

Empirical Analyses of Energy Poverty at the Household Level

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Empirical Analyses of Energy Poverty
at the Household Level

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CERTIFICATE

The undersigned hereby certify that they have read and recommended to the Graduate School of Engineering for the acceptance of this thesis entitled, “*Empirical Analyses of Energy Poverty at the Household Level*” by **Moegi Igawa** in partial fulfillment of the requirements for the degree of **Doctor of Engineering**.

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ABSTRACT

Energy poverty (EP) is defined as the situation where people cannot access clean and affordable energy services at a socially sufficient level. Chapter 1 discusses that EP has been mainly analyzed in the two currents of literature separately: one has been researched in development studies as the accessibility problem, and the other in sociology focuses on heating affordability problems of European countries. Due to this separate development of the literature in particular regions, few studies investigating EP from a global perspective and less evidence in summer-related EP.

In order to fill this gap, this thesis conducts one qualitative review and three empirical analyses on EP from a global and climate perspective. First, to comprehensively understand how EP can be quantified with quantifiable indicators, Chapter 2 describes EP indicators developed in both contexts of low-income and high-income countries. While these EP indicators have been developed from separate currents in low-income countries and high-income countries, this chapter finds common natures regarding the difficulty of identifying EP and the necessary viewpoints for understanding EP more reliably.

Based on the comprehensive understanding of EP indicators, Chapter 3 analyses EP using a survey conducted in 37 countries. These countries include all continents and various economic levels, which enables us to present a global overview of EP at the household level in relation to macro-economic factors and different dimensions of EP. Employing a three-level hierarchical model, we find that EP of country-average households in the accessibility and reliability dimensions shows an improving trend with economic development. The affordability dimension is the worst in countries with a middle level of economic development and greater income inequality. In addition, we find that a higher economic development level and larger income inequality are the most relevant factors in the strong negative association between households' low incomes and EP.

Chapter 4 shifts the focus from the globe to Japan. Japan has essential characteristics of EP contexts. Compared to other high-income countries where EP

studies have been conducted, Japan's hot climate and high prevalence of Air-Conditioners offer a suitable environment for analyzing EP in summer contexts. This chapter shows the overall situation of EP in the summer seasons in Japan. Using machine learning methods, we show that behavioral and psychological factors are also associated with EP in addition to general socio-economic and housing factors employed in the literature. Interestingly, energy-efficient systems installed at home are more associated with the subjective indicator than the objective indicator. These results conclude that both the objective and subjective EP indicators capture different aspects in various EP dimensions.

Going beyond quantifying EP, assessing how EP affects human well-being is crucial. Using the same survey of Japan with Chapter 4, Chapter 5 analyses how cooling energy needs in the hot summer season affect human well-being in relation to income level. Specifically, this chapter examines how much energy consumption increases in response to higher temperatures in the summer season and how the additional energy needs for indoor cooling, in turn, affects subjective well-being (SWB). The results confirm that higher cooling energy needs can reduce SWB. In relation to income level, the lowest-income group faces the highest cooling energy needs, presumably due to lower energy efficiency in housing. In contrast, the negative effect of cooling energy needs on SWB is the largest for the middle-income group. This contradictory finding implies that behavioral aspects matter for the evaluation of SWB.

Chapter 6 concludes that EP, especially in the affordability dimension of the summer season, will become more and more critical as the world economy develops. We note that improving energy efficiency in houses and appliances for lower-income households is essential for a fairer transition to more sustainable systems.

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Chapter 1 Introduction

1.1 Background

Reducing CO₂ emissions originating from fossil-fuel usage is an essential global policy issue to reduce climate change risk (IPCC, 2013). At the same time, securing affordable energy has universal value in light of energy justice (Bartiaux et al., 2018). However, the current climate and economic conditions pose a challenging situation. The soaring temperatures due to climate change and the increasing populations and income levels yield more energy needs on the globe (IEA, 2018; Washington Post, 2019). International Energy Association (IEA) (2018) has projected that the energy demand for indoor cooling will more than triple by 2050. In addition to knowing how countries can achieve more sustainable energy systems, it is crucial to understand whether the current systems offer affordable energy services to all individuals, particularly vulnerable households.

With these issues in mind, discussions on energy poverty (EP) have been gaining momentum in research and practice in recent years (Doll and Pachauri, 2010; Nussbaumer et al., 2011; Heindl, 2015; Lenz and Grgurev, 2017; Bartiaux et al., 2018; Sambodo and Novandra, 2019). Conceptually, EP refers to the situation where people cannot access clean and affordable energy services at a socially sufficient level (Bouzarovski and Petrova, 2015). As can be seen from the ambiguity of this definition, EP is difficult to define quantitatively in the first place. Since it first attracted attention as a research topic in the 1990s, the main research agenda has been limited to developing quantitative indicators (Biermann, 2016).

This thesis contributes to the above research stream by reexamining EP from a global and climate perspective. In the literature, there remains a geographical bias of the research subject. Because EP has been a popular research topic in low-income countries or colder countries such as European countries, few studies have focused on high-income countries with hot climates. Moreover, the global picture of EP is lacking, causing confusion on appropriate indicators for quantifying EP depending on a country's economic levels. Thus, this thesis conducts a comprehensive analysis of EP in a multi-country setting and identifies forms of EP in warmer climates than in Europe. As a secondary contribution, this thesis tries to employ more robust analytical methods. EP is

mainly analyzed with a descriptive and qualitative analysis in sociology, and there is much room for reflecting the results of econometrics and statistics.

1.2 Thesis framework

For this aim, this thesis consists of one qualitative analysis and three empirical analyses. Firstly, **Chapter 2** offers a global view of EP indicators developed separately from two currents of studies: one is the studies in European countries (Bouzarovski, 2014; European Commission, 2020), and the other is from low-income countries in Asia and Africa (Doll and Pachauri, 2010; Nussbaumer et al., 2011; Sambodo and Novandra, 2019). Despite that they have been developed from different contexts (Bouzarovski and Petrova, 2015), we reveal the common nature inherent to the difficulty of identifying EP. We classify these indicators into five categories (the connection-based approach, the energy consumption-based approach, the energy service-based approach, the energy expenditure-based approach, and the consensual-based approach) and discuss the weakness and strengths of each measurement type. This discussion of indicators consists of the base for the subsequent empirical analyses in the following chapters.

Based on the findings in the previous chapter, **Chapter 3** identifies how the nature of EP changes according to macro-economic situations. Using survey data from 37 countries, including all five continents and low-income to high-income countries, we analyzed the correlation between individual EP and individual socioeconomic attributes, macroeconomic factors, and geographic factors by applying a hierarchical model. For identifying EP, we created the five indicators in three dimensions: accessibility, reliabilities, and affordability. The results showed that accessibility and reliability tended to improve with rising GDP, while an inverse U-shaped relationship existed between GDP and affordability indicators. In addition, subjective indicators deteriorated on average for countries with larger income inequality (GINI coefficient). As a contribution, these findings provide a perspective for discussing what kind of EP indicators should be adopted for each country's situation, which has been discussed without reflecting country-specific differences.

In **Chapter 4**, we analyze the current status of EP in Japan in the context of the summer season. We create both objective and subjective EP indicators using electricity expenditure data for households in the summer season. Then, we developed a classification forecasting model based on Machine Learning (ML) methods, showing

which factors have more substantial power for predicting EP. We found that EP with the objective indicator is predicted with high accuracy by socioeconomic, housing, and behavioral factors. On the other hand, EP with the subjective indicator is more associated with psychological factors.

Chapter 5 analyses the impact of climate-induced EP on subjective well-being. Given the increasing energy needs for indoor cooling, it is crucial to understand how cooling energy needs in the hot summer season affect human well-being in relation to income level. Using Japan as a case country, this chapter examines how much energy consumption increases in response to higher temperatures in the summer season and how the additional energy needs for indoor cooling, in turn, affects subjective well-being (SWB). The results confirm that higher cooling energy needs can reduce SWB. In relation to income level, the lowest-income group faces the highest cooling energy needs, presumably due to lower energy efficiency in housing. In contrast, the negative effect of cooling energy needs on SWB is the largest for the middle-income group. This contradictory finding implies that behavioral aspects matter for the evaluation of SWB.

Lastly, **Chapter 6** concludes and notes the policy implications.

References

- Bartiaux, F., Vandeschrick, C., Moezzi, M., Frogneux, N., 2018. Energy justice, unequal access to affordable warmth, and capability deprivation: A quantitative analysis for Belgium. *Applied Energy* 225, 1219–1233. <https://doi.org/10.1016/j.apenergy.2018.04.113>
- Bouzarovski, S., 2014. Energy poverty in the European Union: Landscapes of vulnerability. *Wiley Interdisciplinary Reviews: Energy and Environment* 3, 276–289. <https://doi.org/10.1002/wene.89>
- Bouzarovski, S., Petrova, S., 2015. A global perspective on domestic energy deprivation: Overcoming the energy poverty-fuel poverty binary. *Energy Research and Social Science* 10, 31–40. <https://doi.org/10.1016/j.erss.2015.06.007>
- Doll, C.N.H., Pachauri, S., 2010. Estimating rural populations without access to electricity in developing countries through night-time light satellite imagery. *Energy Policy* 38, 5661–5670. <https://doi.org/10.1016/j.enpol.2010.05.014>
- European Commission, 2020. Energy poverty [WWW Document]. URL https://ec.europa.eu/energy/topics/markets-and-consumers/energy-consumer-rights/energy-poverty_en (accessed 11.4.20).
- Heindl, P., 2015. Measuring Fuel Poverty: General Considerations and Application to German Household Data. *Public Finance Analysis* 71. <https://doi.org/10.2139/ssrn.2304673>
- International Energy Agency (IEA), 2018. The Future of Cooling.
- IPCC, 2013. Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change [Stocker, T.F., D. Qin, G.-K. Plattner, M. Tignor, S.K. Allen, J. Boschung, A. Nauels, Y. Xia, V. Bex and P.M. Midgley (eds.)]. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA.
- Lenz, N.V., Grgurev, I., 2017. Assessment of energy poverty in New European union member states: The case of Bulgaria, Croatia and Romania. *International Journal of Energy Economics and Policy* 7, 1–8.
- Nussbaumer, P., Bazilian, M., Modi, V., Yumkella, K.K., 2011. *Measuring Energy Poverty: Focusing on What Matters*. Oxford.
- Sambodo, M.T., Novandra, R., 2019. The state of energy poverty in Indonesia and its impact on welfare. *Energy Policy* 132, 113–121. <https://doi.org/10.1016/j.enpol.2019.05.029>
- Washington Post, 2019. Europe never understood America’s love of air conditioning — until now. *Washington Post*.

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

This chapter reviews major existing indicators for energy poverty (EP) at the household level.¹ Because the number of existent indicators is vast, this chapter 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 EP indicators 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. Furthermore, we link these approaches to the common two classifications: objective and subjective indicators. We discuss the weaknesses and strengths of each approach, leading us to acknowledge the benefit of comparing different types of indicators in the following chapters.

2.1 Five classifications of energy poverty indicators from a global perspective

(1) The connection-based approach

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 (International Energy Agency [IEA], 2020). 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 (Bhatia and Angelou, 2015).

(2) The energy consumption-based approach

To overcome the shortfall of connection-based approach, the energy consumption-based approach was proposed by several studies (Barnes et al., 2011; Mirza and Szirmai, 2010; Vivien et al., 2000). In this approach, a certain amount of energy

¹ For an exhaustive review of energy poverty indicators in European countries, see Trinomics (2016). Because the number of energy poverty indicators in low-income countries is relatively limited, our paper covers most major existent indicators.

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 (Pachauri and Spreng, 2011). 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 (Nussbaumer et al., 2011).

(3) The energy service-based approach

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. (2011). 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 (Bhatia and Angelou, 2015). 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 (Allcott et al., 2016; Meles, 2020).

(4) The energy expenditure-based approach

The energy expenditure-based approach is mainly adopted for high-income

countries, in which affordability dimension of energy poverty has been the main focus. In the context of high-income countries, EP has been conceptually defined as the situation where households have to use a disproportionately high share of their income on adequate energy services (Boardman, 2010). The pioneering work by Boardman (1991) first suggested the following measure for identifying EP:

$$\textbf{Energy burden} = \frac{\text{Energy prices} \times \text{Required energy}}{\text{Household income}}$$

Boardman (1991) defined households as energy poor if the energy burden exceeds 10%.

Another well-known indicator in the energy expenditure-based approach is Low Incomes and High Costs (LIHC) indicator (Hills, 2012). The LIHC was first 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 instead of “actual” energy. Required energy is a hypothetical amount of necessary energy to attain indoor comfort at a socially adequate level. Thus, required energy cannot be observed without detailed data on achieved indoor environment or housing energy efficiency. Although 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), such modelling-based calculation is not employed in the other countries (Thomson et al., 2017). As a solution, required energy is often replaced with the actual (observed) energy.

(5) The consensual approach

The consensual approach utilizes self-report responses to survey questions (Healy and Clinch, 2002). The consensual approach was firstly proposed in high-income countries to complement the weaknesses of the energy expenditure approach (Healy and Clinch, 2002). A sample question, “*Can you afford to keep your home adequately warm?*” was adopted in the EU statistics on income and living conditions (European Commission, 2019). In the consensual approach, households are identified as energy poor if they answer “yes” to these questions. A large difference of the consensual approach from the

above four approaches is that it 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 (Thomson et al., 2017).

So far, we have categorized the existent indicators into five approaches. The literature often classifies them by whether indicators are based on objective or subjective measures. Among these five approaches, the first four approaches are categorized as objective indicators, while the consensual approach is classified as the subjective indicators.

2.2 Conclusion

Among the five approaches, the connection-based approach, the energy consumption-based approach, and the energy service-based approach were developed in low-income countries, whereas the energy expenditure-based approach and the consensual approach are in high-income countries. Still, there are common difficulty inherent to EP indicators. One is the risk of arbitrary setting for the 'standard' energy service levels. When the concept of "socially adequate" standard is uniformly decided by politics, it can miss the important differences in energy needs among both individuals and cultures (e.g., disabled persons can need more energy services because of their physical vulnerability or longer times spent at home) (Thomson et al., 2017). The second common difficulty is the data collection. Although the newly proposed indicators, such as the GTF in low-income countries and the LIHC in high-income countries, 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 for the LIHC (Thomson et al., 2017).

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 EP and thus provide a better overall picture for policymaking (Thomson, 2020). Based on this background, this thesis uses both objective and subjective measures to identify EP at the household level.

References

- Allcott, H., Collard-Wexler, A., O'connell, S.D., Cropper, M., De Loecker, J., Greenstone, M., Klenow, P., Malik, K., Pande, R., Ryan, N., Sivadasan, J., Sudarshan, A., 2016. How Do Electricity Shortages Affect Industry? Evidence from India. *Am. Econ. Rev.* 106, 587–624. <https://doi.org/10.1257/aer.20140389>
- Barnes, D.F., Khandker, S.R., Samad, H.A., 2011. Energy poverty in rural Bangladesh. *Energy Policy* 39, 894–904. <https://doi.org/10.1016/j.enpol.2010.11.014>
- Bhatia, M., Angelou, N., 2015. Beyond Connections: Energy Access Redefined. ESMAP Technical Report;008/15. Washington, DC.
- Boardman, B., 2010. Fixing fuel poverty: challenges and solutions. Earthscan.
- Boardman, B., 1991. Fuel poverty: From cold homes to affordable warmth. Belhaven Press, London.
- European Commission, 2019. EU statistics on income and living conditions (EU-SILC) methodology [WWW Document]. URL [https://ec.europa.eu/eurostat/statistics-explained/index.php/EU_statistics_on_income_and_living_conditions_\(EU-SILC\)_methodology](https://ec.europa.eu/eurostat/statistics-explained/index.php/EU_statistics_on_income_and_living_conditions_(EU-SILC)_methodology) (accessed 11.6.20).
- Healy, J.D., Clinch, J.P., 2002. Fuel Poverty in Europe: A Cross Country Analysis Using A New Composite Measurement, Environmental Studies Research Series Working Papers. Dublin.
- Hills, J., 2012. Getting the measure of fuel poverty. Final Report of the Fuel Poverty Review. Centre for the Analysis of Social Exclusion. London.
- Meles, T.H., 2020. Impact of power outages on households in developing countries: Evidence from Ethiopia. *Energy Econ.* 91, 104882. <https://doi.org/10.1016/j.eneco.2020.104882>
- Mirza, B., Szirmai, A., 2010. Towards a new measurement of energy poverty: A cross-community analysis of rural Pakistan, Maastricht Economic and social Research and Training Centre on Innovation and Technology. United Nations University.
- Nussbaumer, P., Bazilian, M., Modi, V., Yumkella, K.K., 2011. Measuring Energy Poverty: Focusing on What Matters. Oxford.
- Pachauri, S., Spreng, D., 2011. Measuring and monitoring energy poverty. *Energy Policy* 39, 7497–7504. <https://doi.org/10.1016/j.enpol.2011.07.008>
- Thomson, H., 2020. Quantification beyond expenditure. *Nat. Energy* 5, 640–641. <https://doi.org/10.1038/s41560-020-00682-9>
- Thomson, H., Bouzarovski, S., Snell, C., 2017. Rethinking the measurement of energy poverty in Europe: A critical analysis of indicators and data. *Indoor Built Environ.* 26, 879–901. <https://doi.org/10.1177/1420326X17699260>
- Trinomics, 2016. Selecting Indicators to Measure Energy Poverty.
- Vivien, F., Jean-Philippe, T., Quentin, W., 2000. Energy prices, energy efficiency, and fuel poverty. World Bank, Washington, DC.

Chapter 3 Energy poverty and income inequality: An economic analysis of 37

countries

3.1 Introduction

As reviewed in chapter 2, energy poverty (EP) has been investigated in both low- and high-income countries. However, they have been often considered the separate problems. The research of EP in low-income countries started in the late 2000s (Birol, 2007), and these studies focused on the accessibility to an electricity grid in developing countries (Lee et al., 2020a). In contrast, EP in high-income countries has been the problem of affordability for indoor warmth. This is because the research started in the United Kingdom in the 1970s (Lewis, 1982) and expanded to the other Northern and Western European countries, motivated by countries' low housing energy-efficiency of low-income households (Boardman, 1991; Deller, 2018). Thus, in the EP research, there has existed a dichotomy between 'the problem of accessibility in low-income countries' and 'the problem of affordability for warmth in cold and high-income countries.'

However, at the global scale, the question remains as to how precisely EP can be depicted with this dichotomy. 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 (World Bank, 2020). Reflecting this trend, recent studies on EP in low-income countries have underlined the importance of going beyond electricity connections, and more focus is being placed on reliability and affordability (Aklin et al., 2018; Lee et al., 2020b). Second, 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 (Chafe et al., 2015; Neacsu et al., 2020). Third, the rising interest in EP 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, EP is difficult to measure by the simple application of the same indicators used in studies of low- or high-income countries (Sambodo and Novandra, 2019; Urquiza et al., 2019; Zhang et al., 2019).

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 EP at the household level in a multicountry setting encompassing various development levels. Thus, this chapter aims to present a global picture of households' EP by utilizing survey data covering 37 countries in Europe, Asia, North and South America, Africa, and Australia from approximately 100,000 samples.

This chapter contributes to the literature on EP 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 EP: subjective and objective measures. While many studies have shown the prevalence of EP 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 EP, we create five original indicators with subjective and objective measures in three dimensions: accessibility, reliability, and affordability. As discussed in chapter 2, quantifying EP with both measures is helpful because both measures have each benefits and limitations. Especially, the evidence with subjective measures is scarce when comparing countries of different development levels. In this point, this chapter is the first attempt to compare EP using both objective and subjective measures.

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 (Bouzarovski and Tirado Herrero, 2017), a completely pooled estimation (Healy and Clinch, 2002), or a completely separate estimation (Bouzarovski and Thomson, 2018; Thomson and Snell, 2013). 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.

