

5.4. Methodological limitations

The limitations of this study are as follows. First, the relationship between energy poverty and country-level factors could be bidirectional, as more severe national energy poverty can hamper economic development and expand income inequality. Addressing this issue could shed light on a new perspective, especially for the nexus between economic development and energy consumption. As we discussed, low energy efficiency and the resulting energy poverty can cause serious health problems. Alleviating such negative impacts can reduce government expenditure and enhance economic development.

Second, Kahouli [5] shows that individuals' responses to questions related to energy poverty vary over time, such that from 14 percent to 43 percent of those who were energy poor in a given year were not energy poor in the following year. Thus, the results could vary over time, especially for the countries observed in our study to have the highest levels of energy poverty.

Last, there can be four possible sources of measurement errors. The first concerns the energy burden (the share of income occupied by energy expenditure). While previous studies have calculated the energy burden with continuous data, the results in this study are based on five options ("*10–19%*," "*20–29%*," "*30–39%*," "*40–49%*," and "*50% and above*") and thus are discrete values. Additionally, the question does not specifically mention whether "*income*" includes social allowances and excludes tax payments, which may yield different income criteria depending on the respondents. This hinders us from investigating energy poverty in a more nuanced manner, as has been done in previous studies [85]. The second type of error is related to the calculation method itself, as previous studies have discussed. Both the energy expenditure approach and the consensual approach can overestimate or underestimate energy poverty, as mentioned above. However, this deficiency is generally not avoidable considering the difficulty of collecting detailed data, especially in a multicountry comparison. The use of several measures, as in this study, can compensate for this shortcoming. Third, the difference between objective and subjective measures can be influenced by data structure. While objective measures have continuous values, subjective measures are discrete. This might affect the fit of the overall models and the significance of the coefficients. Last, the number of countries in the analyses differs for each dimension, which might create difficulty in estimating the coefficients of macro level variables when the country sample size is small.

6. Conclusion

Using the original survey data of 37 countries in Europe, Asia, North and South America, Africa, and Australia, this paper is the first to investigate the determinants of energy poverty at the household level from a global perspective and show how they can change according to the economic situation. To do so, we have created five indicators for accessibility, reliability, and affordability with objective and subjective measures. Then, we estimated the three types of associations between energy poverty and household- and country-level predictors. By employing a three-level hierarchical model, we examined (1) how the economic development level and income inequality at the country level are associated with energy poverty for households, (2) how these country-level economic factors influence the relationship between household income and energy poverty, and (3) how other socioeconomic factors at the household level are linked to energy poverty depending on the dimension. For each of the three associations, our main findings are summarized as follows. First, a country's economic development level and income inequality are associated with households' energy poverty differently depending on the three dimensions. In accessibility and reliability, households are more likely to experience energy poverty when their country's economic development level is lower. In affordability, on the other hand, households living in countries with a middle level of economic development and larger income inequality are exposed to a higher risk of energy poverty. Second, the linkage between lower household income and worse energy poverty differs across economic development and income inequality levels. In the accessibility dimension, the association disappears as the economic development level improves. In the affordability dimension, on the other hand, the linkage is strengthened as the economic development level and income inequality increase. Last, various household-level factors are differently associated with energy poverty in each dimension. The most important factors for the global average are income, having children, and mental illness.

CRediT authorship contribution statement

Moegi Igawa: Conceptualization, Investigation, Methodology, Validation, Data curation, Formal analysis, Visualization, Software, Writing – original draft, Writing – review & editing. **Shunsuke Managi:** Funding acquisition, Project administration, Resources, Supervision.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability

The data that support the findings of this study are available from the corresponding author upon reasonable request. The corresponding author, Shunsuke Managi, may be contacted in regard to requests for materials.

Appendix A. Principal component analysis

Tables A.1 and A.2

Table A1
Summary statistics for electric appliances.

