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The Effect of Extreme Temperatures on Energy Poverty in Indonesia

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Abstract

This paper studies the impact of extreme temperatures on the multidimensional energy poverty among Indonesian households in 2012 and 2017 using logistic regression. The results obtained show that there is a significant negative relationship between extreme temperatures and households being in energy poverty. However, the effect of this is minimal, which upon the further breakdown of the results suggests that there are conflicting effects from the components of the multidimensional energy poverty indicator.

Keywords

Energy poverty; Multidimensional energy poverty indicator; ten percent rule; energy consumption; Indonesia; extreme temperatures; climate change; heatwaves

1 Introduction

One of the many consequences of climate change is the changes in the weather distribution which causes temperatures to be more extreme than the previous years (Planton et al., 2008). An implication of this change is that temperatures are the main factor that influences energy demand both in the short term and long term (Parkpoom & Harrison, 2008). Hence, the increased frequency of extreme temperature events would mean that there will be an increase in energy demand, as energy is used to regulate temperature to maintain a comfortable temperature which is used to heat or cool the environment (van Ruijven et al., 2019). Extreme temperature events in this context could be used to refer to heatwaves or coldwaves. Hence, the regulation of the indoors temperature is one of the many methods households used to adapt to extreme temperatures (Feeny et al., 2021). However, the capacity to adapt to extreme temperature events differs for households with different income levels (Feeny et al., 2021; Mazzone et al., 2023). This is because energy demand depends on various factors such as the availability and affordability of energy, and socio-economic factors (e.g.: Income, family size, gender, and age of the household head) (Hartono et al., 2020).

In the Indonesian context, heatwaves are of the concern since the incidence and frequency of heatwaves globally have increased (Perkins-Kirkpatrick & Lewis, 2020). It is also projected by the IPCC that the likelihood of heatwaves in the southeast asia region will increase and intensify when temperatures keep rising (IPCC, 2022). The trend of longer and intense heatwaves has a significant influence on the strategies that could be used by households and policymakers to adapt to it (Perkins-Kirkpatrick & Lewis, 2020). Hence, the main objective of this study is to study the impact of heatwaves on the multidimensional nature of energy poverty among Indonesian households. In this paper, we aim to answer the following research questions.
1. What is the impact of higher temperatures days on the probability of Indonesian households experiencing energy poverty
2. What is the effect of higher temperatures days on the Indonesian households' energy expenditures and energy consumption
3. What is the influence of household's characteristics on energy poverty

Moreover, our results indicate that the impact of higher temperatures on the multidimensional energy poverty of Indonesian households are very minimal and negative in both years 2012 and 2017. There are some possible explanations for this result, which could be due to the conflicting effects of energy consumption and energy expenditures on the measurement of the multidimensional energy poverty. On the other hand, it could be due to other factors such as behavioural changes in households or structural changes in the country that could not be adequately observed from our dataset. Nevertheless, the results remain significant and could provide useful insights for the management of heatwaves and its impact on energy poverty.

The remainder of the thesis is organised as follows. Section 2 reviews the concept of energy poverty, the different measurements of energy poverty, and the methodology used by other researchers in measuring the impact of temperature shocks on energy poverty. Section 3 is an exposition on Indonesia's geography and climate, its energy supply, and the current state of energy poverty in Indonesia. Section 4 will provide a the empirical strategy used and the results obtained with its explanations. Section 5 will be the conclusion and discussion of the thesis.

2 Literature Review

2.1 Energy Poverty

Historically, the concept of energy poverty was introduced by Bradshaw and Hutton (1983), as the inability to afford sufficient fuel to keep a living space at the comfortable warm temperature. It was introduced due to the need to address the fuel crisis of the 1970s which increased the fuel prices steeply. As a consequence, there was a need to design a policy to address the problem of having sufficient fuel to warm homes in Britain (Bradshaw & Hutton, 1983). In the more recent period, where temperatures are more extreme due to climate change, this concept has expanded to include more than the ability to afford adequate warmth at home, in which it can also be interpreted as the ability to afford sufficient energy to keep a comfortable temperature at home (Mazzone et al., 2023).

There are many different ways of defining energy poverty in the existing literature on energy poverty. It can be defined as "the inability to afford adequate warmth at home" (Bradshaw & Hutton, 1983; Mazzone et al., 2023), which in essence only refers to the affordability of energy. In a report by the International Energy Agency (IEA), energy poverty is defined as "the use of traditional biomass in an unsustainable, unsafe, and inefficient way" (IEA, 2007), which refers to the safe and sustainable access to energy. Whilst in another study by Sovacool (2012), it is defined as the lack of choice "in accessing adequate, affordable, reliable, high-quality, safe and environmentally benign energy services to support economic and human development". This definition of energy poverty takes into account the affordability, the access, and reliability of energy, and it is a comprehensive definition of energy poverty.

There are numerous methods to measure energy poverty such as through the use of numerous single indicators and indices (Nussbaumer et al., 2012; González-Eguino, 2015). Furthermore, the indicators used to measure energy poverty can be either subjective or objective indicators (Llorca et al., 2020). The objective measures of energy poverty uses the relationship between the household's income and energy expenditures which can be seen in the indicators that uses household's income or energy expenditures to define energy poverty such as the 10% rule or the residual household income after paying for their energy expenditures must meet the minimum income standard, otherwise the household will be classify as energy poor (Llorca et al., 2020). There are many advantages of using the objective measure as it is standardised and it is easily comparable, due to the standardised nature of the measure (Llorca et al., 2020). However, it does not fully encapsulate the concept of energy poverty as it only measures the affordability part of energy poverty. The subjective measure of energy poverty takes into account the household's differences when experiencing energy poverty (Llorca et al., 2020). This would usually involve the use of alternative indicators that measures the subjective wellbeing of the household in the context of energy deprivation (Llorca et al., 2020). The advantage of using subjective measures is that it could capture the multidimensional nature of energy poverty not just from the affordability point of view. However, there are some challenges of using these subjective measures which can include time consuming data collection as surveys will have to be done to determine a particular household's energy deprivation and its effect.