² For example, Healy (2003), Doll and Pachauri (2010), Nussbaumer et al. (2011), Heindl (2015), Lenz and Grgurev (2017), Bouzarovski and Tirado Herrero (2017), Bartiaux et al. (2018), Deller (2018), and Sambodo and Novandra (2019).

³ For example, Healy and Clinch (2002), Fahmy et al. (2011), Legendre and Ricci (2015), Carvalho (2017), Bouzarovski and Thomson (2018), Muller and Yan (2018), Castaño-Rosa et al. (2019), Recalde et al. (2019), Robinson et al. (2019), Abbas et al. (2020), Awaworyi Churchill and Smyth (2020), and Tabata and Tsai (2020).

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.

The remainder of this chapter is structured as follows. Subsection 3.2 explains the five indicators used in this chapter to identify households in EP. Subsection 3.3 describes the methodology for the empirical analysis. Subsection 3.4 presents the results and discussion. Subsection 3.5 gives the conclusion.

3.2 Energy-poverty indicators and the survey design in this chapter

This subsection explains the indicators employed in this chapter for identifying EP at the household level by relating them with the existent approaches introduced in Chapter 2. Based on the three approaches (the energy-service approach, the energy-expenditure approach, and the consensual approach), we constructed five indicators for EP in the three dimensions of accessibility, reliability, and affordability (Table 3.1). All of them are categorized into either objective or subjective indicators based on the selected approach. We then explain original survey data used for creating these indicators. Although the survey was not specifically designed to examine EP, it includes many questions analogous to the well-used indicators in the literature.

Table 3.1 The indicators for energy poverty in this chapter

Dimensions	Subjective or Objective	Approach	Measures
Accessibility	Objective	Energy services	The first principal component scores 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 smaller when EP 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.

3.2.1 Energy-poverty indicators in this chapter

(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 more

appliances (see Appendix 3.A, Table 3.3.A for summary statistics for electric appliances and Table 3.4.A 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 (Aklin et al., 2016; Lee et al., 2020a; Lee et al., 2020b). Thus, it is plausible to assume that accessibility can include the reliability and affordability dimensions depending on respondents’ situations.

(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., 2016). 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) (Farquharson et al., 2018), our indicator is the first to quantify subjective reliability on a global scale.

(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 EP 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 EP 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 (Legendre and Ricci, 2015; Mattioli et al., 2017). 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 EP.

3.2.2 Survey design and data collection process

The survey includes 37 countries and was conducted in 2015, 2016, or 2017 for each country (see Table 3.5.B in Appendix 3.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. 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 subsection 3.4.

3.3 Methodology and Data

3.3.1 A hierarchical model in this chapter

Our main interests are summarized in two points: (1) how macrolevel factors affect EP at the household level and (2) how macrolevel factors change the relationship between EP and household characteristics, especially household income. Such macrolevel factors are understood in this chapter in terms of contextual effects, namely, the effects of national and regional conditions that—in addition to household characteristics—determine households' EP (Neira et al., 2018). 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 EP 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 (Thomson et al., 2017; Thomson and Snell, 2013).

This chapter considers two types of contextual effects. The first is macrolevel factors that condition the probability of households falling into EP, irrespective of household characteristics. The second is macrolevel factors that change the relationship between EP 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 chapter. Hierarchical models are widely used in many fields, including sociology and economics (Botetzagias et al., 2018; Eichhorn, 2013; Llorca et al., 2020). 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 chapter), 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:

$$EP_{ijk} = \beta_{jk}^0 + \beta_{jk}^1(I_{ijk} - \bar{I}_k) + \sum_{h=2}^H \beta^h(x_{ijk}^h - \bar{x}_k^h) + R_{ijk} \quad (3.1)$$

$$\beta_{jk}^0 = \gamma^0 + \sum_{l=1}^L \gamma^{0,l}(z_k^l - \bar{z}^l) + V_k^0 + U_{jk}^0 \quad (3.2)$$

$$\beta_{jk}^1 = \gamma^1 + \sum_{l=1}^L \gamma^{1,l}(z_k^l - \bar{z}^l) + V_k^1 + U_{jk}^1 \quad (3.3)$$

where subscript I denotes the survey respondent ($I = 1, 2 \dots, N$), j the region ($j = 1, 2 \dots, J$), and k the country ($k = 1, 2 \dots, K$). N , J , and K differ depending on the selected EP indicator due to the availability of data. EP_{ijk} , I_{ijk} , and x_{ijk}^h denote EP, household income, and the other household characteristics, respectively, for household I in region j in country k . $\bar{I}_k$ and $\bar{x}_k^h$ are the country means of I_{ijk} and x_{ijk}^h . z_k^l and $\bar{z}^l$ 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 equations (3.2) and (3.3) into equation (3.1) and reordering, the estimation equation is also expressed as follows.

$$EP_{ijk} = \gamma^0 + \sum_{l=1}^L \gamma^{0,l} (z_k^l - \bar{z}^l) + \{\gamma^1 + \sum_{l=1}^L \gamma^{1,l} (z_k^l - \bar{z}^l)\} (I_{ijk} - \bar{I}_k) + \sum_{h=2}^H \beta^h (x_{ijk}^h - \bar{x}_k^h) + (V_k^1 + U_{jk}^1) (I_{ijk} - \bar{I}_k) + V_k^0 + U_{jk}^0 + R_{ijk} \quad (4)$$

For the household-level predictors, we include twelve variables based on the literature (Princ et al., 2019; Robinson et al., 2019): household income (*income*: household income in natural logarithm evaluated at US dollar purchasing power parity (PPP) after division by the square root of the household size⁴), 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 status⁵ (*mental*: takes a value between 4, for

⁴ 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.

⁵ This is calculated as the average value of the answers to 12 questions on the 12-Item General Health Questionnaire (David and Williams, 1998).

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_{jk}^0 in equation (3.1) captures the contextual effects, and equation (3.2) explains how the contextual effects are predicted. Equation (3.2) includes $z_k^l - \bar{z}^l$, 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 EP is partly determined by country-level and region-level factors in addition to household characteristics. The same applies to β_{jk}^1 in equations (3.1) and (3.3).

For the country-level predictors (z_k^l), 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 EP, 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 no air conditioner 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 (David and Williams, 1998). 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 equation (3.1), the coefficients β_{jk}^1 and β^h capture the effect of the relative position of household I within the country. The literature agrees that lower income exacerbates EP 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 equation (3.3), we model how the slope for household income, β_{jk}^1 , 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' EP. In other words, how households experience relative income poverty is associated with their likelihood of falling into EP. For instance, consider the situation where a household experiences a drop in income because of the 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 EP. On the other hand, in a country where the income slope is more sharply negative, such a situation would put the household in EP. The factors that can potentially reduce the negative value of the slope are the same as those relevant to the intercept and include EP 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 EP 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, EP. 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.

3.3.2 Predictor variables

Household-level predictors are derived from our survey data. As explained above, 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 equations (3.2) and (3.3)) (Gelman and Hill, 2006).

For the macro variables, we used the World Bank database for macro variables, including GDP per capita, GINI coefficients, and PPP conversion factors (World Bank, 2020). For heating degree days, the KAPSARC database was utilized (KAPSARC, 2020). 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. After eliminating questionnaires with non-responses to the income question, the final sample size was 92,081. For the summary statistics of the samples in the analysis, see Appendix 3.B. Table 3.6.B.

3.4 Results and Discussion

3.4.1 The descriptive analysis

Before proceeding with the results of the hierarchical model, we present the country-level aggregation of EP and its relationship with the GDP and GINI coefficients to outline the descriptive features and discuss the validity of our indicators (Figure 3.1 and Figure 3.2) (For the national average values, see Appendix 3.B, Table 3.7.B). As mentioned in subsection 3.3, subjective accessibility in this chapter 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, 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 EP 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 EP 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 EP in this chapter with the electrification rate in the IEA database because this database is the only resource available for the global comparison of EP. Figure 3.1 shows that EP 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 chapter 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 EP 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 EP. 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 countries in quite different ways. For instance, Myanmar is among the countries with the worst EP 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 EP within the surveyed countries, it matters for other countries. For instance, South Africa presents the worst level of EP in all dimensions when considering subjective indicators, while its objective EP is at the middle level. The opposite trend is observed in Mongolia, which holds the lowest rank in terms of objective EP but has an average level of subjective EP. As we discuss later, the empirical results offer an explanation for the differences in the results between the objective and subjective indicators.

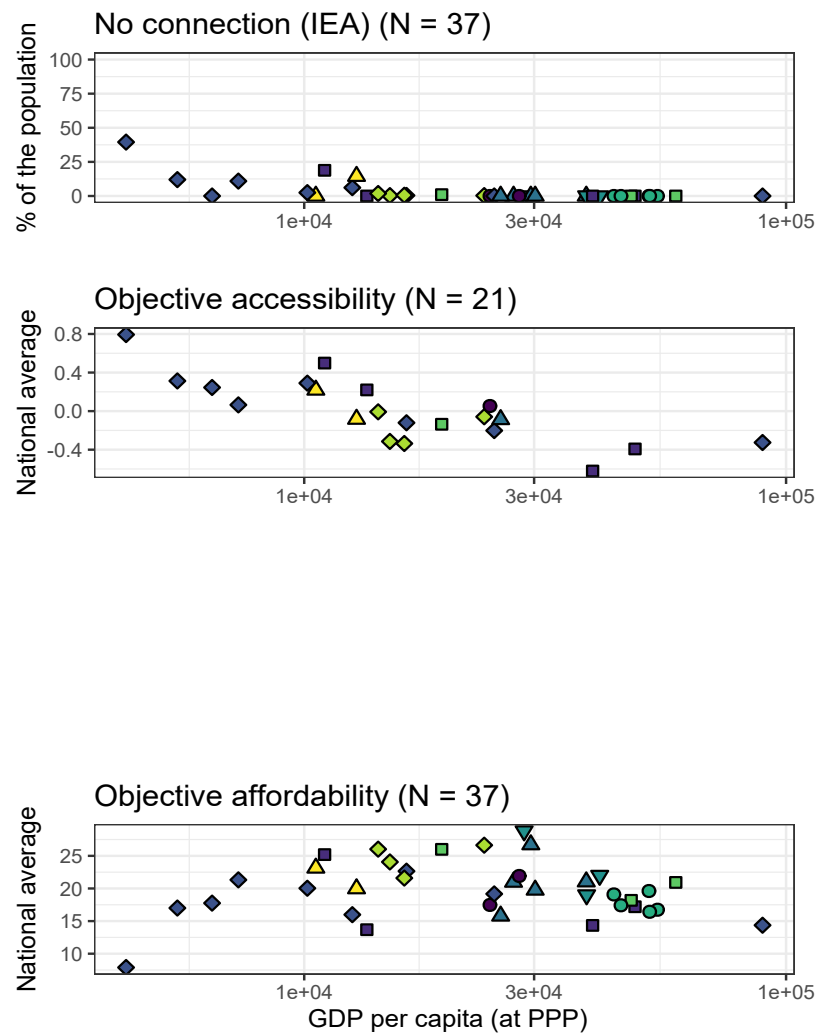


Figure 3.1 Energy poverty and economic development

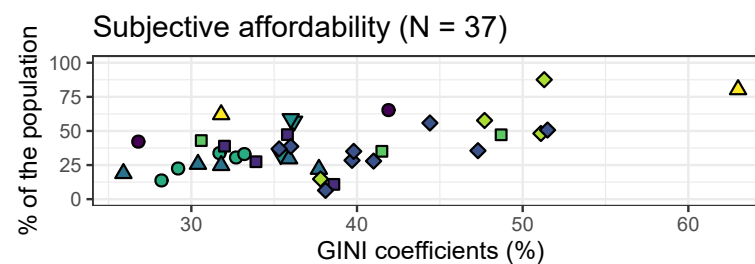
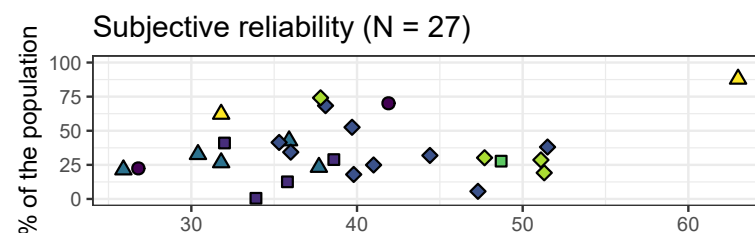
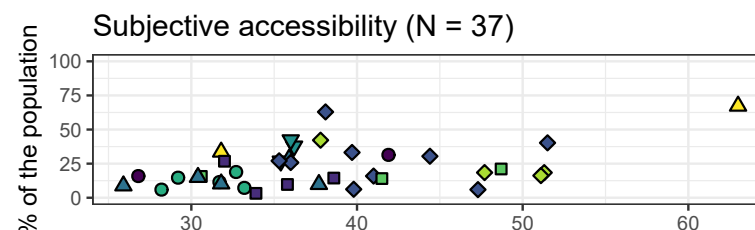
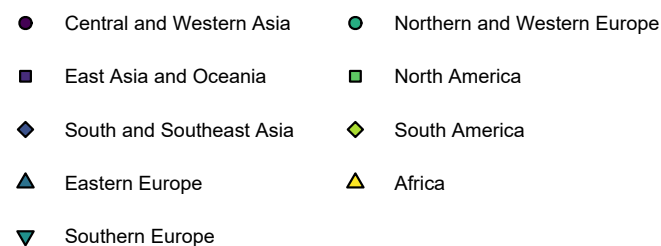
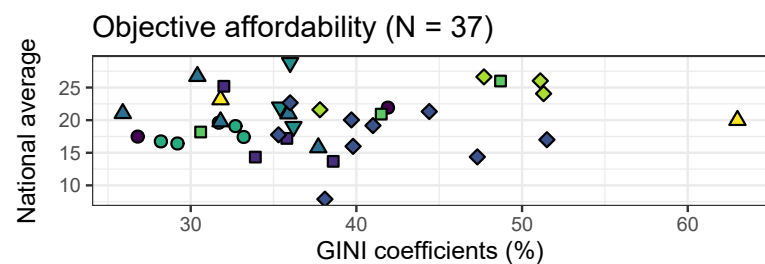
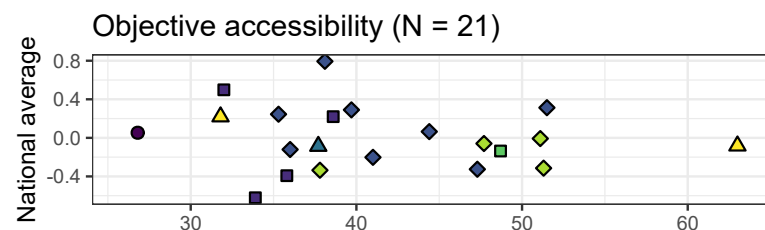
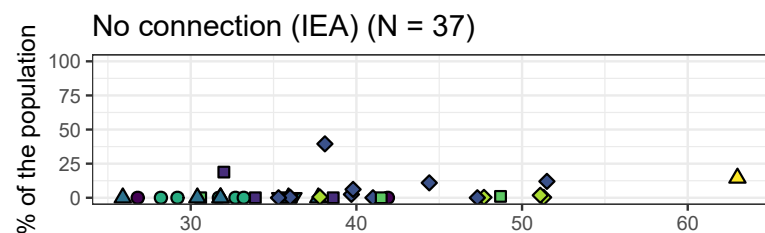


Figure 3.2 Energy poverty and income inequality

3.4.2 Estimation Results

The level-three models show better fit than the level-two models, according to the AIC and BIC (See Appendix 3.C, Table 3.8.C). This implies that regionally specific factors that cannot be captured at the country level have a large impact on EP. The estimation results of the linear regression and the logistic regression are mostly consistent (see Appendix 3.C, Table 3.9.C). Additionally, the consideration of heating degree days does not substantially change the estimated values for the coefficients (see Appendix 3.C, Table 3.10.C). Thus, this subsection explains only the results of the three-level linear hierarchical models (Table 3.2).

Table 3.2 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*** (0.04)	22.32*** (0.78)	0.44*** (0.03)
GDP	-0.31*** (0.06)	-0.11*** (0.03)	-0.19** (0.06)	-0.86 (0.91)	-0.01 (0.04)
GDP^2	0.09 (0.06)	0.02 (0.03)	-0.05 (0.05)	-4.30*** (0.99)	-0.09* (0.04)
GINI	-0.08 (0.05)	0.04 (0.03)	0.04 (0.04)	0.93 (0.78)	0.14*** (0.03)
Income	-0.14*** (0.02)	-0.02** (0.01)	-0.01 (0.01)	-1.60*** (0.23)	-0.03*** (0.01)
Income*GDP	0.08*** (0.02)	-0.00 (0.01)	-0.01 (0.01)	-1.10*** (0.27)	-0.01 (0.01)
Income*GDP^2	-0.01 (0.02)	0.00 (0.01)	0.00 (0.01)	0.25 (0.30)	0.00 (0.01)
Income*GINI	0.00 (0.02)	-0.00 (0.01)	0.01 (0.01)	-0.58* (0.23)	0.01 (0.01)
Female	0.02* (0.01)	-0.02*** (0.00)	-0.01*** (0.00)	0.82*** (0.08)	0.03*** (0.00)
Old	-0.13*** (0.02)	-0.01 (0.00)	-0.00 (0.01)	-1.36*** (0.16)	-0.01 (0.01)
Children	0.15*** (0.01)	0.03*** (0.00)	-0.01* (0.00)	1.04*** (0.10)	0.01*** (0.00)
Student	-0.08*** (0.01)	-0.03*** (0.01)	-0.00 (0.01)	0.16 (0.19)	-0.10*** (0.01)
Unemployed	-0.04*** (0.01)	-0.01* (0.00)	0.01* (0.00)	0.32** (0.12)	0.01 (0.00)

Self-employed	0.01 (0.01)	0.00 (0.00)	0.02** (0.01)	-0.12 (0.15)	0.02*** (0.01)
Education	-0.17*** (0.01)	-0.00 (0.00)	0.02*** (0.00)	-1.53*** (0.09)	-0.03*** (0.00)
Household size	-0.06*** (0.00)	0.01*** (0.00)	0.01*** (0.00)	0.62*** (0.03)	0.02*** (0.00)
Health	-0.03*** (0.00)	-0.01*** (0.00)	0.01*** (0.00)	-0.04 (0.05)	-0.00 (0.00)
Mental	0.03*** (0.01)	0.04*** (0.00)	0.03*** (0.00)	2.43*** (0.09)	0.06*** (0.00)
Rent	0.24*** (0.01)	0.01* (0.00)	-0.01 (0.00)	-0.40*** (0.10)	-0.00 (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	58271	92081	66101	84879	91286
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
$\text{Cov}(U_{jk}^0, U_{jk}^1)$	-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
$\text{Cov}(V_k^0, V_k^1)$	-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.

3.4.2.1 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 (Figure 3.1). 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 3.2). 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 chapter, higher EP 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 chapter finds EP in terms of affordability to be high. Thomson and Snell (2013) show that Eastern and Southern European countries suffer lower levels of energy efficiency than Northern and Western European countries. International Energy Agency (2019) 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 EP might have mitigated EP. Policies addressing EP have been most discussed in EU member states and are stipulated among the targets in the EU policy framework (Dobbins et al., 2019).

Regarding the association with the intercept and GINI coefficients, the coefficient was significantly positive only for subjective affordability (Table 3.2), which is also confirmed in Figure 3.2. This result implies that households living in a country with higher income inequality are more likely to experience higher EP 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.

3.4.2.2 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 3.2). The way GDP changes the association between EP and income differs between accessibility and affordability (Figure 3.3). 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 3.2, Panel A of Figure 3.3)). 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 3.2, Panel B of Figure 3.3)). 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 EP. 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. Figure 3.3 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 chapter 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 3.C, Table 3.8.C). 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 Figure 3.3 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 EP 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 EP.