Statistic	N	Mean	St.Dev.	Min	Max
Lamps	58,271	0.13	0.33	0	1
Fans	58,271	0.26	0.44	0	1
Microwaves	58,271	0.34	0.47	0	1
Fridges	58,271	0.13	0.33	0	1
Air conditioners	58,271	0.4	0.49	0	1
Televisions	58,271	0.12	0.32	0	1
Radios	58,271	0.54	0.5	0	1
Mobile phones	58,271	0.14	0.35	0	1
Personal computers	58,271	0.19	0.39	0	1
Washing machines	58,271	0.21	0.4	0	1
Landline phones	58,271	0.5	0.5	0	1

Table A2
Principal components (PCs)

Electric appliances	PC 1	PC 2	PC 3	PC 4	PC 5	PC 6	PC 7	PC 8	PC 9	PC 10	PC 11
Lamps	0.22	−0.11	0.27	−0.07	0.05	−0.01	0.48	−0.30	0.69	−0.24	0.08
Fans	0.27	−0.11	0.42	0.33	−0.47	0.57	−0.25	0.13	0.03	0.00	0.03
Microwave	0.36	−0.05	−0.45	−0.05	0.49	0.63	0.05	−0.09	−0.02	0.05	−0.04
Fridge	0.26	−0.14	0.15	−0.10	0.11	−0.08	0.16	0.19	−0.49	−0.68	0.31
Air conditioners	0.32	−0.42	−0.51	0.48	−0.32	−0.32	0.14	−0.08	−0.03	0.03	0.00
Televisions	0.24	−0.11	0.26	−0.09	0.05	−0.08	0.27	0.07	−0.25	0.08	−0.83
Radios	0.31	0.70	0.11	0.55	0.24	−0.19	0.02	−0.03	−0.02	0.00	0.02
Mobile phones	0.26	−0.13	0.31	−0.14	0.06	−0.10	0.18	−0.29	−0.33	0.63	0.41
Personal computers	0.33	−0.09	0.06	−0.18	0.10	−0.24	−0.71	−0.48	0.06	−0.17	−0.13
Washing machines	0.35	−0.14	0.04	−0.15	0.21	−0.24	−0.20	0.72	0.34	0.22	0.10
Landline phones	0.36	0.47	−0.28	−0.51	−0.55	0.01	0.11	0.02	0.00	0.00	0.01