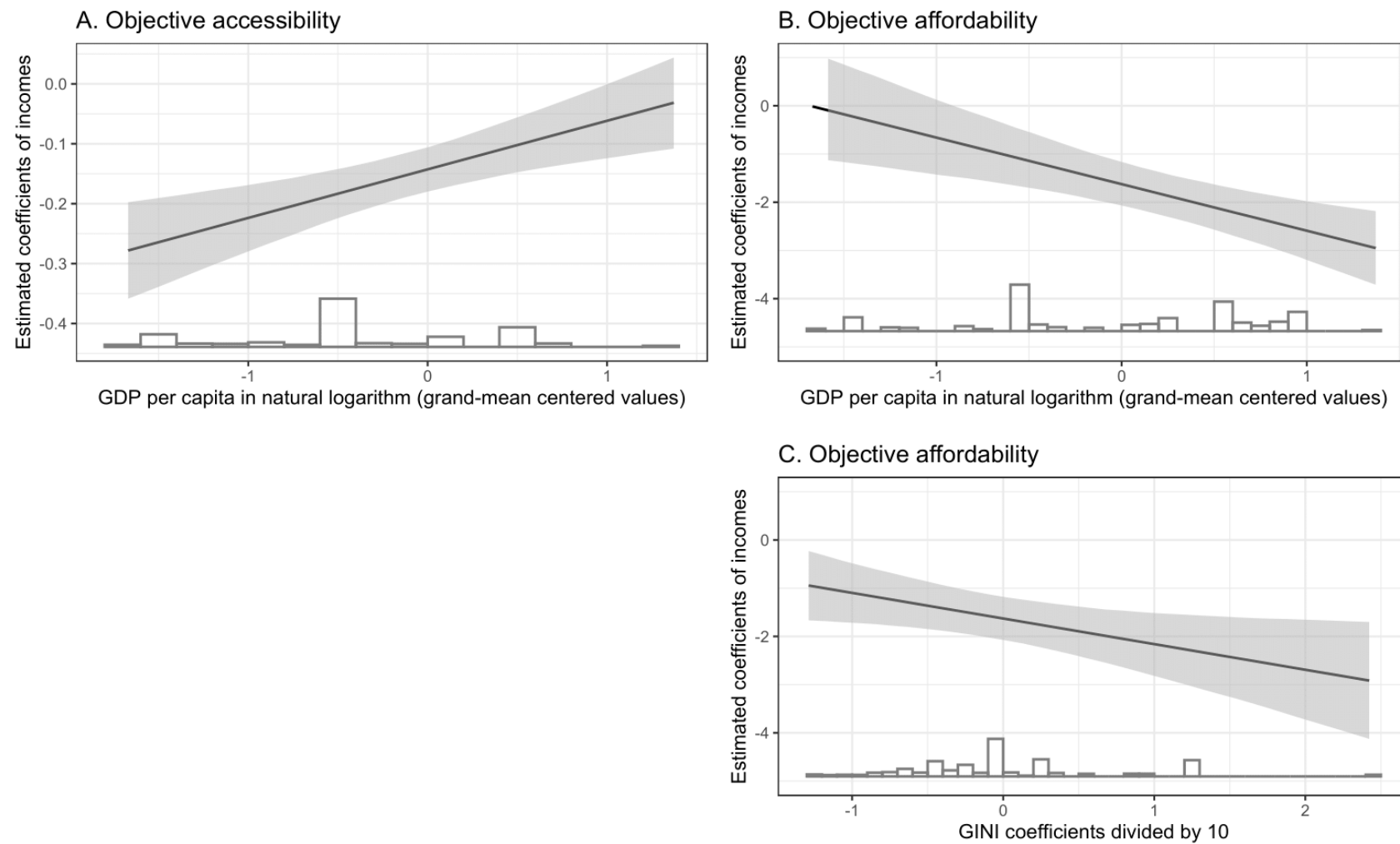


Figure 3.3 The relationship between the estimated coefficients of household income and economic factors

Notes: The histograms in the bottom of the figures indicate the sample distribution in the analysis.

3.4.2.3 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 chapter. However, the overall results can provide a global benchmark of how the relative change in these characteristics within a country affects EP at the household level. Identifying such societal factors can facilitate better targeting of the energy poor by policy supports (Baker et al., 2018).

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

3.4.3 Discussions on policy implications

It is important to identify the determinants of EP because this clarifies which households are more likely to experience EP and thus should be better targeted by policy supports (Baker et al., 2018). 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 EP 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 EP 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 EP. The findings in this chapter provide four policy implications. The first is related to indicators for identifying households in EP. Several recent studies on middle-income countries have attempted to quantify EP with the 10 percent indicator (Sambodo and Novandra, 2019; Urquiza et al., 2019; Zhang et al., 2019). 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 EP 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 EP, considering that the International Energy Agency (2020) 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 EP, reducing income disparity can reduce the EP in a country. Last, in constructing suitable criteria for defining households vulnerable to EP, 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 irrespective of dimension, while the other socioeconomic factors are differently associated with EP depending on the dimension.

3.4.4 Methodological limitations

The limitations of this chapter are as follows. First, the relationship between EP and country-level factors could be bidirectional, as more severe national EP 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 EP can cause serious health problems. Alleviating such negative impacts can reduce government expenditure and enhance economic development.

Second, Kahouli (2020) shows that individuals' responses to questions related to EP 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 EP.

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 chapter 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 EP in a more nuanced manner, as has been done in previous studies (Moore, 2012). 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 EP, 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 chapter, 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.

3.5 Conclusion

Using the original survey data of 37 countries in Europe, Asia, North and South America, Africa, and Australia, this chapter is the first to investigate the determinants of EP 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 EP 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 EP for households, (2) how these country-level economic factors influence the relationship between household income and EP, and (3) how other socioeconomic factors at the household level are linked to EP 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' EP differently depending on the three dimensions. In accessibility and reliability, households are more likely to experience EP 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 EP. Second, the linkage between lower household income and worse EP 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 EP in each dimension. The most important factors for the global average are income, having children, and mental illness.

References

- Abbas, K., Li, S., Xu, D., Baz, K., Rakhmetova, A., 2020. Do socioeconomic factors determine household multidimensional energy poverty? Empirical evidence from South Asia. *Energy Policy* 146, 111754. <https://doi.org/10.1016/j.enpol.2020.111754>
- Aklin, M., Cheng, C.Y., Urpelainen, J., Ganesan, K., Jain, A., 2016. Factors affecting household satisfaction with electricity supply in rural India. *Nat. Energy* 1, 1–6. <https://doi.org/10.1038/nenergy.2016.170>
- Aklin, M., Harish, S.P., Urpelainen, J., 2018. A global analysis of progress in household electrification. <https://doi.org/10.1016/j.enpol.2018.07.018>
- Awaworyi Churchill, S., Smyth, R., 2020. Ethnic diversity, energy poverty and the mediating role of trust: Evidence from household panel data for Australia¹. *Energy Econ.* 86, 104663. <https://doi.org/10.1016/j.eneco.2020.104663>
- Baker, K.J., Mould, R., Restricks, S., 2018. Rethink fuel poverty as a complex problem. *Nat. Energy*. <https://doi.org/10.1038/s41560-018-0204-2>
- Bartiaux, F., Vandeschrick, C., Moezzi, M., Frogneux, N., 2018. Energy justice, unequal access to affordable warmth, and capability deprivation: A quantitative analysis for Belgium. *Appl. Energy* 225, 1219–1233. <https://doi.org/10.1016/j.apenergy.2018.04.113>
- Birol, 2007. Energy Economics: A Place for Energy Poverty in the Agenda? *Energy J.* 28, 1–6.
- Boardman, B., 1991. Fuel poverty: From cold homes to affordable warmth. Belhaven Press, London.
- Botetzagias, I., Tsagkari, M., Malesios, C., 2018. Is the ‘Troika’ Bad for the Environment? An Analysis of EU Countries’ Environmental Performance in Times of Economic Downturn and Austerity Memoranda. *Ecol. Econ.* 150, 34–51. <https://doi.org/10.1016/j.ecolecon.2018.04.001>
- Bouzarovski, S., Thomson, H., 2018. Energy Vulnerability in the Grain of the City: Toward Neighborhood Typologies of Material Deprivation. *Ann. Am. Assoc. Geogr.* 108, 695–717. <https://doi.org/10.1080/24694452.2017.1373624>
- Bouzarovski, S., Tirado Herrero, S., 2017a. The energy divide: Integrating energy transitions, regional inequalities and poverty trends in the European Union. *Eur. Urban Reg. Stud.* 24, 69–86. <https://doi.org/10.1177/0969776415596449>
- Bouzarovski, S., Tirado Herrero, S., 2017b. Geographies of injustice: the socio-spatial determinants of energy poverty in Poland, the Czech Republic and Hungary. *Post-Communist Econ.* 29, 27–50. <https://doi.org/10.1080/14631377.2016.1242257>
- Carvalho, A., 2017. Drivers of reported electricity service satisfaction in transition economies. *Energy Policy* 107, 151–157. <https://doi.org/10.1016/j.enpol.2017.04.040>
- Castaño-Rosa, R., Sherriff, G., Thomson, H., Solís Guzmán, J., Marrero, M., 2019. Transferring the index of vulnerable homes: Application at the local-scale in England to assess fuel poverty vulnerability. *Energy Build.* 203, 109458. <https://doi.org/10.1016/j.enbuild.2019.109458>
- Chafe, Z., Brauer, M., Héroux, M.-E., Klimont, Z., Lanki, T., Salonen, R.O., Smith, K.R., 2015. Residential heating with wood and coal: health impacts and policy options in Europe and North America. WHO Regional Office for Europe, Copenhagen.
- David, G., Williams, P., 1998. A user’s guide to the General Health Questionnaire. NFER-

- Nelson, Windsor.
- Deller, D., 2018. Energy affordability in the EU: The risks of metric driven policies. *Energy Policy* 119, 168–182. <https://doi.org/10.1016/j.enpol.2018.03.033>
- Dobbins, A., Fusco Nerini, F., Deane, P., Pye, S., 2019. Strengthening the EU response to energy poverty. *Nat. Energy*. <https://doi.org/10.1038/s41560-018-0316-8>
- Doll, C.N.H., Pachauri, S., 2010. Estimating rural populations without access to electricity in developing countries through night-time light satellite imagery. *Energy Policy* 38, 5661–5670. <https://doi.org/10.1016/j.enpol.2010.05.014>
- Eichhorn, J., 2013. Unemployment Needs Context: How Societal Differences between Countries Moderate the Loss in Life-Satisfaction for the Unemployed. *J. Happiness Stud.* 14, 1657–1680. <https://doi.org/10.1007/s10902-012-9402-y>
- Fahmy, E., Gordon, D., Patsios, D., 2011. Predicting fuel poverty at a small-area level in England. *Energy Policy* 39, 4370–4377. <https://doi.org/10.1016/j.enpol.2011.04.057>
- Farquharson, D.V., Jaramillo, P., Samaras, C., 2018. Sustainability implications of electricity outages in sub-Saharan Africa. *Nat. Sustain.* 1, 589–597. <https://doi.org/10.1038/s41893-018-0151-8>
- Gelman, A., Hill, J., 2006. *Data Analysis Using Regression and Multilevel/Hierarchical Models*. Cambridge University Press. <https://doi.org/10.1017/CBO9780511790942>
- Healy, J., 2003. Fuel Poverty and Policy in Ireland and the European Union, in: *Studies in Public Policy*. Dublin 2.
- Healy, J.D., Clinch, J.P., 2002. Fuel Poverty in Europe : A Cross Country Analysis Using A New Composite Measurement, *Environmental Studies Research Series Working Papers*. Dublin.
- Heindl, P., 2015. Measuring Fuel Poverty: General Considerations and Application to German Household Data. *Public Finance Anal.* 71. <https://doi.org/10.2139/ssrn.2304673>
- International Energy Agency, 2020. Energy Efficiency Indicators – Analysis [WWW Document]. URL <https://www.iea.org/reports/energy-efficiency-indicators> (accessed 12.10.20).
- International Energy Agency, 2019. Fuel Economy in Major Car Markets: Technology and Policy Drivers 2005-2017 – Analysis [WWW Document]. URL <https://www.iea.org/reports/fuel-economy-in-major-car-markets#country-database> (accessed 12.10.20).
- Kahouli, S., 2020. An economic approach to the study of the relationship between housing hazards and health: The case of residential fuel poverty in France. *Energy Econ.* 85, 104592. <https://doi.org/10.1016/j.eneco.2019.104592>
- KAPSARC, 2020. Global Degree-Days Database [WWW Document]. URL <https://www.kapsarc.org/research/projects/global-degree-days-database/> (accessed 12.11.20).
- Lee, Kenneth, Miguel, E., Wolfram, C., 2020a. Does Household Electrification Supercharge Economic Development? *J. Econ. Perspect.* 34, 122–144. <https://doi.org/10.1257/jep.34.1.122>
- Lee, Kenneth, Miguel, E., Wolfram, C., 2020b. Experimental Evidence on the Economics of Rural Electrification, *Journal of Political Economy*.
- Legendre, B., Ricci, O., 2015. Measuring fuel poverty in France: Which households are

- the most fuel vulnerable? *Energy Econ.* 49, 620–628. <https://doi.org/10.1016/j.eneco.2015.01.022>
- Lenz, N.V., Grgurev, I., 2017. Assessment of energy poverty in New European union member states: The case of Bulgaria, Croatia and Romania. *Int. J. Energy Econ. Policy* 7, 1–8.
- Lewis, P., 1982. Fuel Poverty Can be Stopped. Natl. Right Fuel Campaign.
- Llorca, M., Rodriguez-Alvarez, A., Jamasb, T., 2020. Objective vs. subjective fuel poverty and self-assessed health. <https://doi.org/10.1016/j.eneco.2020.104736>
- Mattioli, G., Lucas, K., Marsden, G., 2017. Transport poverty and fuel poverty in the UK: From analogy to comparison. *Transp. Policy* 59, 93–105. <https://doi.org/10.1016/j.tranpol.2018.02.019>
- Moore, R., 2012. Definitions of fuel poverty: Implications for policy. *Energy Policy* 49, 19–26. <https://doi.org/10.1016/j.enpol.2012.01.057>
- Muller, C., Yan, H., 2018. Household fuel use in developing countries: Review of theory and evidence. *Energy Econ.* 70, 429–439. <https://doi.org/10.1016/j.eneco.2018.01.024>
- Neacsu, A., Panait, M., Muresan, J.D., Voica, M.C., 2020. Energy poverty in european union: Assessment difficulties, effects on the quality of life, mitigation measures. Some evidences from Romania. *Sustainability* 12, 1–28. <https://doi.org/10.3390/SU12104036>
- Neira, I., Bruna, F., Portela, M., García-Aracil, A., 2018. Individual Well-Being, Geographical Heterogeneity and Social Capital. *J. Happiness Stud.* 19, 1067–1090. <https://doi.org/10.1007/s10902-016-9840-z>
- Nussbaumer, P., Bazilian, M., Modi, V., Yumkella, K.K., 2011. *Measuring Energy Poverty: Focusing on What Matters*. Oxford.
- Primc, K., Slabe-Erker, R., Majcen, B., 2019. Energy poverty: A macrolevel perspective. *Sustain. Dev.* 27, 982–989. <https://doi.org/10.1002/sd.1999>
- Recalde, M., Peralta, A., Oliveras, L., Tirado-Herrero, S., Borrell, C., Palència, L., Gotsens, M., Artazcoz, L., Mari-Dell'olmo, M., 2019. Structural energy poverty vulnerability and excess winter mortality in the European Union: Exploring the association between structural determinants and health. *Energy Policy* 133, 110869. <https://doi.org/10.1016/j.enpol.2019.07.005>
- Robinson, C., Lindley, S., Bouzarovski, S., 2019. The Spatially Varying Components of Vulnerability to Energy Poverty. *Ann. Am. Assoc. Geogr.* 109, 1188–1207. <https://doi.org/10.1080/24694452.2018.1562872>
- Sambodo, M.T., Novandra, R., 2019. The state of energy poverty in Indonesia and its impact on welfare. *Energy Policy* 132, 113–121. <https://doi.org/10.1016/j.enpol.2019.05.029>
- Tabata, T., Tsai, P., 2020. Fuel poverty in Summer: An empirical analysis using microdata for Japan. *Sci. Total Environ.* 703, 135038. <https://doi.org/10.1016/j.scitotenv.2019.135038>
- Thomson, H., Snell, C., 2013. Quantifying the prevalence of fuel poverty across the European Union. *Energy Policy* 52, 563–572. <https://doi.org/10.1016/j.enpol.2012.10.009>
- Thomson, H., Snell, C., Bouzarovski, S., 2017. Health, well-being and energy poverty in Europe: A comparative study of 32 European countries. *Int. J. Environ. Res. Public Health* 14, 1–20. <https://doi.org/10.3390/ijerph14060584>

- Urquiza, A., Amigo, C., Billi, M., Calvo, R., Labraña, J., Oyarzún, T., Valencia, F., 2019. Quality as a hidden dimension of energy poverty in middle-development countries. Literature review and case study from Chile. *Energy Build.* 204, 109463. <https://doi.org/10.1016/j.enbuild.2019.109463>
- World Bank, 2020. World Bank Open Data [WWW Document]. URL <https://data.worldbank.org/> (accessed 11.1.20).
- Zhang, D., Li, J., Han, P., 2019. A multidimensional measure of energy poverty in China and its impacts on health: An empirical study based on the China family panel studies. *Energy Policy* 131, 72–81. <https://doi.org/10.1016/j.enpol.2019.04.037>

Appendix 3.A Principal component analysis

Table 3.3.A 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 3.4.A 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 3.B Data and descriptive statistics

Table 3.5.B 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	2015/07/25	2015/08/11	6,700
Indonesia	South and Southeast Asia	Internet	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	2015/07/18	2015/07/28	1,741
Total					100,956

Table 3.6.B 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
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 3.7.B Average energy poverty at the country level

Country name	No connection	Accessibility		Reliability	Affordability	
		Objective	Subjective	Subjective	Objective	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 3.C Estimation results

Table 3.8.C Two-level hierarchical linear model

	Accessibility		Reliability	Affordability	
	Objective	Subjective	Subjective	Objective	Subjective
Intercept	-0.16** (0.06)	0.22*** (0.03)	0.34*** (0.05)	22.25*** (0.78)	0.43*** (0.03)
GDP	-0.31*** (0.07)	-0.10** (0.03)	-0.17** (0.06)	-0.71 (0.91)	-0.00 (0.04)
GDP^2	0.10 (0.06)	0.02 (0.03)	-0.04 (0.06)	-4.21*** (0.99)	-0.07 (0.04)
GINI	-0.08 (0.05)	0.04 (0.03)	0.03 (0.04)	1.01 (0.78)	0.14*** (0.03)
Income	-0.13*** (0.02)	-0.02** (0.01)	-0.02* (0.01)	-1.63*** (0.23)	-0.03*** (0.01)
Income*GDP	0.08*** (0.02)	0.01 (0.01)	0.00 (0.01)	-0.97*** (0.27)	-0.01 (0.01)
Income*GDP^2	-0.03 (0.02)	-0.00 (0.01)	0.00 (0.01)	0.39 (0.30)	0.01 (0.01)
Income*GINI	0.01 (0.02)	0.00 (0.01)	0.01 (0.01)	-0.53* (0.23)	0.01 (0.01)
Female	0.02** (0.01)	-0.02*** (0.00)	-0.01*** (0.00)	0.80*** (0.08)	0.03*** (0.00)
Old	-0.14*** (0.02)	-0.01* (0.00)	-0.00 (0.01)	-1.43*** (0.16)	-0.01 (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	58271	92081	66101	84879	91286
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
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Notes: *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$. Standard errors in parentheses.