Appendix B. Data and descriptive statistics

Tables B.1–B.3

Table B1
Survey information

Country name	Continental group	Survey method	Survey period		Sample size
Australia	East Asia and Oceania	Internet	2016/02/10	2016/02/22	2,029
Brazil	South America	Internet	2015/07/23	2015/07/26	2,298
Canada	North America	Internet	2016/09/01	2016/09/13	1,333
Chile	South America	Internet	2015/07/24	2015/07/28	1,192
China	East Asia and Oceania	Internet	2016/01/12	2016/02/29	20,744
Colombia	South America	Internet	2015/07/24	2015/07/27	1,115
Czechia	Eastern and Southern Europe	Internet	2017/03/08	2017/03/16	1,400
Egypt	Africa	Interview	2015/09/14	2015/10/27	1,016
France	North and Western Europe	Internet	2016/08/26	2016/09/07	2,138
Germany	North and Western Europe	Internet	2016/08/26	2016/09/07	3,165
Greece	Eastern and Southern Europe	Internet	2016/08/31	2016/09/12	1,382
Hungary	Eastern and Southern Europe	Internet	2017/03/08	2017/03/15	1,354
India	South and Southeast Asia	Internet and interview	2015/07/25	2015/08/11	6,700
Indonesia	South and Southeast Asia	Internet and interview	2015/07/18	2015/07/23	2,412
Italy	Eastern and Southern Europe	Internet	2016/08/29	2016/09/10	2,106
Japan	East Asia and Oceania	Internet	2015/07/14	2015/08/05	11,167
Kazakhstan	Central and Western Asia	Interview	2015/08/25	2015/09/24	1,000
Malaysia	South and Southeast Asia	Internet	2015/07/23	2015/07/29	1,106
Mexico	North America	Internet	2015/07/24	2015/07/27	1,678
Mongolia	East Asia and Oceania	Interview	2015/08/19	2015/09/03	500
Myanmar	South and Southeast Asia	Interview	2015/07/06	2015/08/10	1,083
Netherlands	North and Western Europe	Internet	2016/08/29	2016/09/10	1,371
Philippines	South and Southeast Asia	Internet	2015/07/15	2015/07/22	1,686
Poland	Eastern and Southern Europe	Internet	2017/03/08	2017/03/17	2,227
Romania	Eastern and Southern Europe	Internet	2017/03/08	2017/03/18	1,386
Russia	Eastern and Southern Europe	Internet	2015/08/31	2015/09/14	2,221
Singapore	South and Southeast Asia	Internet	2015/07/15	2015/07/21	587
South Africa	Africa	Internet	2015/07/15	2015/07/23	1,123
Spain	Eastern and Southern Europe	Internet	2016/08/26	2016/09/07	2,116
Sri Lanka	South and Southeast Asia	Interview	2017/03/09	2017/03/30	500
Sweden	North and Western Europe	Internet	2016/08/31	2016/09/12	1,330
Thailand	South and Southeast Asia	Internet	2015/07/18	2015/07/23	1,127
Turkey	Central and Western Asia	Internet	2017/03/07	2017/03/20	2,120
United Kingdom	North and Western Europe	Internet	2016/08/16	2016/08/28	2,993
United States	North America	Internet	2016/08/16	2016/08/28	10,683
Venezuela	South America	Internet	2015/07/24	2015/08/05	827
Vietnam	South and Southeast Asia	Internet and interview	2015/07/18	2015/07/28	1,741
Total					100,956

Table B2
Summary statistics.

Statistic	N	Mean	St. Dev.	Min	Max
Objective accessibility	58,271	0	0.86	−0.92	2.36
Subjective accessibility	92,081	0.19	0.39	0	1
Subjective reliability	66,101	0.29	0.45	0	1
Objective affordability	84,879	17.99	12.69	0	55
Subjective affordability	91,286	0.33	0.47	0	1
Log (Income equivalized by household size)	92,081	9.75	1.04	4.01	13.27

(continued on next page)

Table B2 (*continued*)

Statistic	N	Mean	St. Dev.	Min	Max
Female	92,081	0.49	0.5	0	1
Household size	92,081	3.26	1.58	1	10
Old	92,081	0.08	0.28	0	1
Children	92,081	0.22	0.41	0	1
Unemployed	92,081	0.17	0.38	0	1
Self-employed	92,081	0.08	0.27	0	1
Student	92,081	0.06	0.23	0	1
University degree	92,081	0.57	0.49	0	1
Health	92,081	2.18	0.89	1	5
Mental	92,081	1.98	0.53	1	4
Rent	92,081	0.26	0.44	0	1
GDP	92,081	28,963.86	18,335.29	4,268.50	89,366.31
Log (GDP)	92,081	10.03	0.75	8.36	11.4
GINI (divided by 10)	92,081	3.88	0.66	2.59	6.3
Log (HDD)	92,081	3.61	1.06	0	4.46
Log (Income equivalized by household size) (NC)	92,081	0	0.94	−5.15	3.8
Female (NC)	92,081	0	0.5	−0.55	0.59
Household size (NC)	92,081	0	1.43	−3.96	7.74
Old (NC)	92,081	0	0.27	−0.21	1
Children (NC)	92,081	0	0.41	−0.4	0.89
Unemployed (NC)	92,081	0	0.37	−0.45	0.94
Self-employed (NC)	92,081	0	0.26	−0.24	0.99
Student (NC)	92,081	0	0.23	−0.14	0.98
University degree (NC)	92,081	0	0.48	−0.79	0.7
Health (NC)	92,081	0	0.85	−1.55	3.3
Mental (NC)	92,081	0	0.51	−1.25	2.38
Rent (NC)	92,081	0	0.42	−0.61	0.92
Log (GDP) (GC)	92,081	0	0.75	−1.67	1.37
GINI (GC)	92,081	0	0.66	−1.29	2.42
Log (HDD) (GC)	92,081	0	1.06	−3.61	0.84

Notes: NC and GC denote variables centered at the national mean and grand mean, respectively.