Table 3.9.C Comparison with the nonlinear model

	Subjective accessibility		Subjective reliability		Subjective affordability	
	Linear	Nonlinear	Linear	Nonlinear	Nonlinear	Linear
Intercept	0.22*** (0.03)	-1.42*** (0.16)	0.35*** (0.04)	-0.82** (0.25)	0.44*** (0.03)	-0.27 (0.16)
GDP	-0.11*** (0.03)	-0.73*** (0.18)	-0.19** (0.06)	-1.30*** (0.34)	-0.01 (0.04)	0.03 (0.18)
GDP^2	0.02 (0.03)	-0.03 (0.20)	-0.05 (0.05)	-0.47 (0.32)	-0.09* (0.04)	-0.48* (0.20)
GINI	0.04 (0.03)	0.21 (0.16)	0.04 (0.04)	0.23 (0.25)	0.14*** (0.03)	0.68*** (0.16)
Income	-0.02** (0.01)	-0.10*** (0.03)	-0.01 (0.01)	-0.07* (0.03)	-0.03*** (0.01)	-0.12*** (0.03)
Income*GDP	-0.00 (0.01)	-0.05 (0.03)	-0.01 (0.01)	-0.13* (0.06)	-0.01 (0.01)	-0.06 (0.03)
Income*GDP^2	0.00 (0.01)	-0.01 (0.04)	0.00 (0.01)	-0.04 (0.05)	0.00 (0.01)	-0.00 (0.04)
Income*GINI	-0.00 (0.01)	-0.00 (0.03)	0.01 (0.01)	0.06 (0.03)	0.01 (0.01)	0.06* (0.03)
Female	-0.02*** (0.00)	-0.13*** (0.02)	-0.01*** (0.00)	-0.07*** (0.02)	0.03*** (0.00)	0.15*** (0.02)
Old	-0.01 (0.00)	-0.15*** (0.04)	-0.00 (0.01)	-0.04 (0.06)	-0.01 (0.01)	-0.03 (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	92081	92081	66101	66101	91286	91286
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

$\text{Cov}(U_{jk}^0, U_{jk}^1)$	-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
$\text{Cov}(V_k^0, V_k^1)$	-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 3.10.C 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*** (0.02)	-0.01 (0.00)	-0.00 (0.01)	-1.36*** (0.16)	-0.01 (0.01)
Children	0.15*** (0.01)	0.03*** (0.00)	-0.01* (0.00)	1.04*** (0.10)	0.01*** (0.00)
Student	-0.08*** (0.01)	-0.03*** (0.01)	-0.00 (0.01)	0.16 (0.19)	-0.10*** (0.01)
Unemployed	-0.04*** (0.01)	-0.01* (0.00)	0.01* (0.00)	0.32** (0.12)	0.01 (0.00)
Self-employed	0.01 (0.01)	0.00 (0.00)	0.02** (0.01)	-0.12 (0.15)	0.02*** (0.01)
Education	-0.17*** (0.01)	-0.00 (0.00)	0.02*** (0.00)	-1.53*** (0.09)	-0.03*** (0.00)
Household size	-0.06*** (0.00)	0.01*** (0.00)	0.01*** (0.00)	0.62*** (0.03)	0.02*** (0.00)
Health	-0.03*** (0.00)	-0.01*** (0.00)	0.01*** (0.00)	-0.04 (0.05)	-0.00 (0.00)
Mental	0.03*** (0.01)	0.04*** (0.00)	0.03*** (0.00)	2.43*** (0.09)	0.06*** (0.00)
Rent	0.24*** (0.01)	0.01* (0.00)	-0.01 (0.00)	-0.40*** (0.10)	-0.00 (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	58271	92081	66101	84879	91286
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
$\text{Cov}(U_{jk}^0, U_{jk}^1)$	-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
$\text{Cov}(V_k^0, V_k^1)$	-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.

Chapter 4 Predicting summer-related energy poverty in Japan: A machine learning approach

4.1 Introduction

Predicting who is more likely to be energy-poor is important to offer necessary policy support. With this motivation, a body of literature has tried to specify the driving factors of Energy poverty (EP) using traditional regression methods (See Chapter 2). As noted in Chapter 2, EP studies in high-income countries have focused on energy poverty (EP) caused by lacking indoor warmth in winter. This is because the EP studies started in the UK, where most households were built a few hundred years ago and thus suffered from the low energy efficiency of buildings and cold climate. Recently, indoor cooling is starting to draw more attention with the ongoing climate change (Tabata and Tsai, 2020b; Thomson et al., 2019). Hotter summers can increase the risk of EP because higher outdoor temperatures increase the necessary energy for indoor cooling (Thomson et al., 2019). Thus, there exists an urgent need to understand summer-related EP and its predictors. However, a number of studies for summer-related EP is still lacking compared to the large number of studies of winter-related EP in European countries (Sanchez-Guevara et al., 2019; Tabata and Tsai, 2020b).

To fill this gap, this chapter focuses on summer-related EP in Japan and identifies its predictors. In this chapter, we construct a summer-related EP indicator using seasonal electricity expenditure data in the summer season. In addition, we define a subjective indicator of EP to show how the difference in EP indicators can affect the predictive power of variables. As the subjective indicator, we use subjective evaluation of electricity expenditure. Although this subjective evaluation is not limited to the summer season, as

noted in Chapter 2, it is important to quantify EP with several measures because both objective and subjective measures have each strengths and weaknesses.

As another contribution of this chapter, we identify predictors using Machine Learning (ML) methods. With the current development of computational easiness in ML methods, a few recent studies have started to apply ML methods for predicting EP in high-income countries (Dalla Longa et al., 2021; van Hove et al., 2022). As candidates of predictors, these studies adopted general socioeconomic factors such as income, housing floor size, and built years of homes. They used tree-based ensemble methods such as XGBoost or Random Forests. While their models offer high accuracy scores for predicting EP ranging between 65 % and 82 %, there can be other possible predictors which can be more powerful for high accuracy. Especially behavioral and regional factors can also be powerful for predicting EP because several studies have shown that these factors also affect the energy usage of households and thus affect EP (Bouzarovski, 2014). In addition, it would be of interest to know how much power the behavioral and regional factors have for predicting EP compared to the general socioeconomic factors. Thus, we incorporate behavioral and regional factors in addition to general predictors such as socioeconomic and housing factors. As indicated in the literature, the origins of EP can be very complex: one predictor can be more linked to EP when another predictor occurs at the same time, which is known as the interaction effect in a statistical sense. ML methods can be more useful than traditional regression methods because the strength of ML methods is its capacity to incorporate more predictors and their interactions. Thus, applying an ML method to the prediction of EP allows us to investigate EP's complex nature in a more robust way. As an ML method, we employ Random Forest, which is a well-known tree-based ensemble method.

The structure of this chapter is as follows. Subsection 4.2 explains the data and methods. Subsection 4.3 shows the results of ML prediction. Subsection 4.4 concludes.

4.2 Data and methods

4.2.1 Data

We use a large amount of data from a nationwide internet survey conducted via a third-party company (Nikkei Research Company) between October and December 2015 and 2016 in Japan. To approximate the population aged 17 years or older in Japan, the survey respondents were recruited based on gender, age, and residential region to match the population distribution.

As a general problem inherent to internet-based surveys, respondents tend to be younger than the general population because older adults are generally known to have limited access to the internet. Our survey is no exception: The share of the respondents older than or equal to 65 years is 12% in the 2015 survey, while official statistics show that this number is 26.6% of the households in Japan (Ministry of Health, Labor, and Welfare, 2015). As a consequence, the average values of the household size and household income in the survey are slightly larger than the official statistics: 2.78 and 6.7 million yen in the survey mean and 2.47 and 5.5 million yen in the official statistics, respectively. To adjust this bias, we used the weighing factor when calculating the national share of EP. The weighting factor is based on gender, age, and prefectures in the 2010 National census survey. Still, we note that our study's results represent a slightly younger and wealthier population than the actual population.

Although the survey was not specifically designed to analyze of this chapter, the questions cover various topics on energy systems, SWB, and urban planning. For the

main analysis, we use the data from the 2015 wave because some questions for the important predictors were not included in the 2016 wave. The original sample size in the 2015 wave is 153,645. After excluding observations with missing values for income, electricity expenditures, and postal codes, the sample size is 105,486. For the descriptive statistics, see Appendix 4.A.

4.2.2 Energy poverty indicators

As the main EP indicators of our interest, we use the Low Income and High Costs (LIHC) indicator and subjective affordability indicator. The LIHC indicator is one of the influential objective indicators in EP literature and is used in similar studies employing ML methods (Dalla Longa et al., 2021; van Hove et al., 2022). With the LIHC indicator, one is regarded as energy-poor if (1) their (required) energy expenditure is over the national median and (2) their residual income is under the poverty line (e.g., 60 % of the national median income) (Hills, 2012). As noted in Chapter 2, the required energy is, however, unobservable because its calculation needs detailed data such as actual energy services achieved within homes (e.g., indoor temperature). Thus, we assigned actual energy expenditure in the summer season (between July and September) values instead of required energy expenditure. This replacement, of course, can cause over or under estimation of EP because high observed energy expenditure does not mean high required energy expenditure.

In this regard, the use of subjective affordability indicator can complement this limitation of the LIHC. In this chapter, the subjective affordability indicator defines energy-poor if they answered they felt their energy expenditure was ‘extremely high.’ Thus, subjective affordability is not based on income or actual energy expenditure. Furthermore, the subjective affordability can reflect the gap people are feeling between

the ideal level of energy services and the actual level of energy services. Thus, the subjective affordability might reflect some aspects of required energy that the objective indicator cannot measure. However, as one limitation specific to our data, the question for subjective affordability is not necessarily summer-specific: the survey question does not limit the seasons with which one feels electricity expenditure is expensive. Thus, with our survey data, the subjective indicator can be regarded as the overall measure for EP in all seasons.

Table 4.1 shows the average share of EP with both indicators and the average values of general socio-economic and housing characteristics. The summary statistics show that the subjective indicators, the values are higher than the objective indicators: With the LIHC indicator, the share of EP is 9.1 %, while it is 27.3% with the subjective affordability indicator.

Comparison with the statistics of the similar climate and economic-level countries would give a benchmark of whether this share in Japan's summer-specific EP is high or not. In this regard, Australia is in a similar situation to Japan due to its climate and economic level. With Australia's longitudinal survey data, Awaworyi Churchill et al. (2020) calculates the national EP share with the LIHC indicator. With the LIHC, the share of EP in Australia is 5.4%, which is 3.7% lower than in Japan. As one limitation for comparison, Awaworyi Churchill et al. (2020) uses the yearly average expenditure for defining EP. Thus, a simple comparison is not adequate. Still, it can be said that Japan's EP is relatively higher than the other similar country's EP.

Table 4.1 The national share of energy poverty and the national average of socioeconomic and housing characteristics

Variables		National shares (%) or averages
Energy poverty indicators	LIHC	9.1%
	Subjective affordability	27.3%
Socioeconomic characteristics	Household income	2621 (USD)
	Income poverty	20.9%
	Household size	2.6
	Age of a respondent	54.3
Housing characteristics	Floor size	92.6 m ²

4.2.3 Predictors and data sources

We define six sets of predictors: income, socio-economic factors other than income, housing factors, behavioral factors, health-related factors, and regional factors. Each category includes from one to seven variables. A detailed explanation is presented in the following table.

Table 4.2 Predictors for energy poverty

Sets of predictors	Variables	How they are created	Sources
Income	Income (log)	The natural logarithm of household income (yen)	Survey
Socio-economic factors	Female	Takes the value of 1 for women and 0 for men	Survey

Sets of predictors	Variables	How they are created	Sources
	Age (10 categorical values)	10 categorical values for binned age between 15 and 99	Survey
	Marriage	Takes the value of 1 if the respondent is married	Survey
	Household size	The number of household size	Survey
	Dependent children	Takes the value of one if the respondent has children under seven years of age	Survey
	Respondent's education	Takes the value of one if the respondent has a university degree	Survey

Sets of predictors	Variables	How they are created	Sources
	Rent	For households that answer that they own a home, we assigned imputed rent estimated at the prefecture-level by using the regional difference index (RDI) of consumer prices from the Japanese official database. For those living in a rental home, we used rent data on the website for July September 2015 extracted from a commercial database provided by LIFULL Co., Ltd. (2019), one of the largest internet companies for residential rental homes. The total sample size is approximately 3,000,000. We calculated the average rent per floor space (yen/m ²) for the smallest unit of municipalities (1902 in total). To avoid small sample bias, we assigned no values for municipalities where there were fewer than 100 rent data samples. For the estimated values to be in the same unit as the RDI, we divided these values by the national mean. For the point estimate of each municipality, we used median values to avoid the influence of extreme values.	Survey and LIFULL Co., Ltd. (2019)
Housing factors	Rental house	Takes the value of one if the respondent lives in a rental home	Survey
	Floor space	Floor space in m ² , natural logarithm form	Survey
	Built year	The year in which the house was built	Survey

Sets of predictors	Variables	How they are created	Sources
Behavioral factors	Loan	Takes the value of one if the respondent is paying a home loan	Survey
	Time at home	The survey asks whether the respondent stays at home almost all the time during (1) weekdays or (2) holidays. We define two dummy variables for (1) and (2) which takes 1 if the respondent chooses 'yes'. Then, we calculate the average values for staying at home as follows. $Time\ at\ home = ((1) \times 5 + (2) \times 2)/7$	Survey
	Energy saving behavior	The sum of 10 daily energy-saving behavior options, namely, "turning off electricity frequently," "reducing the amount of time to open a refrigerator," "using electric fans with air conditioners," "adjusting wattage or the number of light bulbs," "turning off the main power switches," "using power-saving taps," "reconsidering contract amperes," "reconsidering electricity plans," "recording bills and electricity consumption," and "others"	Survey
	Knowledge	Takes the value of one if the respondent is very knowledgeable about the deregulation of the electricity market	Survey
	Website	Takes the value of one if the respondent looks at a retailer's website for personal electricity consumption data	Survey

Sets of predictors	Variables	How they are created	Sources
	Energy efficiency	Owning energy-efficient systems; the sum of 10 energy efficiency measures implemented. The measures include (1) solar generation systems, (2) solar water systems, (3) a heat pump, (4) a combined residential heat and power system, (5) a gas-powered water heater, (6) fuel cells for combined heat and power, (7) home storage batteries, (8) an eco-car charge system, (9) a smart meter, and (10) a home energy management system.	Survey
Health-related factors	Mental health	Takes a value between 1 (best) and 4 (worst) ⁶	Survey
	Subjective health	Takes a value between 1 and 5 for the question “How would you describe your overall health condition?”, where 1 = “very good”, 2 = “good”, 3 = “neither”, 4 = “poor”, and 5 = “very poor”	Survey
	Stress	The survey asks whether the respondent feels (1) high stress and (2) low stress. We define two dummy variables for (1) and (2) which takes 1 if the respondent chooses ‘yes’. Then, we calculate the average values for stress as follows. $Stress = (1) \times 0.8 + (2) \times 0.2$	Survey

⁶ Mental health is calculated as the average value of the 12 questions in the 12-Item General Health Questionnaire (David and Williams, 1998).

Sets of predictors	Variables	How they are created	Sources
Regional factors	Cooling Degree Days (CDD)	CDD is calculated with the threshold of 18 °C as the wet bulb globe temperature (WBGT). The values are standardized. To identify the CDD values for the survey respondents, we merge the CDD dataset provided by Mistry (2019) with the survey dataset by the respondents' postal codes. Mistry (2019) provides a high-resolution (0.25°) historical global gridded dataset of monthly CDD, and we use these data during the corresponding period for the analysis (between July and September 2015 and 2016).	Mistry (2019)

4.2.4 Predicting energy poverty with random forests algorithm

To predict EP, we employ the random forest approach (Breiman, 2001), which is one of the most well-known ML algorithms. The random forest is based on ‘bagging’ (also called ‘bootstrap aggregation’) of a large collection of de-correlated trees (Hastie et al., 2009). Bagging is to average approximately unbiased models. When the correlation between each model is smaller, bagging benefits from the reduced variance compared to the variance of each model. In the tree growing process, predictors (often called ‘features’ in ML literature) are randomly selected. Because this random selection makes the correlation of the trees smaller, averaging these trees makes the variance of random forests smaller compared to the variance of each tree. Because the weakness and strength of tree-based models are their high variance and low bias, bagging de-

correlated trees overcomes the high variance of tree-based models while it still benefits from low bias.

Because the share of EP is much smaller than the share of non-EP, applying the original dataset can be overfitting to non-EP (Dalla Longa et al., 2021). To solve this, we first subset the class of non-EP to the size equal to the class of EP, which is called down-sampling. Then, we add weights to the downsampled EP class equal to the factor by which the EP class is downsampled. By doing so, we can avoid overfitting while still keeping the original ratio of EP and non-EP.

For the hyper-parameter tuning (the number and depth of trees), we tried a range of parameter sets with grid search. Withing the grid search, we conducted five-folded cross-validation to check the more reliable scores independent from the selected, trained data.

4.3 Results and discussion

This subsection summarizes the main results using standard performance scores in RF for each objective and subjective EP indicator. The results show that behavioral and psychological factors are also associated with EP, in addition to general socio-economic and housing factors employed in the literature. In addition, we find a large difference in powerful predictors between the objective and subjective indicators.

4.3.1 The result with the objective indicator

Table 4.3 summarizes the results of RF classification with the three test scores: accuracy, precision, and true positive rate (TPR). Accuracy is the proportion rate of correctly predicted samples over all samples. The precision score is the proportion rate of true positives over the sum of true positives and false positives. TPR is the proportion rate

of true positives over the sum of true positives and false negatives. Thus, precision tells how many truly positive samples are included within the whole samples which is predicted positive, while TPR captures how much true positive samples are actually predicted as positive. Both scores by precision and TPR are calculated depending on which EP or non-EP is defined as ‘positive’ labels. In Table 4.3, one column considers EP = 1 to be ‘positive,’ and the other column regards EP = 0 as ‘positive.’ All the scores are calculated based on the test dataset after cross-validation. In addition to the ML approach, we conducted the logistic regression to confirm the overall relationship between EP and predictors (See Appendix 4.B). In addition to these overall test scores for assessing the RF model’s precision, Permutation Feature Importance (PFI) is calculated to understand which features are powerful for predicting EP. PFI calculates the importance of a predictor (feature) by comparing the original prediction error with the increased prediction error after permuting the feature’s values (Breiman, 2001). PFI is based on the idea that if the feature is ‘important,’ the permutation of the feature’s value yields a larger prediction error compared to the original prediction error. Thus, the larger PFI value of a feature means that the feature is important to predicting the outcomes. We calculated PFI using test data.

In training data, we tried the combination of predictor sets as follows: income only, income plus one of the predictor sets (‘socioeconomic,’ ‘health,’ ‘housing,’ ‘behavioral’ or ‘regional’ as described in the previous subsection), and all the predictors. In this subsection, we only show the results, including influential predictors.

In column (1) of Table 4.3, only income is selected as the input feature. Because the LIHC indicator is based on income and energy expenditure criteria, it is natural that the income variable has a powerful predictive power. Still, the accuracy is not high,

80%. Thus, EP is indeed a different status from income poverty. In column 2, the results are shown when socioeconomic features are added to the income feature. Scores of TPR for non-EP (EP=0) or EP (EP =1) are both high, 90% and 99%, respectively. In a practical view, this high TPR is preferable because socioeconomic data is easily identifiable from the official statistics, making periodical observation of EP easier. However, the precision score when EP = 1 is low, 39 %, compared to the high score of non-EP, 100%. Generally, precision and TPR are in the trade-off: higher TPR is compensation for low precision scores. In the RF algorithm, one can choose which scores the algorithm tries to improve. This chapter considers improving TPR rather than precision is more important because identifying households in EP is more important to offer necessary political help than misclassifying non-EP as EP. Compared to the failure of missing households in EP, overestimating them at the cost of misclassifying non-energy poor can be less problematic.

In column (3), all the variables are added to predictors. Compared to the result in column (2), the scores are slightly worsened: 1 % and 4% lower for EP = 1 in TPR and precision score. This can happen when irrelevant variables are included because such inclusion hampers the true predictive variables from being selected at splits points of trees (Hastie et al., 2009). However, this result does not mean that only socioeconomic predictors are influential for EP. Figure 4.1 shows PFI to see which features are powerful for predicting EP. In Figure 4.1, income and household size have the largest predictive power, which is natural because EP is defined on these predictors. Still, housing and behavioral factors, including rental home, floor space, and time at home, are influential next to income and household size. Because these housing and behavioral factors are highly correlated with the socioeconomic variable set, not

including these predictors does not affect the prediction score. Still, from the result, it can be said that these housing and behavioral factors are more important than the other socioeconomic variables, including age, gender, having dependent children, or education.

As a policy implication, the importance of time at home for predicting EP should be highlighted. As the quarantine period is long due to the Covid 19 pandemic, the time spent at home has been becoming larger. Because the survey was conducted before the Covid 19 pandemic began, there is a large difference in time spent at home between households. The high PFI of time spent at home indicates that EP in summer seasons might have worsened because people stay at home longer.

Table 4.3 Results of random forest classification with the objective indicator

		Energy poverty indicator: the LIHC (the objective indicator)					
		(1)		(2)		(3)	
		EP = 0	EP = 1	EP = 0	EP = 1	EP = 0	EP = 1
		13,729 912		13,729 912		13,729 912	
No. of samples in test dataset		13,729	912	13,729	912	13,729	912
Scores	True Positive Rate (TPR)	79%	98%	90%	99%	88%	98%
	Precision	100%	23%	100%	39%	100%	35%
	Accuracy	80%		90%		89%	
Features	Income	✓		✓		✓	
	Socioeconomic			✓		✓	
	Health					✓	
	Housing					✓	
	Behavioral					✓	
	Regional (CDD)					✓	
Parameters	No. of trees	600		600		600	
	Depth of trees	1		10		15	

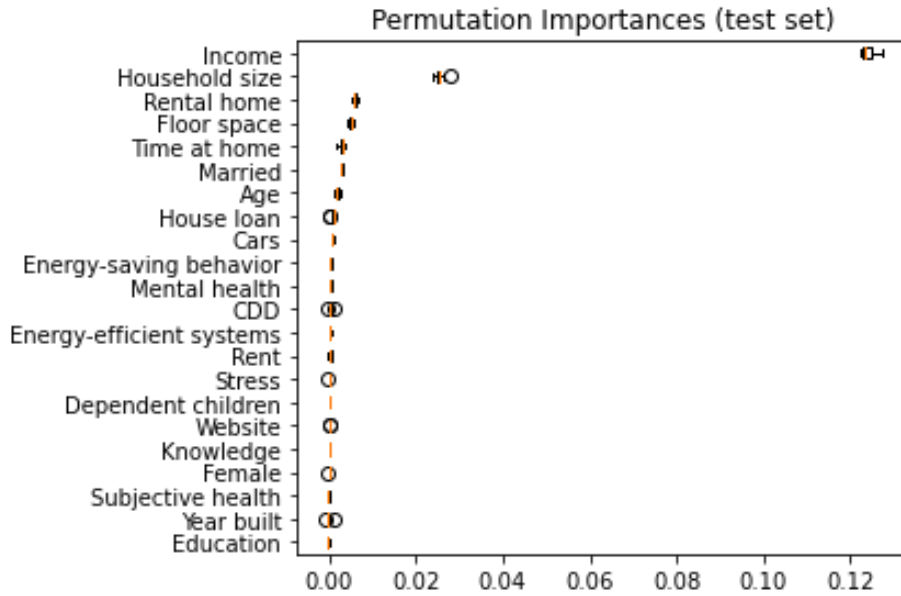


Figure 4.1 Permutation Feature Importance (PFI) for prediction with the objective energy poverty indicator

4.3.2 The result with the subjective indicator

Next, this subsection shows the results with the subjective affordability indicator using the same scores and figures above. Overall, the scores of correct predictions are worse than those with the objective indicator: The highest TPR for EP = 1 is 63 % when socioeconomic predictors are used. The accuracy ranges between 55% and 60%, which is about 30% worse than the scores with the objective indicator. This result of low scores is not surprising because the subjective indicator is not based on any observable predictor variables, while the objective EP is defined using income, energy expenditure, and household size.

Interestingly, however, household size is also the most influential predictor of the subjective EP. Income, on the other hand, is not important for predicting people's feeling that energy expenditure is high. The large different point from the objective

indicator is that all health-related predictors are influential for the subjective EP. It can be said that subjective feeling of energy expenditure is largely affected by psychological factors.

Another interesting point is that energy-efficient systems installed at home are more associated with the subjective indicator than the objective indicator. Generally, energy-systems are expected to decrease energy expenditure. Then, energy-efficient systems can also be influential in predicting the objective EP. However, such a result is not confirmed in the previous subsection. We posit a possible hypothesis for this reason. As noted in Chapter 2, the strength of the subjective indicator is that it can capture a respondent's subjective evaluation of the mismatch between required and actual energy. On the other hand, the weakness of the objective indicator is that 'required energy' is not observable and replaced with the actual energy, which cannot reflect the level of energy services achieved. The high PFI of energy-efficient systems with the subjective indicator might be because people evaluate the higher level of energy services achieved by energy-efficient systems.

Table 4.4 Results of random forest classification with the subjective indicator

			EP: Subjective affordability					
			EP = 0	EP = 1	EP = 0	EP = 1	EP = 0	EP = 1
			(1)		(2)		(3)	
No. of samples in test dataset			10151	4490	10151	4490	10151	4490
Scores	True Positive Rate (TPR)		47%	58%	52%	63%	59%	62%
	Precision		72%	33%	76%	36%	78%	40%
	Accuracy		57%		55%		60%	
Features	Income		✓		✓		✓	
	Socioeconomic				✓		✓	
	Health						✓	
	Housing						✓	
	Behavioral						✓	
	Regional (CDD)						✓	
Parameters	No. of trees		600		800		1000	
	Depth of trees		3		10		10	

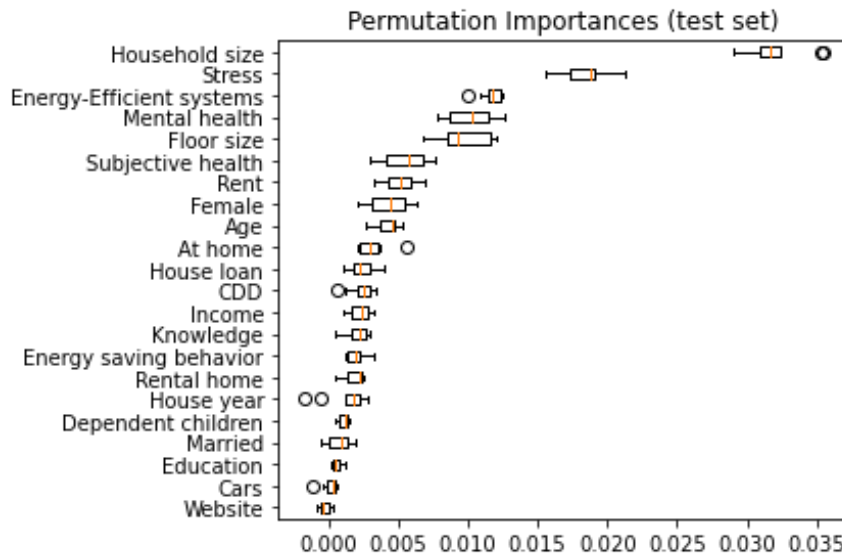


Figure 4.2 Permutation Feature Importance (PFI) for prediction with the subjective indicator

4.4 Conclusion

In this chapter, we highlight the summer-related EP with a case country of Japan. This chapter also used both the objective and subjective indicators for identifying EP. We found that EP with the objective measure is indeed a different problem from income poverty: housing and behavioral factors are powerful in predicting EP in addition to income and household size. On the other hand, EP with the subjective indicator also shows a high correlation with mental factors such as psychological stress. Although both indicators are not perfect for identifying the real EP situation, this chapter shows the possible pathways for better measuring EP in the summer context by combining both indicators.

References

- Bouzarovski, S., 2014. Energy poverty in the European Union: Landscapes of vulnerability. *Wiley Interdisciplinary Reviews: Energy and Environment* 3, 276–289. <https://doi.org/10.1002/wene.89>
- Breiman, L., 2001. Random Forests. *Machine Learning* 45, 5–32.
- Dalla Longa, F., Sweerts, B., van der Zwaan, B., 2021. Exploring the complex origins of energy poverty in The Netherlands with machine learning. *Energy Policy* 156, 112373. <https://doi.org/10.1016/j.enpol.2021.112373>
- David, G., Williams, P., 1998. A user's guide to the General Health Questionnaire. NFER-Nelson, Windsor.
- Hastie, T., Tibshirani, R., Friedman, J., 2009. *The Elements of Statistical Learning*, 2nd ed. Springer New York, NY.
- Hills, J., 2012. Getting the measure of fuel poverty. Final Report of the Fuel Poverty Review. Centre for Analysis of Social Exclusion, London School of Economics and Political Science, London.
- LIFULL Co., Ltd., 2019. LIFULL HOME'S Dataset. Informatics Research Data Repository, National Institute of informatics. (dataset). <https://doi.org/10.32130/idr.6.0>
- Ministry of Health, Labor, and Welfare, 2015. Comprehensive Survey of Living Conditions [WWW Document]. URL <https://www.mhlw.go.jp/toukei/saikin/hw/k-tyosa/k-tyosa15/index.html>
- Mistry, M.N., 2019. Historical global gridded degree-days: A high-spatial resolution database of CDD and HDD. *Geoscience Data Journal*. <https://doi.pangaea.de/10.1594/PANGAEA.903123>
- Sanchez-Guevara, C., Núñez Peiró, M., Taylor, J., Mavrogianni, A., Neila González, J., 2019. Assessing population vulnerability towards summer energy poverty: Case studies of Madrid and London. *Energy and Buildings* 190, 132–143. <https://doi.org/10.1016/j.enbuild.2019.02.024>
- Tabata, T., Tsai, P., 2020. Fuel poverty in Summer: An empirical analysis using microdata for Japan. *Science of the Total Environment* 703, 135038. <https://doi.org/10.1016/j.scitotenv.2019.135038>
- Thomson, H., Simcock, N., Bouzarovski, S., Petrova, S., 2019. Energy poverty and indoor cooling: An overlooked issue in Europe. *Energy and Buildings* 196, 21–29. <https://doi.org/10.1016/j.enbuild.2019.05.014>
- van Hove, W., Dalla Longa, F., van der Zwaan, B., 2022. Identifying predictors for energy poverty in Europe using machine learning. *Energy and Buildings* 264, 112064.

<https://doi.org/10.1016/j.enbuild.2022.112064>

Wang, H., Maruejols, L., Yu, X., 2021. Predicting energy poverty with combinations of remote-sensing and socioeconomic survey data in India: Evidence from machine learning. *Energy Economics* 102, 105510. <https://doi.org/10.1016/j.eneco.2021.105510>

Appendix 4.A Descriptive statistics

Table 4.5 Descriptive statistics

Variables	N	Mean	Min	Max
EP (LIHC)	105,486	0.07	0.00	1.00
EP (10 %)	105,486	0.02	0.00	1.00
EP (2 Median)	105,486	0.13	0.00	1.00
EP (Subjective affordability)	105,486	0.30	0.00	1.00
Electricity expenditure	105,486	10,585.19	2,500.00	35,000.00
Income poverty	105,486	0.16	0.00	1.00
Income (log)	105,486	15.52	14.22	17.37
Female	105,486	0.37	0.00	1.00
Age (10 categorical values)	105,486	4.48	1.00	8.00
Marriage	105,486	0.71	0.00	1.00
Household number	105,486	2.78	1.00	10.00
Dependent children	105,486	0.12	0.00	1.00
Respondent's education	105,486	0.50	0.00	1.00
Rent	105,315	0.91	0.50	1.95
Rent house	105,486	0.26	0.00	1.00
Floor space	88,292	4.32	2.89	5.19
Built year	101,159	18.82	1.00	45.00
Loan	105,486	0.30	0.00	1.00
Time at home	105,486	0.56	0.00	1.00
Energy saving behavior	105,486	0.21	0.00	1.00

Variables	N	Mean	Min	Max
Knowledge	105,486	0.05	0.00	1.00
Website	105,486	0.09	0.00	1.00
Energy efficiency	105,486	0.03	0.00	1.00
Mental health	105,486	2.09	1.00	4.00
Subjective health	105,486	2.53	1.00	5.00
Stress	105,486	0.14	0.00	1.00
CDD (18 degree, standardized)	90,054	-0.23	-3.01	1.11

Appendix 4.B Results with logistic regression

Table 4.6 Results with logistic regression (the LIHC indicator)

Predictors	AME	SE	z	p	lower	upper
Age	0.186	0.025	7.416	0.000	0.137	0.235
Time at home	0.233	0.022	10.566	0.000	0.190	0.277
Dependent children	-0.244	0.033	-7.374	0.000	-0.309	-0.179
Education	-0.058	0.021	-2.766	0.006	-0.099	-0.017
Energy efficient systems	-0.019	0.024	-0.773	0.439	-0.065	0.028
Website	-0.028	0.019	-1.424	0.155	-0.066	0.010
Female	-0.108	0.022	-4.934	0.000	-0.151	-0.065
Housing loan	0.033	0.028	1.181	0.238	-0.022	0.089
Floor space	0.282	0.025	11.488	0.000	0.233	0.330
Rental house	-0.200	0.027	-7.434	0.000	-0.253	-0.148
Household size	0.569	0.024	23.425	0.000	0.521	0.616
Built year	0.078	0.020	3.803	0.000	0.038	0.118
Income	-2.748	0.034	-80.474	0.000	-2.815	-2.681
Knowledge	-0.011	0.022	-0.497	0.619	-0.055	0.033
Marriage	0.110	0.024	4.626	0.000	0.063	0.156
Rent	0.026	0.024	1.088	0.276	-0.021	0.073
Save	-0.212	0.020	-10.583	0.000	-0.252	-0.173
CDD	0.219	0.022	9.931	0.000	0.176	0.262

Predictors	AME	SE	z	p	lower	upper
Subjective health	0.095	0.021	4.564	0.000	0.054	0.136
Mental health	0.007	0.022	0.306	0.760	-0.036	0.050
Stress	0.039	0.022	1.804	0.071	-0.003	0.082

Table 4.7 Results with logistic regression (the subjective affordability indicator)

Predictors	AME	SE	z	p	lower	upper
Age	0.048	0.011	4.260	0.000	0.026	0.071
Time at home	0.069	0.009	7.633	0.000	0.051	0.086
Dependent children	-0.045	0.010	-4.694	0.000	-0.064	-0.026
Education	-0.008	0.009	-0.918	0.359	-0.025	0.009
Energy efficient systems	-0.163	0.009	-18.065	0.000	-0.181	-0.146
Website	0.019	0.008	2.436	0.015	0.004	0.035
Female	-0.120	0.009	-12.732	0.000	-0.138	-0.101
Housing loan	0.103	0.010	10.462	0.000	0.083	0.122
Floor space	0.140	0.011	12.197	0.000	0.118	0.163
Rental house	-0.011	0.012	-0.922	0.357	-0.034	0.012
Household size	0.271	0.010	26.225	0.000	0.251	0.291
Built year	0.026	0.010	2.635	0.008	0.007	0.045
Income	-0.083	0.010	-8.358	0.000	-0.103	-0.064
Knowledge	0.091	0.008	11.999	0.000	0.076	0.106
Marriage	-0.002	0.011	-0.172	0.863	-0.023	0.019
Rent	0.153	0.009	16.541	0.000	0.135	0.171
Save	0.010	0.008	1.238	0.216	-0.006	0.027
CDD	-0.058	0.009	-6.322	0.000	-0.076	-0.040
Subjective health	0.090	0.009	9.907	0.000	0.072	0.108
Mental health	0.114	0.009	12.035	0.000	0.096	0.133

Predictors	AME	SE	z	p	lower	upper
Stress	0.191	0.009	21.613	0.000	0.174	0.209

Chapter 5 The impact of cooling energy needs on subjective well-being:

Evidence from Japan

5.1 Introduction

In this chapter, we further proceed the understanding of EP by showing its impact. Because the literature of EP has focused on developing the suitable indicators, studies for examining the EP's impact is scarce. The few exceptional studies include Awaworyi Churchill et al. (2020), Biermann (2016) and Kahouli (2020). With the case countries of Europe and Australia, these studies have shown that EP has a negative impact on well-being, which is proxied by subjective well-being (SWB). However, these studies do not address summer-related EP, which results in no evidence of the well-being impact of cooling affordability. As shown in chapter 3, in emerging economies such as Africa and Asia, the affordability problem is still not on the main agenda because their low level of income still makes accessibility and reliability issues more important. Still, in the current context of climate change and economic growth, how cooling affordability matters for human well-being is important because the need for indoor cooling is accelerating around the world (IEA, 2018). In emerging economies, such as Africa and Asia, increasing income levels and populations stimulate the need for ACs (IEA, 2018). In Europe, the soaring frequency and intensity of heatwaves enhance people's willingness to purchase air conditioners (ACs) (IEA, 2018; Washington Post, 2019).

To fill this gap, this chapter aims to show how energy needs in summer affect well-being with the case country of Japan. Specifically, we ask the following two questions: (1) How does a rise in temperature affect energy usage in the summer season, and, in turn, how does it affect well-being? (2) Are there any heterogeneous effects on this relationship in relation to income level? Answering these questions can provide a

better picture to consider how cooling affordability matters for human well-being and what types of policy interventions are expected to achieve energy justice.

To answer these questions, we use the same survey data with that of chapter 4. The survey is unique in that it includes seasonal electricity expenditure data for summer (between July and September), detailed geographical information at the postal code level, and SWB measures. Japan's characteristics are suitable for the research question in this chapter because it has the largest adaptation rate of ACs on the globe, namely, 91% (IEA, 2018), and large geographical heterogeneity in the use of cooling energy. By merging satellite data of Cooling Degree Days (CDD) with the survey data, this chapter identifies climate conditions for each household in the summer season. Then, we use household-level CDD as the instrumental variable (IV) for observed energy to extract the variation in energy needs for indoor cooling.

As an additional contribution, this CDD-based IV strategy allows us to examine EP's well-being impact in a more fundamental way. As discussed in chapter 2, the literature on EP has been concerned with the concept of "required energy." Required energy is a concept understood as necessary energy to attain basic energy services at a socially sufficient level (Bouzarovski and Petrova, 2015). Importantly, climate conditions are one of the driving factors for required energy because higher outdoor temperatures in the summer season increase the necessary energy to keep a home at a certain temperature. Required energy is different from actual, observed energy because households can consume less or more than required energy (Thomson et al., 2017b). As an important problem, researchers cannot know the actual amount of required energy because its calculation requires detailed data, such as housing and appliance energy efficiency. As a result, researchers cannot distinguish whether observed high energy is consumed as

needed or implicates consumers' high preferences for energy services beyond the necessary level. By using the IV of CDD, which calculates energy needs for buildings based on outdoor temperatures, this chapter aims to differentiate the impact of cooling energy needs from that of preference-based energy consumption for usage other than cooling. This strategy allows us to examine EP in a more meaningful way because the energy variation induced by a higher CDD is close to the concept of required energy. Although this observed vs. required energy issue has been well debated in definitional aspects (Papada and Kaliampakos, 2018), only a few empirical studies have paid attention to it (Rodriguez-Alvarez et al., 2019; Welsch and Biermann, 2017).