Table B3
Average energy poverty at the country level

Country name	No connection	Accessibility		Reliability	Affordability	
		Objective	Subjective	Subjective	Subjective	Subjective
Australia	100%	−0.39	10%	13%	17%	47%
Brazil	100%	−0.31	18%	19%	24%	88%
Canada	100%	NA	16%	NA	18%	43%
Chile	100%	−0.06	18%	30%	27%	58%
China	100%	0.22	14%	29%	14%	11%
Colombia	98%	−0.01	16%	29%	26%	48%
Czechia	100%	NA	9%	21%	21%	19%
Egypt	100%	0.22	34%	62%	23%	62%
France	100%	NA	19%	NA	19%	31%
Germany	100%	NA	12%	NA	20%	34%
Greece	100%	NA	42%	NA	29%	59%
Hungary	100%	NA	15%	33%	27%	26%
India	88%	0.31	40%	38%	17%	51%
Indonesia	98%	0.29	33%	53%	20%	28%
Italy	100%	NA	27%	NA	22%	33%
Japan	100%	−0.62	3%	0%	14%	27%
Kazakhstan	100%	0.05	16%	22%	17%	42%
Malaysia	100%	−0.20	16%	25%	19%	28%
Mexico	99%	−0.14	21%	28%	26%	47%
Mongolia	81%	0.50	27%	41%	25%	39%
Myanmar	61%	0.79	63%	68%	8%	6%
Netherlands	100%	NA	6%	NA	17%	14%
Philippines	89%	0.06	30%	32%	21%	56%
Poland	100%	NA	10%	27%	20%	25%
Romania	100%	NA	28%	43%	21%	30%
Russia	100%	−0.09	10%	23%	16%	22%
Singapore	100%	−0.33	6%	6%	14%	36%
South Africa	86%	−0.08	67%	88%	20%	80%
Spain	100%	NA	38%	NA	19%	57%
Sri Lanka	94%	NA	6%	18%	16%	35%
Sweden	100%	NA	15%	NA	16%	22%
Thailand	100%	−0.12	26%	34%	23%	39%
Turkey	100%	NA	31%	70%	22%	65%
United Kingdom	100%	NA	7%	NA	17%	33%
United States	100%	NA	14%	NA	21%	35%
Venezuela	99%	−0.34	42%	74%	22%	15%
Vietnam	100%	0.25	27%	41%	18%	37%

Appendix C. Estimation results

Tables C.1–C.3

Table C1
Two-level hierarchical linear model

	Accessibility		Reliability	Affordability	
	Objective	Subjective	Subjective	Objective	Subjective
Intercept	−0.16**	0.22***	0.34***	22.25***	0.43***
	(0.06)	(0.03)	(0.05)	(0.78)	(0.03)
GDP	−0.31***	−0.10**	−0.17**	−0.71	−0.00
	(0.07)	(0.03)	(0.06)	(0.91)	(0.04)
GDP^2	0.10	0.02	−0.04	−4.21***	−0.07
	(0.06)	(0.03)	(0.06)	(0.99)	(0.04)
GINI	−0.08	0.04	0.03	1.01	0.14***
	(0.05)	(0.03)	(0.04)	(0.78)	(0.03)
Income	−0.13***	−0.02**	−0.02*	−1.63***	−0.03***
	(0.02)	(0.01)	(0.01)	(0.23)	(0.01)
Income*GDP	0.08***	0.01	0.00	−0.97***	−0.01
	(0.02)	(0.01)	(0.01)	(0.27)	(0.01)
Income*GDP^2	−0.03	−0.00	0.00	0.39	0.01
	(0.02)	(0.01)	(0.01)	(0.30)	(0.01)
Income*GINI	0.01	0.00	0.01	−0.53*	0.01
	(0.02)	(0.01)	(0.01)	(0.23)	(0.01)
Female	0.02**	−0.02***	−0.01***	0.80***	0.03***
	(0.01)	(0.00)	(0.00)	(0.08)	(0.00)
Old	−0.14***	−0.01*	−0.00	−1.43***	−0.01
	(0.02)	(0.00)	(0.01)	(0.16)	(0.01)
Children	0.16***	0.03***	−0.01**	1.13***	0.01**
	(0.01)	(0.00)	(0.00)	(0.10)	(0.00)
Student	−0.09***	−0.03***	−0.00	0.17	−0.10***
	(0.01)	(0.01)	(0.01)	(0.19)	(0.01)
Unemployed	−0.03**	−0.01	0.01**	0.27*	0.01*
	(0.01)	(0.00)	(0.00)	(0.12)	(0.00)
Self-employed	0.00	0.00	0.02***	−0.08	0.02***
	(0.01)	(0.00)	(0.01)	(0.15)	(0.01)
Education	−0.19***	−0.00	0.02***	−1.51***	−0.03***
	(0.01)	(0.00)	(0.00)	(0.09)	(0.00)
Household size	−0.06***	0.01***	0.01***	0.61***	0.02***
	(0.00)	(0.00)	(0.00)	(0.03)	(0.00)
Health	−0.03***	−0.01***	0.01***	−0.06	−0.00
	(0.00)	(0.00)	(0.00)	(0.05)	(0.00)
Mental	0.01	0.04***	0.03***	2.44***	0.05***
	(0.01)	(0.00)	(0.00)	(0.09)	(0.00)
Rent	0.23***	0.01*	−0.01	−0.38***	−0.01
	(0.01)	(0.00)	(0.00)	(0.10)	(0.00)
AIC	130909.74	77363.64	71635.30	659214.34	104813.48
BIC	131116.12	77580.54	71844.58	659429.37	105030.18
Log Likelihood	−65431.87	−38658.82	−35794.65	−329584.17	−52383.74
N	58,271	92,081	66,101	84,879	91,286
K	21	37	27	37	37
φ_0^2	0.04	0.01	0.04	12.36	0.02
φ_1^2	0.00	0.00	0.00	0.90	0.00
Cov (V_k^0, V_k^1)	0.00	−0.00	0.00	0.09	−0.00
σ^2	0.55	0.13	0.17	137.68	0.18

Notes: ***p < 0.001; **p < 0.01; *p < 0.05. Standard errors in parentheses.