The remainder of this chapter is structured as follows. Subsection 5.2 presents the theoretical assumptions about how cooling energy needs affect well-being and describes the empirical strategy for identifying the impact of cooling energy needs on SWB. Subsection 5.3 presents the estimation results. Subsection 5.4 discusses the findings and policy implications. Subsection 5.5 concludes.

5.2 Hypothesis, empirical strategy and data

We hypothesize that higher outdoor temperatures can lower well-being by increasing the required energy. The intuitive mechanism of this hypothesis is as follows. Assume that someone has a certain fixed budget, and their welfare depends on energy services beyond the necessary (minimum) level and non-energy services. When the energy required for indoor cooling increases through higher outdoor temperatures, the amount of energy services consumed beyond the necessary level is reduced. In addition, the increasing costs of required energy can reduce the income left for non-energy services. With these two channels, welfare, which can be proxied by SWB, can be reduced. In relation to income

levels, it is natural to assume that the negative well-being effect of required energy increases as income decreases because lower-income households face a larger share of their incomes on energy expenditures. For the mathematical background, see Appendix 5.A.

Japan's features provide favorable conditions to examine this hypothesis. Japan has the highest share of ACs and refrigerators worldwide and large heterogeneity in the severity of summer seasons (see Appendix 5.B, Figure 5.1.B for graphical details). In the summer season, air conditioning and refrigeration account for the largest share of energy consumption (Japanese Ministry of the Environment, 2013). Both technologies need more energy to obtain a certain level of energy services when CDD is higher. Thus, with higher outdoor temperatures, the required energy is also expected to be higher. With this assumption, the observed variation in energy induced by the outdoor temperature is likely to capture some type of cooling energy needs.

In addition to large geographical heterogeneity, Japan's CDD varies considerably between the summer and winter seasons. While a large diffusion rate of ACs implies high cooling needs in the summer season across Japan, heating needs in the winter season are also substantial. In addition to large regional differences in cooling needs in the summer season, there are large regional differences in the EP of heating needs (Okushima, 2019). Since we use data from the summer season, this chapter only highlights cooling needs in Japan.

As the IV for observed energy, we use CDD, which is a well-known index for predicting the energy needs of buildings. This strategy enables us to extract the temperature-induced variation in observed energy, which is close, if not identical, to the

concept of required energy for indoor cooling.⁷ The dataset for the analysis includes unique information that enables us to meet the conditional independence assumption of IVs and avoid sample selection bias regarding temperatures.

5.2.1 Regressing SWB on observed energy with CDD as the IV

When using observed energy as a proxy for required energy, an ordinary least squares (OLS) estimation can underestimate the magnitude of the expected negative effect of required energy. The reason is that observed energy includes an unobserved preference for energy services beyond the energy level needed. To address this problem, this chapter uses CDD as the IV for observed energy.

Specifically, we consider the following regression equation:

$$S_i = \alpha ENE_i + X_i' \beta + \varepsilon_i \quad (5.1)$$

where subscript i denotes a respondent, S_i denotes SWB, ENE_i represents observed energy expenditures, X_i is a vector of intercept and control variables, and ε_i is the error term. α and β are the parameter and parameter vector to be estimated, respectively. If we simply estimate the relationship between SWB and observed energy expenditures with Equation (5.1) through the OLS approach, then we will not be able to identify whether the observed variation in energy expenditures is due to an increase in required energy or an increase in energy beyond a necessary level. Specifically, an increase in ENE_i can be induced by high preferences for the use of electric appliances, i.e., highly convenient electric appliances, such as dishwashers and robotic vacuums, or the long-term usage of general electric appliances. Such preference-based use of energy

⁷ As an example of similar studies that use IVs for temperature-induced variation, Feng et al. (2010) examine the effect of temperature-induced crop yields on migration, where climate conditions are used as the IV for crop yields.

services can increase SWB. In this case, replacing the required energy with the observed energy fails to evaluate the impact of the required energy. If these preference-based factors also positively affect SWB and are not controlled for, then parameter α can have a positive bias.

By using CDD as an IV for observed energy, this chapter aims to show the impact of temperature-induced energy on SWB, which is assumed to be close to cooling energy needs. The first-stage Equation in the IV estimation is expressed as follows:

$$ENE_i = \gamma CDD_{ri} + X_i' \beta + \epsilon_i \quad (5.2)$$

where CDD_{ri} is the CDD in region r where respondent i lives and ϵ_i is the random error. The regional unit is the postal code. Parameter γ estimated through OLS can be viewed as the impact of CDD on observed energy, which is also of interest.

As an important limitation, an IV estimation captures the effect of temperature-induced energy on SWB only for populations that respond to CDD increases by increasing their energy consumption (Wooldridge, 2010).⁸ This means that the effect of CDD-induced energy cannot be identified for populations that do not increase their energy usage when CDD increases. We further discuss this point when checking the results.

5.2.2 Validity of the IV

For the externality condition of the IV, we carefully ensured that CDD was not correlated with ϵ_i in Equation (5.1). The noncorrelation between CDD and ϵ_i means that CDD, which is calculated based on the outdoor temperature, does not directly affect SWB in

⁸ This argument is analogous to the better-established idea of "complies" in the local average treatment effect (LATE) framework, which assumes that a treatment variable and an IV are binary variables (Angrist and Pischke, 2009).

Equation (5.2) but affects SWB only by increasing observed energy. We assume noncorrelation between CDD and ε_i for three reasons.

First, a key idea is a distinction between indoor and outdoor temperatures. Which temperature is likely to directly affect people's SWB in the context of high-income countries? We assume that it is indoor temperature because most people in high-income countries spend their time within a building, and people can adapt to a rise in outdoor temperature by adjusting the indoor air conditioning. Several studies support the idea that the outdoor temperature does not directly affect SWB. Using a survey specifically designed to reveal the climatic impact on SWB in Australia, Zander et al. (2019) show that perceived heat stress is not associated with SWB. Quinn et al. (2014) argue that heatstroke cases are affected more by the underconsumption of indoor cooling than by the outdoor temperature. Noelke et al. (2016), on the other hand, identified the negative impact of ambient temperature on SWB with a case country of the US. However, they do not explicitly distinguish between indoor and outdoor temperature and do not include energy expenditures in their regression model. Thus, their finding of the climatic impact might be caused by insufficient indoor cooling or higher cooling energy caused by a higher ambient temperature.

Nevertheless, one can assume that the outdoor temperature matters to some people. For instance, it is possible that someone moved or will move seeking favorable temperatures. If this is true, the samples with these preferences can concentrate on regions with better temperatures, such as less hot regions. If their life satisfaction is higher due to favorable temperatures, the IV of CDD can be correlated directly with ε_i , causing a violation of the externality condition for the valid IV. To address this concern, as the second strategy, we excluded samples that are expected to have a preference for

temperatures. Specifically, our survey has four questions related to people's reasons for moving. These questions ask the (1) reasons for moving within the last ten years (*Past moving*), (2) reasons for selecting the current residence (*Current moving*), (3) reasons for moving if the respondent is planning to move (*Future moving*), and (4) hypothetical reasons if the respondent were going to move (*Potential moving*). "Temperatures" are among the available response options for these questions. By excluding the samples that selected "climate conditions" for any of these four questions, we assume that the IV does not directly affect life satisfaction other than energy usage.

Finally, we considered various sets of respondent characteristics so that CDD become independent from ε_i conditional on these characteristics. If some factors are correlated with both CDD and SWB when we do not control for these variables in Equation (2), then CDD can be correlated with SWB through the characteristics included in ε_i other than observed energy. We explain the selection of these characteristics in the following subsection.

5.2.3 Selection of variables

(1) SWB

For SWB, we use life satisfaction as rated on a five-point scale (5. "very satisfied," 4. "slightly satisfied," 3. "neither satisfied nor dissatisfied," 2. "slightly dissatisfied," and 1. "very dissatisfied") because among several SWB indicators (e.g., happiness and the Cantril ladder), life satisfaction is the measure that is the most related to a respondent's material well-being (Brand-Correa and Steinberger, 2017). Additionally, life satisfaction is used in similar studies (Awaworyi Churchill et al., 2020; Delugas and Brau, 2021; Welsch and Biermann, 2017).

(2) Observed energy

The main variable of interest is the observed energy instrumented by CDD. To focus on EP in summer, we use the average monthly electricity expenditures between July and September (summer season). The values are obtained from the survey questionnaire. A question asks the respondent which out of 16 bands the household belongs to. We assign the midpoint of each band and regard these values as a pseudo-continuous variable. To consider economies of scale, we divide the values by the square root of the household size (Hills, 2012). For estimation, we take the natural logarithm of the observed energy.

(3) CDD

As the main IV, we use CDD, which is calculated with the threshold of 23 °C as the wet bulb globe temperature (WBGT). The choice of threshold is crucial for assuming the level of indoor temperature that is regarded as a necessity. The reason for our choice of 23 °C as the WBGT is that it is the average threshold around which the Japanese government cautions against the risk of heatstroke (The Japanese Ministry of the Environment, 2021). The WBGT is a well-established index for predicting heat stress (Ma et al., 2019). However, because this choice is somewhat arbitrary and the choice of a threshold may affect the results, we also use four other thresholds, i.e., 18 °C, 22 °C, 24 °C, and 25 °C, as supplementary IVs.

To identify the CDD values for the survey respondents, we merge the CDD dataset provided by Mistry (2019) with the survey dataset by the respondents' postal codes. Mistry (2019) provides a high-resolution (0.25°) historical global gridded dataset of monthly CDD, and we use these data during the corresponding period for the analysis (between July and September 2015 and 2016). Because this dataset does not cover some points in Japan, such as small islands, there are some omitted samples due to this lack of CDD data.

(4) Control variables

To eliminate the effects of confounding factors between SWB and observed energy and to ensure that the IV meets the conditional independence assumption, we consider five sets of control variables. Table 5.1 shows the combination of control variables for each set and the possible reasons for inconsistent estimations if they are not controlled for. For a detailed explanation of how these variables are created, see Appendix 5.C, Table 5.7.C.

Table 5.1 Five sets of control variables

Sets of control variables	Variables	Reasons
Base	Income (log)	The literature suggests that basic socioeconomic and health characteristics and energy-saving behavior can affect both energy consumption and SWB (Binder et al., 2020; Thomson et al., 2017c; Trotta, 2018).
	Female	
	Old	
	Young	
	Marriage	
	Household size	
	Children	
	Respondent education	
	Partner education	
	Subjective health	
	Mental health	
	Energy-saving behavior	
Housing	Loan	These housing factors are related to energy consumption and can reflect some aspects of wealth and, thus, well-being (Delugas and Brau, 2021; Galvin and Sunikka-Blank, 2018).
	Rental house	
	Car	
	Energy efficiency	
	Floor space	
	Year built (of the home)	
Time at home	Time at home on weekdays	When one spends a longer amount of time at home, the amount of energy that one needs is greater. Additionally, the allocation of time
	Time at home on holidays	

		spent at home indoors or outdoors might affect SWB.
Knowledge	Knowledge (of electricity deregulation)	Knowledge of the electricity market and bills can reduce energy consumption, and those with such knowledge are more likely to be good at managing other life issues and, thus, have higher SWB.
	Website (for checking energy bills)	
Price	Rent	Non-energy prices are correlated with dense areas and, thus, some regions with higher CDD, and are likely to reduce SWB through reduced consumption of non-energy goods and services.
	Regional difference index (RDI) (in the consumer price index)	

5.2.4 Data

We use the same survey with Chapter 4. As noted in Subsection 4.2, the survey was conducted via a third-party company between October and December 2015 and 2016 in Japan. To approximate the population aged 17 years or older in Japan, the survey respondents were recruited based on gender, age, and residential region to match the population distribution. For the main analysis, we use the data from the 2015 wave for two reasons. First, some questions for the important control variables were not included in the 2016 wave. Second, deregulation of the retail electricity market for households took place in April 2016. This change means that energy prices were no longer exogenous, and we cannot access detailed data on the electricity prices of each electricity retailer in these periods.

The original sample size in the 2015 wave is 153,645. After excluding observations with missing values for income, electricity expenditures, and postal codes, the sample size is 105,486. The sample size removed due to reasons for moving was 9.4% of the samples, which led to reducing the sample size to 95,574. We confirm that there is no significant difference in the main variables (observed energy and SWB) before and after excluding these samples. Due to the missing values of CDD and control variables, the final sample sizes for the analysis range between 66,530 and 81,725, depending on a selected set of the control variables. For more details on the sample size and descriptive statistics, see Appendix 5.C, Table 5.8.C and Table 5.9.C.

5.3 Results

The results support our hypothesis that increasing temperature-induced energy, which we regard as cooling energy needs, can reduce SWB. Contrary to the theoretical assumption

in subsection 5.2, this negative effect was the largest for the middle-income group, not for the lowest-income group. We discuss the possible reason for this contradictory finding by considering behavioral issues in the SWB evaluation and the nature of the IV estimation. We conducted several robustness analyses to confirm our main results.

5.3.1 The effects of cooling energy needs on SWB

We discuss our findings by presenting the three types of regressions, namely, the first-stage regression, IV regression, and reduced-form regression. Table 5.2 presents the results of each regression. In Panel A, the results of first-stage regression are presented, where observed energy is regressed on the CDD and control variables (the temperature-energy relationship). Panel B presents the energy-well-being relationship, which offers the key result for the impact of cooling energy needs on SWB. We show both the results of OLS and IV estimations to compare how temperature-induced energy impacts differ from the simple correlation between energy and SWB. In Panel C, we show the reduced-form regression between CDD and well-being, which captures the direct temperature-SWB relationship. Regarding the selection of the control variables, we show only the results with the control variable sets of “Base” because the selection did not largely affect the main results.⁹

As the first-stage regression in the IV estimation (Table 5.2, Panel A), the results confirm that any of the five CDD variables are positively correlated with observed energy. This positive correlation is in line with our hypothesis that a higher CDD induces an increase in energy usage by households. The strength of the association tested by the F-statistics is strong enough for any of the CDD variables to be valid as IV for observed

⁹ The estimation results with all sets of control variables are available from the corresponding author on request.

energy (Stock et al., 2002). This strong association between CDD and observed energy also holds when including a variety of controls.

The OLS and IV estimation results offer evidence that each estimation identifies different sources of energy increases. In the IV estimation, most of the estimated coefficients of observed energy are negative and statistically significant (Table 5.2, Panel B). In contrast, the OLS estimation results show smaller effects in magnitude compared to the IV estimation. As discussed in subsection 5.3, the difference between the IV and OLS can be caused by the difference between the required energy and preference-based energy. The OLS estimation can include energy variation due to higher preferences for energy usage. Such preference-based variation can positively affect SWB. In contrast, the IV estimation can produce more analogous effects of required energy by extracting the temperature-induced variation in observed energy. The results in the IV estimation support our hypothesis that additional cooling energy needs (a temperature-induced energy increase) can reduce SWB. In addition, the findings suggest the importance of distinguishing the negative effect of temperature-induced required energy from the positive effect of preference-based energy.

Regarding the selection of the CDD variable's thresholds, the results of the IV estimation and reduced-form estimation show that the effects are negatively larger when higher CDD thresholds are used as the IV (Table 5.2, Panels B and C). This result might explain that CDDs of higher thresholds are more associated with an increase in required energy than CDDs of lower thresholds. As explained in subsection 3.3, we chose 23 °C in the WBGT as the most suitable threshold for extracting cooling energy needs because it is the average threshold around which the Japanese government cautions against the risk of heatstroke (The Japanese Ministry of the Environment, 2021). Then, energy

variation by CDDs with lower thresholds (e.g., 18 and 22 in our case) can capture an increase in energy usage, which is not necessarily crucial to human health. For instance, some people might turn on their ACs, preferring favorable working conditions even though WBGT is lower than 23 °C and thus not generally crucial to their health. When using CDDs of lower thresholds, the CDD-induced variation in observed energy can reflect such cases and be more associated with preference-based energy variation, as discussed in the OLS estimation above. On the other hand, others only turn on their ACs for the first time at the higher WBGT (e.g., 25 °C) because they think that without air conditioning, they can risk heat stroke. Thus, when using CDDs of higher thresholds, the CDD-induced energy variation is more likely to capture the variation in "required energy," which is the key concept in the EP literature. In other words, as the thresholds of CDD become larger, CDD-induced energy variation can be closer to the variation in required energy for indoor cooling. Then, the result of the larger negative impact with higher thresholds of CDDs is in line with our main hypothesis that cooling energy needs (higher required energy for indoor cooling) have a larger negative impact on well-being

Table 5.2 Linkages among temperature, energy, and SWB

Panel A: The effects of CDD on energy (first-stage regression, the temperature-energy relationship)																
		Independent variable														
		CDD 25		CDD 24		CDD 23		CDD 22		CDD 18						
CDD		0.025***	(194)	0.029***	(280)	0.034***	(384)	0.041***	(533)	0.055***	(840)					
Panel B: The effect of cooling energy needs on SWB (IV estimation, the energy-well-being relationship)																
OLS		IV														
		CDD 25		CDD 24		CDD 23		CDD 22		CDD 18						
Energy	-0.012**	(0.006)	-	0.731***	(0.135)	-	0.616***	(0.110)	-	0.519***	(0.093)	-	0.361***	(0.078)	-0.142**	(0.062)
Panel C: The effect of CDD on SWB (reduced-form estimation between CDD and SWB, the temperature-SWB relationship)																
		Independent variable														
		CDD 25		CDD 24		CDD 23		CDD 22		CDD 18						
CDD		-	0.018***	(0.003)	-	0.018***	(0.003)	-	0.018***	(0.003)	-	0.015***	(0.003)	-0.008**	(0.003)	

Notes: Each coefficient is obtained from a separate regression. The sample sizes are 81,725. The F-statistics for testing weak instruments are in parentheses in Panel A, and the robust standard errors are in parentheses in Panels B and C. *** p < 0.01, ** p < 0.05, * p < 0.1.

5.3.2 How is a low-income level related to the impact of cooling energy needs on SWB?

As discussed in subsection 5.2, for lower-income households, the negative impact of cooling energy needs on well-being is expected to be greater. To confirm whether this hypothesis is supported, we estimated the same regression as that in the previous subsection for each income quartile group. Among the five IV candidates for the CDD's threshold, only the result of CDD 23 is shown in this subsection.

The result of the first-stage regression shows that the marginal effects of CDD 23 on observed energy are the largest in the lowest-income group, namely, 0.043, and the smallest in the highest-income group, specifically, 0.026 (Table 5.3, Panel A). These results imply that the lowest-income group uses more energy to adapt to a higher number of CDD. This finding is consistent with some studies on temperature impacts on energy consumption (Li et al., 2018). The difference among income levels may be due to the uncontrolled energy efficiency levels of appliances and buildings. Several studies have shown that lower-income households are less likely to afford energy-efficient appliances and to live in energy-efficient buildings (Galvin and Sunikka-Blank, 2018).

In the IV regression, the results show that there are no statistically significant effects of cooling energy needs for the first income quartile group (lowest-income group). The largest negative impact is found for the second income quartile group, followed by the third income quartile group, while the fourth income quartile group (highest-income group) shows no statistically significant effect (Table 5.3, Panel B). This result contradicts our assumption explained in subsection 5.2 that lower income could strengthen the negative effect of cooling energy needs. As one possible explanation, one might think that there can be less variation in SWB for each income-quartile group.

However, the distribution of SWB shows almost equal variation for every income quartile group (see Appendix 5.C, Figure 5.2.C).