Table C2
Comparison with the nonlinear model

	Subjective accessibility		Subjective reliability		Subjective affordability	
	Linear	Nonlinear	Linear	Nonlinear	Nonlinear	Linear
Intercept	0.22***	−1.42***	0.35***	−0.82**	0.44***	−0.27
	(0.03)	(0.16)	(0.04)	(0.25)	(0.03)	(0.16)
GDP	−0.11***	−0.73***	−0.19**	−1.30***	−0.01	0.03
	(0.03)	(0.18)	(0.06)	(0.34)	(0.04)	(0.18)
GDPˆ2	0.02	−0.03	−0.05	−0.47	−0.09*	−0.48*
	(0.03)	(0.20)	(0.05)	(0.32)	(0.04)	(0.20)
GINI	0.04	0.21	0.04	0.23	0.14***	0.68***
	(0.03)	(0.16)	(0.04)	(0.25)	(0.03)	(0.16)
Income	−0.02**	−0.10***	−0.01	−0.07*	−0.03***	−0.12***
	(0.01)	(0.03)	(0.01)	(0.03)	(0.01)	(0.03)
Income*GDP	−0.00	−0.05	−0.01	−0.13*	−0.01	−0.06
	(0.01)	(0.03)	(0.01)	(0.06)	(0.01)	(0.03)
Income*GDPˆ2	0.00	−0.01	0.00	−0.04	0.00	−0.00
	(0.01)	(0.04)	(0.01)	(0.05)	(0.01)	(0.04)
Income*GINI	−0.00	−0.00	0.01	0.06	0.01	0.06*
	(0.01)	(0.03)	(0.01)	(0.03)	(0.01)	(0.03)
Female	−0.02***	−0.13***	−0.01***	−0.07***	0.03***	0.15***
	(0.00)	(0.02)	(0.00)	(0.02)	(0.00)	(0.02)
Old	−0.01	−0.15***	−0.00	−0.04	−0.01	−0.03
	(0.00)	(0.04)	(0.01)	(0.06)	(0.01)	(0.03)
Children	0.03***	0.23***	−0.01*	−0.04	0.01***	0.07***
	(0.00)	(0.02)	(0.00)	(0.02)	(0.00)	(0.02)
Student	−0.03***	−0.21***	−0.00	−0.01	−0.10***	−0.59***
	(0.01)	(0.04)	(0.01)	(0.04)	(0.01)	(0.04)
Unemployed	−0.01*	−0.08**	0.01*	0.07*	0.01	0.02
	(0.00)	(0.03)	(0.00)	(0.03)	(0.00)	(0.02)
Self-employed	0.00	−0.00	0.02**	0.11**	0.02***	0.10**
	(0.00)	(0.03)	(0.01)	(0.03)	(0.01)	(0.03)
Education	−0.00	−0.03	0.02***	0.10***	−0.03***	−0.17***
	(0.00)	(0.02)	(0.00)	(0.02)	(0.00)	(0.02)
Household size	0.01***	0.05***	0.01***	0.07***	0.02***	0.08***
	(0.00)	(0.01)	(0.00)	(0.01)	(0.00)	(0.01)
Health	−0.01***	−0.04***	0.01***	0.07***	−0.00	−0.00
	(0.00)	(0.01)	(0.00)	(0.01)	(0.00)	(0.01)
Mental	0.04***	0.32***	0.03***	0.19***	0.06***	0.30***
	(0.00)	(0.02)	(0.00)	(0.02)	(0.00)	(0.02)
Rent	0.01*	0.05*	−0.01	−0.05*	−0.00	−0.02
	(0.00)	(0.02)	(0.00)	(0.03)	(0.00)	(0.02)
AIC	76761.94	78709.23	70332.74	66061.99	103560.84	98761.43
BIC	77007.13	78944.99	70569.31	66289.47	103805.81	98996.97
Log Likelihood	−38354.97	−39329.62	−35140.37	−33006.00	−51754.42	−49355.71
N	92,081	92,081	66,101	66,101	91,286	91,286
J	1054	1054	832	832	1052	1052
K	37	37	27	27	37	37
τ_0^2	0.00	0.09	0.01	0.18	0.00	0.09
τ_1^2	0.00	0.01	0.00	0.01	0.00	0.02
Cov (U_{jk}^0, U_{jk}^1)	−0.00	0.00	0.00	0.03	0.00	0.02
φ_0^2	0.01	0.49	0.03	1.11	0.02	0.49
φ_1^2	0.00	0.01	0.00	0.01	0.00	0.01
Cov (V_k^0, V_k^1)	−0.00	0.02	−0.00	0.05	−0.00	−0.02
σ^2	0.13		0.17		0.18	

Notes: ***$p < 0.001$; **$p < 0.01$; *$p < 0.05$. Standard errors in parentheses.