To infer why there are no statistically significant effects of cooling energy needs on SWB for the lowest-income group, an understanding of the behavioral aspects of SWB evaluation may offer a hint. The key idea is the situations that people regard as a given standard. Studies show that SWB evaluation is largely susceptible to comparisons with others (Fleurbaey, 2009; Perez-Truglia, 2020). Additionally, Mi et al. (2019) show that daily energy consumption behavior is affected by a "reference group." The reference group is understood as the social group that one refers to when making decisions on consumption. As suggested by the fact that most heatstroke cases occur inside homes, some people with the lowest level of income cannot even afford the energy level necessary to avoid heatstroke. Suppose that such a situation is a reference point for people when evaluating their SWB. In this case, people with the lowest level of income who could increase their energy usage might evaluate the positive aspect of increasing their energy usage, such as avoiding health risks and increasing their comfort, rather than the negative aspect of increasing their energy costs. In contrast, people with a middle-income level (third income group) might regard such health benefits as the given standard. These people might put more emphasis on the negative financial effects of increasing their energy usage.

Table 5.3 The effects of cooling energy needs on SWB by income quartile subgroups

	Q1 (Lowest)	Q2	Q3	Q4 (Highest)
a. Average monthly household income (USD)	1,194	2,036	2,944	5,381
b. Average monthly electricity expenditures (USD)	51	51	54	59
c. Share (b/a)	4.7%	2.5%	1.8%	1.2%
Panel A: The effects of CDD on energy (first-stage regression, the temperature-energy relationship)				
CDD 23	0.043*** (0.003)	0.033*** (0.004)	0.034*** (0.003)	0.026*** (0.004)
Panel B: The effect of cooling energy needs on SWB (IV estimation, the energy-well-being relationship)				
Energy	-0.140 (0.153)	-0.879*** (0.225)	-0.914*** (0.186)	-0.311 (0.216)
Panel C: The effect of CDD on SWB (reduced-form estimation between CDD and SWB, the temperature-SWB relationship)				
CDD 23	-0.006 (0.007)	-0.029*** (0.007)	-0.031*** (0.006)	-0.008 (0.006)

Notes: CDD 23 is used as the IV. Each coefficient is obtained from a separate regression. The whole sample sizes are 81,725. The robust standard errors are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

5.3.3 Using EP indicators instead of observed energy as the variable of interest

In similar studies, indicator variables of EP are more commonly used than absolute values of energy, as done in the previous subsection (Awaworyi Churchill et al., 2020; Biermann, 2016; Kahouli, 2020; Delugas and Brau, 2021). The indicator variable of EP takes the value of 1 if a respondent is regarded as energy-poor and 0 otherwise by particular criteria. These criteria are generally based on combining the criteria of higher electricity expenditures and lower household income. Table 5.4 shows four EP indicators in this chapter that were developed in the literature and have been widely used in related applied studies: the 10% indicator (*10%*), the Low Income High Costs indicator (*LIHC*), and the 2 median indicator (*2 M*).

Such binary measures for identifying EP are often used in the general poverty literature. The difference between the coefficients of observed energy and binary EP indicators is that the former only captures the impact of higher energy needs, while the latter is also affected by the low-income level. In the previous subsection, we found that there is no statistically significant effect of higher cooling energy needs for the lowest-income quartile. However, this does not mean that EP, which is generally identified by the joint criteria of low-income and high energy needs, does not matter. Indeed, similar studies have shown that EP indicators with low-income criteria have a negative impact on SWB (Awaworyi Churchill et al., 2020; Kahouli, 2020; Delugas and Brau, 2021). To confirm whether this is true in Japan, we also conducted the analysis using EP indicators as the variable of interest. In the analysis, we use the same IV strategy as in the previous subsections.

Table 5.4 EP indicators

Energy poverty indicators	Calculation procedure
10% (Boardman, 1991)	Takes the value of one if the ratio of energy expenditures to income exceeds 10%
2 Median (Trinomics, 2016)	Takes the value of one if the share of income spent on energy expenditures is two times more than the national median
LIHC (Low Income High Costs) (Hills, 2012)	Takes the value of one if energy expenditures exceed the national median and the residual income is below 60% of the national median income

Notes: For the computation of the national median of income and electricity expenditures, we adopted weighted medians with the weighting factors of age and gender.

The results show that the estimated coefficients with the three indicators are negative (Table 5.5). Thus, the result is consistent with similar studies in that EP indicators have a negative impact on SWB. A slightly confusing point is why there is no effect of higher cooling energy needs for the lowest-income group in the previous subsection, while EP indicators show a negative impact in this subsection. The former shows the effect of higher cooling energy needs *conditional on a low income* (the so-called Conditional Average Treatment Effect, CATE), while the latter shows the effect of higher cooling energy needs *and* low income (understood as the Average Treatment Effect, ATE). What is implied in the previous subsection is that higher cooling energy needs do not lead to lower SWB for low-income households by themselves. However, the results in this subsection show that being in low-income and high cooling energy

needs can lower SWB compared to being neither on low-income nor higher cooling energy needs.

Regarding the result with the 10% indicator, a caveat is necessary. The result shows an unrealistic value, which exceeds the maximum SWB value. The reason may be because the share of EPs with the 10% indicator was substantially small, specifically, 1.5%.

Table 5.5 The effects of the EP indicators on SWB (IV estimation)

	Energy poverty indicators					
	(1) 10%		(2) LIHC		(3) 2 Median	
% of the samples	1.5%		6.9%		12.8%	
IV results	-7.289***	(1.860)	-1.945***	(0.384)	-1.350***	(0.261)

Notes: Each coefficient is obtained from a separate regression. As the IV, CDD 23 is used. The sample sizes are 81,725. Robust standard errors are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

5.3.4 Robustness checks

We confirm the robustness of our analysis by conducting three types of estimations (Table 5.6). The first uses financial stress instead of SWB because CDD is more likely to meet the externality condition when financial stress is the dependent variable. The financial stress variable takes the value of 1 when respondents feel financial stress and 0 otherwise. Thus, the expected estimated coefficient is expected to be positive, and the result is in line with this expectation. The second estimation addresses income endogeneity by using parental education as the IV for household income (Awaworyi Churchill et al., 2020). Because unobserved preferences for energy beyond a minimum required level are likely to be correlated with income, the income variable in Equation (2) in subsection 5.3 is also likely to be endogenous. As expected, the result confirms the statistically significant negative effect. The third estimation employs a pooled estimation that uses both 2015 and 2016 data. Again, these results are not essentially different from our main estimation results. In addition to these three types of estimations, we checked for possible omitted variable biases by adding various control variables. These checks offer some robustness to our main results.

One can assume that fixed effects (or first-difference) methods are another candidate for additional estimation procedures for robustness checks. However, we did not conduct this analysis for the following reason. Generally, fixed effects (or first-difference) methods are susceptible to biases if variables have measurement errors (Angrist and Pischke, 2009). In our case, this measurement error problem can be serious because of SWB and observed energy. SWB can be greatly affected by people's temporary feelings in their daily lives, which means that year-to-year variation in SWB indicated might not correctly report the true values (Fleurbaey, 2009). The electricity

expenditure variables are also susceptible to measurement errors due to respondents' vague memories. Furthermore, because the electricity expenditure variable comes from the mean values of 16 discrete options in the survey, this variable might fail to capture important differences induced by year-to-year variation in CDD.

Table 5.6 Robustness checks

	Financial stress		Income endogeneity		Pooled estimation	
Energy	0.184***	(0.048)	-0.861***	(0.250)	-0.649***	(0.121)

Notes: CDD 23 is used as the IV for observed energy. In the financial stress and income endogeneity models, the sample sizes are 81,725. In the pooled estimation, the sample sizes are 120,153. The robust standard errors are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

5.4 Discussion and policy implications

Using Japan as a case country allows us to show the negative impact of cooling energy needs on SWB by exploiting the country's large regional heterogeneity in outdoor temperature conditions. We discuss our contributions by relating them to the two streams of literature on the temperature-energy relationship and the energy-well-being relationship. Then, we offer contextual factors peculiar to Japan and policy implications from a global perspective.

Regarding the temperature-energy relationship, this chapter adds new evidence from Japan. We find that lower-income households may face a larger marginal increase in energy due to higher outdoor temperatures. In this regard, studies have shown inconsistent results. Some findings show that the positive effect of temperature on energy usage increases as income increases (Du et al., 2020), and others show that the effect decreases as income increases (Li et al., 2018; Randazzo et al., 2020). This chapter supports the latter relationship. As an important limitation, our study might suffer from a bias in estimating this effect because we used cross-sectional or pooled data with two survey waves. As Auffhammer and Mansur (2014) note, people might adapt to specific temperatures, which might cause bias in cross-sectional studies. This is because people living in hotter regions might consume less energy than others would consume if they lived in hotter regions.

The most related body of literature consists of studies on the energy–well-being relationship in the EP literature. In these studies, required energy has been a key concept for identifying EP. Required energy is understood as the hypothetical amount of energy consumption to obtain comfort at a socially adequate level (Bouzarovski, 2014). The required energy is unobservable from the observed energy because detailed data are

necessary to calculate it. Although the EP literature has acknowledged this point, most studies simply use observed energy as a proxy for required energy. As shown in subsection 5.3, this replacement can lead to a bias of the expected negative effect. By extracting the temperature-induced variation in observed energy, this chapter aims to extract the variation in required energy for indoor cooling. This strategy enables us to offer new evidence that the source of energy increase matters for well-being impact.

Another contribution of this chapter to the EP literature is that it reveals the damaging impact of energy increases separately from that of a low-income level. Existing studies prefer to use binary EP indicators with low-income criteria, such as those in Table 5.4 in subsection 5.3 (Awaworyi Churchill et al., 2020; Kahouli, 2020; Delugas and Brau, 2021). Using such binary indicators cannot separately estimate the impact of an energy increase from the impact of a lower income level. Indeed, this chapter found unexpected results: Higher energy needs for indoor cooling might not have negative impacts for the lowest-income households, while it can when higher energy needs occur with the low-income level, as implied in the negative impact of binary EP indicators.

We note that no well-being impact of cooling energy needs for the lowest-income quartile does not suggest that low-income households do not face EP. As shown in the climate-energy relationship, they face the largest increase in observed energy by higher CDDs. That is, in terms of objective measures, they face the largest energy needs for indoor cooling. Although SWB is becoming widely used to evaluate policy-relevant factors (Lindberg et al., 2020; Yuan et al., 2018), our findings suggest that subjective evaluation is not always in line with the expected results with objective measures. As discussed in subsection 5.4, SWB evaluation can be largely influenced by adaptation to

particular circumstances and relative positions within society. While SWB is beneficial in its simplicity, it is worthwhile to bear in mind these limitations of SWB.

Nevertheless, we think that it is important to see how people's evaluation mechanisms can differ from what is implied by objective measures and what is the possible background for it. Our results show a disparity between the first income quartile group and the other higher-income groups for the evaluation mechanism of the energy-SWB relationship. Indeed, there are several contextual factors that might partly explain the smaller or nonsignificant effect of cooling energy needs on SWB for the lowest-income group. In the traditional Japanese view, indoor cooling is regarded as a "luxury" good even though 90% of Japanese households own ACs. In fact, within the Japanese welfare scheme, the purchasing costs of ACs were not financially supported until the recent policy change in 2018.¹⁰ Additionally, cooling needs have attracted less attention than heating needs. The welfare system offers recipients living in colder regions additional financial support during the winter season for heating energy (Okushima, 2017). In contrast, there is no corresponding support for welfare recipients living in hotter regions during the summer season for cooling energy.

The new efforts in Japan in recent years might change this traditional view of air conditioning. At the municipal level, new subsidies for ACs for older people have started to be implemented to negate heatstroke at home during the lockdown period of the COVID-19 outbreak (Ibaraki Newspaper, 2021). As our study suggests, more national-

¹⁰ In the policy change in 2018, a financial subsidy of no more than 54,000 yen (\$438 USD at 123.27 yen/USD) for the purchase of ACs was allowed. However, the eligibility to receive this support is still restricted to, for example, elderly or disabled individuals who need special assistance to avoid heatstroke.

level consideration may be encouraged, while regional heterogeneity in temperature also needs to be considered. Energy efficiency policies that target low-income households may help achieve the goals of reducing both EP and inefficient energy usage, which is the strategy outlined in EU policy packages (Dobbins et al., 2019).

5.5 Conclusion

Using a nationwide survey of Japan and the IV approach, this chapter is the first to show that increasing cooling energy needs may reduce SWB in the hot summer season. In relation to income level, the negative effect is the largest for the middle-income group, while the lowest- and highest-income groups are less likely to be affected. In contrast, we find that the lowest-income group faces the highest energy needs to adapt to higher outdoor temperatures. This contradictory finding implies that behavioral aspects matter for the evaluation of SWB.

As an important limitation, our estimation strategy captures the effect of temperature-induced energy on SWB only for those who respond to higher CDDs by increasing their energy usage. This methodological feature means that the effect of temperature-induced energy on SWB is unclear for those who do not increase their energy usage when facing a higher outdoor temperature. Because this limitation is an inherent characteristic of IV methods, further research could be expected that uses other methods, such as randomized controlled trials.

References

- Angrist, J., Pischke, J.-S., 2009. *Mostly Harmless Econometrics: An Empiricist's Companion*. Princeton University Press.
- Auffhammer, M., Mansur, E.T., 2014. Measuring climatic impacts on energy consumption: A review of the empirical literature. *Energy Economics* 46, 522–530. <https://doi.org/10.1016/j.eneco.2014.04.017>
- Awaworyi Churchill, S., Smyth, R., Farrell, L., 2020. Fuel poverty and subjective wellbeing. *Energy Economics* 86, 104650. <https://doi.org/10.1016/j.eneco.2019.104650>
- Biermann, P., 2016. *How fuel poverty affects subjective well-being: Panel evidence from Germany*, Oldenburg Discussion Papers in Economics.
- Binder, M., Blankenberg, A.-K., Guardiola, J., 2020. Does it have to be a sacrifice? Different notions of the good life, pro-environmental behavior and their heterogeneous impact on well-being. *Ecological Economics* 167, 106448. <https://doi.org/10.1016/j.ecolecon.2019.106448>
- Boardman, B., 1991. *Fuel poverty: From cold homes to affordable warmth*. Belhaven Press, London.
- Bouzarovski, S., 2014. Energy poverty in the European Union: Landscapes of vulnerability. *Wiley Interdisciplinary Reviews: Energy and Environment* 3, 276–289. <https://doi.org/10.1002/wene.89>
- Bouzarovski, S., Petrova, S., 2015. A global perspective on domestic energy deprivation: Overcoming the energy poverty-fuel poverty binary. *Energy Research and Social Science* 10, 31–40. <https://doi.org/10.1016/j.erss.2015.06.007>
- Brand-Correa, L.I., Steinberger, J.K., 2017. A Framework for Decoupling Human Need Satisfaction From Energy Use. *Ecological Economics* 141, 43–52. <https://doi.org/10.1016/j.ecolecon.2017.05.019>
- Delugas, E., Brau, R., 2021. Evaluating the Impact of Energy Poverty in a Multidimensional Setting. *Energy Journal* 42, 39–66. <https://doi.org/10.5547/01956574.42.1.edel>
- Dobbins, A., Fuso Nerini, F., Deane, P., Pye, S., 2019. Strengthening the EU response to energy poverty. *Nature Energy* 4, 2–5. <https://doi.org/10.1038/s41560-018-0316-8>
- Du, K., Yu, Y., Wei, C., 2020. Climatic impact on China's residential electricity consumption: Does the income level matter? *China Economic Review* 63, 101520. <https://doi.org/10.1016/j.chieco.2020.101520>
- Feng, S., Krueger, A.B., Oppenheimer, M., 2010. Linkages among climate change, crop

- yields and Mexico-US cross-border migration. *Proceedings of the National Academy of Sciences* 107, 14257–14262. <https://doi.org/10.1073/pnas.1002632107>
- Fleurbaey, M., 2009. Beyond GDP: The Quest for a Measure of Social Welfare. *Journal of Economic Literature* 47, 1029–1075. <https://doi.org/10.1257/jel.47.4.1029>
- Galvin, R., Sunikka-Blank, M., 2018. Economic Inequality and Household Energy Consumption in High-income Countries: A Challenge for Social Science Based Energy Research. *Ecological Economics* 153, 78–88. <https://doi.org/10.1016/j.ecolecon.2018.07.003>
- Hills, J., 2012. Getting the measure of fuel poverty. Final Report of the Fuel Poverty Review. Centre for Analysis of Social Exclusion, London School of Economics and Political Science, London.
- Ibaraki Newspaper, 2021. Chikusei city in Ibaraki prefecture, to assist in purchasing air conditioners for elderly households with upper limit 50,000 yen.
- International Energy Agency (IEA), 2018. The Future of Cooling.
- Kahouli, S., 2020. An economic approach to the study of the relationship between housing hazards and health: The case of residential fuel poverty in France. *Energy Economics* 85, 104592. <https://doi.org/10.1016/j.eneco.2019.104592>
- Li, J., Yang, L., Long, H., 2018. Climatic impacts on energy consumption: Intensive and extensive margins. *Energy Economics* 71, 332–343. <https://doi.org/10.1016/j.eneco.2018.03.010>
- Lindberg, K., Swearingen, T., White, E.M., 2020. Parallel Subjective Well-Being and Choice Experiment Evaluation of Ecosystem Services: Marine and Forest Reserves in Coastal Oregon, USA. *Social Indicators Research* 149, 347–374. <https://doi.org/10.1007/s11205-019-02239-0>
- Ma, R., Zhong, S., Morabito, M., Hajat, S., Xu, Z., He, Y., Bao, J., Sheng, R., Li, C., Fu, C., Huang, C., 2019. Estimation of work-related injury and economic burden attributable to heat stress in Guangzhou, China. *Science of The Total Environment* 666, 147–154. <https://doi.org/10.1016/j.scitotenv.2019.02.201>
- Mi, L., Zhu, H., Yang, J., Gan, X., Xu, T., Qiao, L., Liu, Q., 2019. A new perspective to promote low-carbon consumption: The influence of reference groups. *Ecological Economics* 161, 100–108. <https://doi.org/10.1016/j.ecolecon.2019.03.019>
- Mistry, M.N., 2019. Historical global gridded degree-days: A high-spatial resolution database of CDD and HDD. *Geoscience Data Journal*. <https://doi.pangaea.de/10.1594/PANGAEA.903123>
- Noelke, C., McGovern, M., Corsi, D.J., Jimenez, M.P., Stern, A., Wing, I.S., Berkman,

- L., 2016. Increasing ambient temperature reduces emotional well-being. *Environmental Research* 151, 124–129. <https://doi.org/10.1016/j.envres.2016.06.045>
- Okushima, S., 2019. Understanding regional energy poverty in Japan: A direct measurement approach. *Energy & Buildings* 193, 174–184. <https://doi.org/10.1016/j.enbuild.2019.03.043>
- Okushima, S., 2017. Energy poverty, energy vulnerability and energy justice: Present situation and future issues in Japan. *Kagaku* 87, 1019–1027.
- Papada, L., Kaliampakos, D., 2018. A Stochastic Model for energy poverty analysis. *Energy Policy* 116, 153–164. <https://doi.org/10.1016/j.enpol.2018.02.004>
- Perez-Truglia, R., 2020. The Effects of Income Transparency on Well-Being: Evidence from a Natural Experiment. *American Economic Review* 110, 1019–1054. <https://doi.org/10.1257/aer.20160256>
- Quinn, A., Tamerius, J.D., Perzanowski, M., Jacobson, J.S., Goldstein, I., Acosta, L., Shaman, J., 2014. Predicting indoor heat exposure risk during extreme heat events. *Science of The Total Environment* 490, 686–693. <https://doi.org/10.1016/j.scitotenv.2014.05.039>
- Randazzo, T., De Cian, E., Mistry, M.N., 2020. Air conditioning and electricity expenditure: The role of climate in temperate countries. *Economic Modelling* 90, 273–287. <https://doi.org/10.1016/j.econmod.2020.05.001>
- Rodriguez-Alvarez, A., Orea, L., Jamasb, T., 2019. Fuel poverty and Well-Being: A consumer theory and stochastic frontier approach. *Energy Policy* 131, 22–32. <https://doi.org/10.1016/j.enpol.2019.04.031>
- Stock, J.H., Wright, J.H., Yogo, M., 2002. A Survey of Weak Instruments and Weak Identification in Generalized Method of Moments. *Journal of Business & Economic Statistics* 20, 518–529.
- The Japanese Ministry of the Environment, 2021. Heat Illness Prevention Information provided by MoE [WWW Document]. URL <https://www.wbgt.env.go.jp/en/> (accessed 10.22.21).
- The Japanese Ministry of the Environment, 2013. The survey on households' electricity consumption in 2013.
- Thomson, H., Bouzarovski, S., Snell, C., 2017a. Rethinking the measurement of energy poverty in Europe: A critical analysis of indicators and data. *Indoor and Built Environment* 26, 879–901. <https://doi.org/10.1177/1420326X17699260>
- Thomson, H., Snell, C., Bouzarovski, S., 2017b. Health, well-being and energy poverty in Europe: A comparative study of 32 European countries. *International Journal*