Table C3
Sensitivity check with heating degree days (HDD)

	Accessibility		Reliability	Affordability	
	Objective	Subjective	Subjective	Objective	Subjective
Intercept	−0.14*	0.23***	0.35***	22.37***	0.44***
	(0.06)	(0.03)	(0.04)	(0.80)	(0.03)
GDP	−0.30***	−0.11***	−0.18**	−0.94	−0.01
	(0.07)	(0.03)	(0.06)	(0.93)	(0.04)
GDP^2	0.10	0.02	−0.04	−4.23***	−0.08
	(0.06)	(0.03)	(0.06)	(1.01)	(0.04)
GINI	−0.08	0.05	0.04	1.03	0.15***
	(0.05)	(0.03)	(0.04)	(0.82)	(0.03)
HDD	0.02	0.01	0.01	0.21	0.02
	(0.03)	(0.01)	(0.02)	(0.45)	(0.02)
Income	−0.14***	−0.02**	−0.01	−1.60***	−0.03***
	(0.02)	(0.01)	(0.01)	(0.23)	(0.01)
Income*GDP	0.08***	0.00	−0.01	−1.08***	−0.01
	(0.02)	(0.01)	(0.01)	(0.29)	(0.01)
Income*GDP^2	−0.01	0.00	0.00	0.24	−0.00
	(0.02)	(0.01)	(0.01)	(0.30)	(0.01)
Income*GINI	0.01	−0.00	0.01	−0.60*	0.01
	(0.02)	(0.01)	(0.01)	(0.24)	(0.01)
Income*HDD	0.01	−0.00	−0.00	−0.04	−0.00
	(0.01)	(0.00)	(0.00)	(0.13)	(0.00)
Female	0.02*	−0.02***	−0.01***	0.82***	0.03***
	(0.01)	(0.00)	(0.00)	(0.08)	(0.00)
Old	−0.13***	−0.01	−0.00	−1.36***	−0.01
	(0.02)	(0.00)	(0.01)	(0.16)	(0.01)
Children	0.15***	0.03***	−0.01*	1.04***	0.01***
	(0.01)	(0.00)	(0.00)	(0.10)	(0.00)
Student	−0.08***	−0.03***	−0.00	0.16	−0.10***
	(0.01)	(0.01)	(0.01)	(0.19)	(0.01)
Unemployed	−0.04***	−0.01*	0.01*	0.32**	0.01
	(0.01)	(0.00)	(0.00)	(0.12)	(0.00)
Self-employed	0.01	0.00	0.02**	−0.12	0.02***
	(0.01)	(0.00)	(0.01)	(0.15)	(0.01)
Education	−0.17***	−0.00	0.02***	−1.53***	−0.03***
	(0.01)	(0.00)	(0.00)	(0.09)	(0.00)
Household size	−0.06***	0.01***	0.01***	0.62***	0.02***
	(0.00)	(0.00)	(0.00)	(0.03)	(0.00)
Health	−0.03***	−0.01***	0.01***	−0.04	−0.00
	(0.00)	(0.00)	(0.00)	(0.05)	(0.00)
Mental	0.03***	0.04***	0.03***	2.43***	0.06***
	(0.01)	(0.00)	(0.00)	(0.09)	(0.00)
Rent	0.24***	0.01*	−0.01	−0.40***	−0.00
	(0.01)	(0.00)	(0.00)	(0.10)	(0.00)
AIC	128913.29	76780.60	70350.14	658442.36	103577.71
BIC	129164.53	77044.66	70604.91	658704.13	103841.52
Log Likelihood	−64428.64	−38362.30	−35147.07	−329193.18	−51760.86
N	58,271	92,081	66,101	84,879	91,286
J	654	1054	832	1051	1052
K	21	37	27	37	37
τ_0^2	0.01	0.00	0.01	2.15	0.00
τ_1^2	0.00	0.00	0.00	1.51	0.00
Cov (U_{jk}^0, U_{jk}^1)	−0.00	−0.00	0.00	−0.62	0.00
φ_0^2	0.04	0.01	0.03	12.44	0.02
φ_1^2	0.00	0.00	0.00	0.77	0.00
Cov (V_k^0, V_k^1)	−0.00	−0.00	−0.00	0.30	−0.00
σ^2	0.53	0.13	0.17	135.00	0.18

Notes: ***$p < 0.001$; **$p < 0.01$; *$p < 0.05$. Standard errors in parentheses.

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