- of Environmental Research and Public Health 14, 1–20.
<https://doi.org/10.3390/ijerph14060584>
- Trinomics, 2016. Selecting Indicators to Measure Energy Poverty.
- Trotta, G., 2018. Factors affecting energy-saving behaviours and energy efficiency investments in British households. *Energy Policy* 114, 529–539.
<https://doi.org/10.1016/j.enpol.2017.12.042>
- Washington Post, 2019. Europe never understood America’s love of air conditioning — until now. Washington Post.
- Welsch, H., Biermann, P., 2017. Energy affordability and subjective well-being: Evidence for European Countries. *Energy Journal* 38, 159–176.
<https://doi.org/10.5547/01956574.38.3.hwel>
- Wooldridge, J.M., 2010. *Econometric Analysis of Cross Section and Panel Data*, 2nd ed. MIT Press, Cambridge, MA, USA.
- Yuan, L., Shin, K., Managi, S., 2018. Subjective Well-being and Environmental Quality: The Impact of Air Pollution and Green Coverage in China. *Ecological Economics* 153, 124–138. <https://doi.org/10.1016/j.ecolecon.2018.04.033>
- Zander, K.K., Moss, S., Garnett, S.T., 2019. Climate Change–Related Heat Stress and Subjective Well-Being in Australia. *Weather, Climate, and Society* 11, 505–520.
<https://doi.org/10.1175/WCAS-D-18-0074.1>

Appendix 5.A Welfare model of the required energy impact

To model how required energy affects people's welfare in relation to income level, we follow the approach employed by Welsch and Biermann (2017),¹¹ who regard SWB as a proxy for utility and develop a utility model with the Stone–Geary function. Using the Stone–Geary function allows us to explicitly address the concept of required energy. Specifically, we define the utility as follows:

$$u = U(E, N; R) = a(E - R)^\alpha N^{1-\alpha} = aL^\alpha N^{1-\alpha} \quad (5.1.A)$$

where E is the observed energy consumption, N is a non-energy good, R is a minimum level of necessary energy (required energy), and L is defined as $E - R$. We call L excess energy because it captures the amount of energy consumed beyond a minimum required level. a is the scaling parameter, which takes positive values when $E - R$ is nonnegative and zeroes otherwise ($0 \leq a \leq 1$).

Welsch and Biermann (2017) show the welfare impact of a price increase, whereas we focus on the welfare impact of required energy.¹² By denoting household

¹¹ Welsch and Biermann's (2017) study is one of the exceptional studies that explicitly discusses the role of required energy and attempts to examine its effect on SWB by using energy prices as the proxy.

¹² A general way of using the Stone–Geary function treats a minimum required level as prefixed to investigate how prices are determined when certain goods are subsistence (Moschini and Rizzi, 2006). Because our analysis is based on a short period and our interest is related to the heterogeneity of a minimum level of required energy, this study considers that a minimum level of required energy is determined by exogenous factors such as temperatures and energy efficiency levels. Price is treated as prefixed.

income and energy prices as I and p , respectively, and treating a non-energy good as the numeraire, the budget constraint is expressed as $pE + N = I$. From the maximum utility problem, the demand functions for energy, excess energy, and a non-energy good are $E = R + a\left(\frac{I}{p} - R\right)$, $L = E - R = a\left(\frac{I}{p} - R\right)$, and $N = (1 - a)(I - pR)$, respectively. By defining the indirect utility function as $V \equiv f(I, p, R)$ and expressing the X-elasticity of Y as $\eta_{XY} = \frac{\frac{\partial Y}{Y}}{\frac{\partial X}{X}}$, the welfare effect of an increase in required energy is calculated as follows:

$$\eta_{UL}\eta_{LR} = \frac{-apR}{(I-pR)} < 0 \quad (5.2.A)$$

$$\eta_{UN}\eta_{NR} = \frac{-(1-a)pR}{(I-pR)} < 0 \quad (5.3.A)$$

$$\eta_{VR} = \eta_{UL}\eta_{LR} + \eta_{UN}\eta_{NR} = \frac{-apR}{I-pR} + \frac{-(1-a)pR}{I-pR} = \frac{-pR}{I-pR} < 0 \quad (5.4.A)$$

where Equation (5.4.A) shows that the entire welfare effect of an increase in required energy is negative and affects utility through two channels. The first is through a decrease in excess energy, as shown in Equation (5.2.A). Because $\eta_{ER} = \frac{(1-a)R}{E} \leq 1$, the model expects that actual energy will not increase more than required energy, which means that excess energy will decrease, and, in turn, welfare will be reduced. The second channel is through a decrease in a non-energy good, as shown in Equation (5.3.A). Furthermore, the welfare effect of required energy in relation to an increasing income level is calculated as follows:

$$\frac{\partial \eta_{VR}}{\partial I} = \frac{pR}{(I - pR)^2} > 0$$

which means that the negative welfare effect of required energy decreases as income increases.

Appendix 5.B Regional heterogeneity in CDD

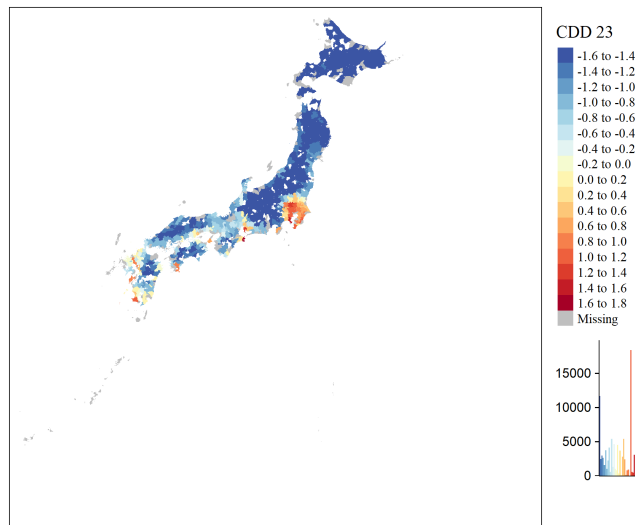


Figure 5.1.B Regional heterogeneity in CDD

Notes: We use Japanese CDD data covering July September 2015 from Mistry (2019).

The CDD values are standardized. The histogram shows the sample distribution of the survey respondents' CDD.

Appendix 5.C Descriptive statistics

Table 5.7.C Description of the control variables

Sets of control variables	Variables	How they are created	Sources
Base	Income (log)	The natural logarithm of household income (yen) divided by the square root of household size to consider economies of scale	Survey
	Female	Takes the value of 1 for women and 0 for men	
	Old	Takes the value of 1 if the respondent's age is 65 years or more	
	Young	Takes the value of 1 if the respondent's age is 35 years or under	
	Marriage	Takes the value of 1 if the respondent is married	
	Household size	Household size	
	Children	Takes the value of one if the respondent has children under seven years of age	
	Respondent education	Takes the value of one if the respondent has a university degree	
	Partner education	Takes the value of one if the respondent's partner has a university degree	

	Subjective health	Takes a value between 1 and 5 for the question “How would you describe your overall health condition?”, where 1 = “very good”, 2 = “good”, 3 = “neither”, 4 = “poor”, and 5 = “very poor”	
	Mental health	Takes a value between 1 (best) and 4 (worst) ¹³	
	Energy-saving behavior	The sum of 10 daily energy-saving behavior options, namely, “turning off electricity frequently,” “reducing the amount of time to open a refrigerator,” “using electric fans with air conditioners,” “adjusting wattage or the number of light bulbs,” “turning off the main power switches,” “using power-saving taps,” “reconsidering contract amperes,” “reconsidering electricity plans,” “recording bills and electricity consumption,” and “others”	
Housing	Loan	Takes the value of one if the respondent is paying a home loan	Survey

¹³ Mental health is calculated as the average value of the 12 questions in the 12-Item General Health Questionnaire (David and Williams, 1998).

	Rental house	Takes the value of one if the respondent lives in a rental home	
	Car	The number of cars owned	
	Energy efficiency	Owning energy-efficient systems; the sum of 10 energy efficiency measures implemented. The measures include (1) solar generation systems, (2) solar water systems, (3) a heat pump, (4) a combined residential heat and power system, (5) a gas-powered water heater, (6) fuel cells for combined heat and power, (7) home storage batteries, (8) an eco-car charge system, (9) a smart meter, and (10) a home energy management system.	
	Floor space	Floor space in m ² , natural logarithm form	
	Year built	The year in which the house was built	
Time at home	Time at home on weekdays	Takes the value of one if the respondent spends almost all day at home on weekdays	Survey
	Time at home on holidays	Takes the value of one if the respondent spends almost all day at home on holidays	
Knowledge	Knowledge	Takes the value of one if the respondent is very knowledgeable about the	Survey

		deregulation of the electricity market	
Website		Takes the value of one if the respondent looks at a retailer's website for personal electricity consumption data	
Price	Rent	For households that answer that they own a home, we assigned imputed rent estimated at the prefecture-level by using the regional difference index (RDI) of consumer prices from the Japanese official database. For those living in a rental home, we used rent data on the website for July September 2015 extracted from a commercial database provided by LIFULL Co., Ltd. (2019), one of the largest internet companies for residential rental homes. The total sample size is approximately 3,000,000. We calculated the average rent per floor space (yen/m ²) for the smallest unit of municipalities (1902 in total). To avoid small sample bias, we assigned no values for municipalities where there were fewer than 100 rent data samples. For	Survey and LIFULL Co., Ltd. (2019)

the estimated values to be in the same unit as the RDI, we divided these values by the national mean. For the point estimate of each municipality, we used median values to avoid the influence of extreme values.

Regional difference index (RDI)	The RDI of all items other than rent for those living in a rental home and the RDI of all items other than imputed rent for those living in an owned home	The Japanese Ministry of Internal Affairs and Communications (2015)
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Table 5.8.C The sample size of the datasets

Dataset	Sample size		
	2015	2016	Pooled
Original	153,645	67,009	220,654
After excluding missing values	105,486	48,814	154,300
After excluding samples for the reasons for moving	95,574	44,769	140,343

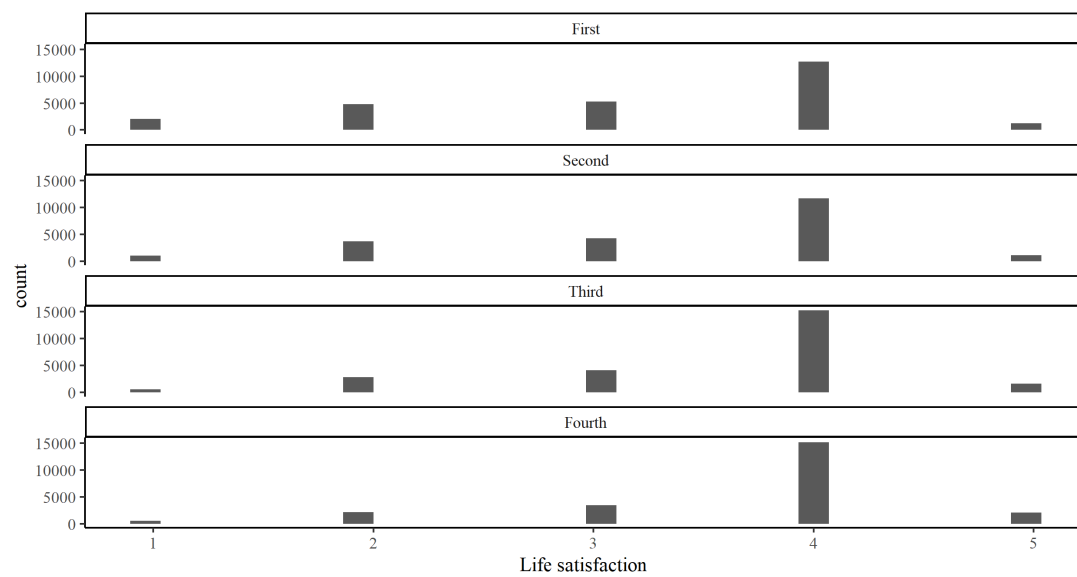
Table 5.9.C Descriptive statistics

Variable	N		Mean		Min	Max
	2015	2016	2015	2016		
Life satisfaction	105,486	48,814	3.46	3.49	1	5
Financial stress	105,486	—	0.29	—	0	1
Electricity expenditure	105,486	48,814	10,585	9,855	2,500	35,000
Electricity expenditure (equivalized)	105,486	48,814	6,566	6,197	790	35,000
Electricity expenditure (log)	105,486	48,814	9.12	9.05	7.82	10.46
Electricity expenditure (log, equivalized)	105,486	48,814	8.67	8.62	6.67	10.46
EP (10%)	105,486	48,814	0.02	0.01	0	1

EP (LIHC)	105,486	48,814	0.07	0.07	0	1
EP (2 Median)	105,486	48,814	0.13	0.12	0	1
CDD 25	90,054	41,825	0.13	0.14	0.00	4.02
CDD 24	90,054	41,825	2.12	2.19	0.00	19.22
CDD 23	90,054	41,825	8.71	10.17	0.00	42.25
CDD 22	90,054	41,825	19.69	23.96	0.00	68.73
CDD 18	90,054	41,825	94.29	118.53	0.00	187.00
CDD 25 (standardized)	90,054	41,825	-0.01	0.02	-0.69	20.10
CDD 24 (standardized)	90,054	41,825	-0.01	0.02	-1.05	8.33
CDD 23 (standardized)	90,054	41,825	-0.07	0.16	-1.43	5.14
CDD 22 (standardized)	90,054	41,825	-0.12	0.25	-1.81	4.10
CDD 18 (standardized)	90,054	41,825	-0.23	0.49	-3.02	2.51
Parental education	105,486	48,814	0.28	0.27	0	1
Income	105,486	48,814	6,722,797	6,672,389	1,500,000	35,000,000
Income (equivalized)	105,486	48,814	4,238,015	4,246,793	474,342	35,000,000
Income (log)	105,486	48,814	15.52	15.51	14.22	17.37
Income (equivalized, log)	105,486	48,814	15.08	15.08	13.07	13.07

Female	105,486	48,814	0.37	0.33	0	1
Old	105,486	48,814	0.12	0.16	0	1
Young	105,486	48,814	0.12	0.06	0	1
Marriage	105,486	48,814	0.71	0.71	0	1
Household number	105,486	48,814	2.78	2.68	1	10
Children	105,486	48,814	0.12	0.09	0	1
Respondent education	105,486	48,814	0.50	0.53	0	1
Partner education	105,486	48,814	0.26	0.25	0	1
Subjective health	105,486	48,814	2.53	2.63	1	5
Mental health	105,486	—	2.09	—	1	4
Energy-saving behavior	105,486	—	0.21	—	0	1
Loan	105,486	48,814	0.30	0.28	0	1
Rental house	105,486	48,814	0.26	0.23	0	1
Car	105,486	48,814	1.16	1.11	0	5
Energy efficiency	105,486	48,814	0.03	0.02	0	1
Floor space	88,292	42,263	87.00	90.41	18	180
Year built	101,159	46,826	18.82	20.67	1	46
Time at home on weekdays	105,486	48,814	0.50	0.54	0	1

Time at home on holidays	105,486	48,814	0.70	0.74	0	1
Knowledge	105,486	48,814	0.05	0.10	0	1
Website	105,486	—	0.09	—	0	1
Rent	105,315	48,728	0.91	0.92	0.50	1.95
RDI	105,486	48,814	1.00	1.00	0.96	1.04



(5. 'Very satisfied', 4. 'Slightly satisfied', 3. 'Neither', 2. 'Slightly unsatisfied', 1. 'Very unsatisfied')

Figure 5.2.C Distribution of SWB for each income quartile

Chapter 6 Conclusion

Securing affordable energy services for all people has universal value. At the same time, reducing the risk of climate change through fossil fuel-originated carbon dioxide emissions is one of the critical global agendas. Energy poverty (EP) is a problem related to both aspects because it hinders people from accessing affordable energy services while it is stemmed from inefficient energy usage. This thesis offers new pieces of evidence on the EP literature by reexamining EP from a global and climate perspective.

Chapter 2 reviewed the existing EP indicators developed in low-income and high-income countries and developed the basis for quantifying EP at the global scale. Although these indicators have been developed from the separate current literature, we underscore the shared nature of the challenges in identifying EP. The chapter concluded that using both objective and subjective indicators can offer better evidence for understanding EP situations.

In chapter 3, we depicted the global picture of EP with the different economic situations. Drawing on the insights in Chapter 2, Chapter 3 depicted EP with a multi-country setting including various development levels in all the six continents. In addition, we used both objective and subjective indicators, which can help us understand how people in low-income countries regard their situation of lower energy usage compared to the other countries. We found that as the economy size and inequality of a country becomes larger, the EP can become more severe in the affordability dimension. This finding is essential to consider for the coming economic growth in the current low-income countries. In addition, we found that subjective affordability is worse when income inequality is more significant. We highlighted that subjective evaluation could be affected by comparing the neighbors' situation within a country.

Chapter 4 highlights the summer-related EP with a case country of Japan. This chapter also used both the objective and subjective indicators for identifying EP. We found that EP with the objective measure is indeed a different problem from income poverty: housing factors are influential in predicting EP in addition to income and household size. On the other hand, EP with the subjective indicator also shows a high correlation with mental factors such as psychological stress. Although both indicators are not perfect for identifying the actual EP situation, this chapter discusses the possible pathways for better measuring EP in the summer context.

Going beyond quantifying EP, Chapter 5 examined the impact of EP on subjective well-being (SWB). Using a large heterogeneity in climate conditions in Japan's summer season, the chapter showed how people increase energy usage when temperature increases and how this temperature-induced energy usage affects SWB. The results suggest a complex relationship between income, cooling affordability, and SWB. Overall, the results confirmed that increasing cooling energy needs might reduce SWB in the hot summer. In relation to income level, we find that the lowest-income group faces the highest energy needs to adapt to higher outdoor temperatures. On the other hand, the well-being impact of cooling affordability was the largest for the middle-income group. This contradictory finding implies that even within a country, there is a difference of views on the 'standard' level of energy usage.

We note policy implications from a global and climate perspective with these findings. Our findings suggest a challenging situation for global climate actions of reducing emissions and ensuring developing countries' well-being and economic growth. The findings suggest that EP problems in low-income countries might worsen in the affordability dimension, even after accessibility and reliability are ensured. In a climate

context, the case study of Japan revealed that affordability still matters even in Japan for adapting to higher outdoor temperatures in the summer season. For lower-income countries not to experience the same results and achieve the global emission reduction goals, diffusing energy-efficient housing and appliances is critical in achieving better well-being more sustainably.