Firstly, the single indicators that can be used to measure energy poverty are indicators that are used to measure poverty (Nussbaumer et al., 2012). For example, Nussbaumer et al. (2012) suggested using the international poverty line proposed by the World Bank to measure energy poverty. Furthermore, another possible indicator that is commonly used to measure energy poverty is by defining a household as energy poor if the household spends more than ten percent of their income on energy (Hartono et al., 2020). The advantage of using these indicators is that it is easy to compare across different economies. However, the disadvantage of using these indicators to measure energy poverty is that it does not fully measure the multidimensional nature of energy poverty since it only measures the affordability of energy.

Moreover, other common methods of measuring energy poverty is through the use of indices such as Energy Indicators for Sustainable Development, Energy inconveniences indicators, Multidimensional Energy Poverty Index (MEPI), Human Development Index and Energy for Development Index, among many other possible indices (Nussbaumer et al., 2012; Wang et al., 2015).

The Energy Indicators for Sustainable Development was developed by the International Atomic Energy Agency (IAEA) which consists of a list of 30 single indicators that can be used to measure energy poverty through social, economic and environmental dimensions. However, due to the length and descriptions of the 30 indicators, it would be difficult to summarise each indicator here. The essence of the indicators were the themes it covered such as the equity, health, and security of the energy used in a country (IAEA, 2005).

The Energy Inconveniences indicator consists of the unweighted average of the two indices which measures energy inconveniences and energy deficiency (Wang et al., 2015). The energy inconvenience indicator developed by Mirza & Szirmai (2010) used seven different factors such as;

1. Frequency of buying or collecting a source of energy
2. Distance from household travelled
3. Means of transport used
4. Household member's involvement in energy acquisition
5. Time spent on energy collection per week
5. Household health
6. Children's involvement in energy collection

The first step involves constructing an index for each seven factors, then it is aggregated and the unweighted average is computed, which gives the Energy Inconvenience Index. The Energy Deficiency Index calculates the shortfall of energy needed by households to meet their basic needs (Mirza & Szirmai, 2010). It calculates the percentage difference between actual energy consumption per capita and basic energy requirements per capita (Mirza & Szirmai, 2010). The advantage of using this method to measure energy poverty is that it is comprehensive as it also tries to measure energy poverty through the access to energy and the quality of energy. The disadvantage of using this method is that it measures the intensity of energy poverty indirectly through the use of energy consumption (Nussbaumer et al., 2012) and it could inaccurately define an energy saving household as energy poor (Robles-Bonilla & Cedano, 2021).

The MEPI has six equal weighted indicators which represent five dimensions of energy poverty which are cooking, lighting, services provided by means of household appliances, entertainment & education, and communication (Nussbaumer et al., 2012). A weighting vector which sums to one is used to weight the indicators (Nussbaumer et al., 2012). Then, for the indicators, a cut-off is determined when it satisfies the conditions and the value is one when it is satisfied (Nussbaumer et al., 2012). An advantage of this method is that it can measure the intensity of being energy poor in households as the value increases if a person is considered poor in one dimension but not poor in another dimension (Nussbaumer et al., 2012). A disadvantage of this method is that it would require comprehensive household data since it requires specific information from the household. At the same time, it does not take into account if the household uses the appliances that they claim to have (Mazzone et al., 2023).

2.2 Extreme temperature effects on Energy Poverty

First, a similar study on the effects of extreme temperatures on the MEPI was done by Feeny et al. (2021) in Vietnam from 2010 to 2016 and by defining temperature shocks as a deviation from the long term average temperature. The extreme temperatures have an effect on incomes as it was found by Feeny et al. (2021) that it reduces agricultural income and labour productivity. This is because extreme temperatures reduce the output of the agricultural sector which is mainly dependent on the weather and it is a sector that has a significant impact from climate change (Feeny et al., 2021). This in turn would affect the household's affordability and access to energy, due to income constraints (Feeny et al., 2021). Consequently, the result that was obtained by Feeny et al. (2021), was that the impact of extreme temperatures are positive on the MEPI, such that an increase in temperature would meant that the households are likely to be in energy poverty. Interestingly, the results obtained by Feeny et al. (2021), shows that the impact of the extreme temperatures are smaller in the Southern region of Vietnam than the Northern region, which Feeny et al. (2021) supposed that it is likely that the Southern region has less variation in temperature throughout the year and are more adapted to the heat than the Northern region.

Moreover, the study by Masuda et al. (2019), focuses on the rural communities in Kalimantan, Indonesia in 2017. The main takeaway was that the extreme temperatures affect labour productivity as workers whose workplace are primarily outdoors are more exposed to the heat, and would take more breaks and work less (Masuda et al., 2019). In a similar study by Matsumoto (2019) on the impact of extreme temperatures on the labour productivity of workers globally, using data from different regions around the world which includes Indonesia. The extreme temperatures also affect workers whose workplace are indoors as the indoor temperatures are affected by the thermal environment (Matsumoto, 2019). It has also been found by Matsumoto (2019), that the labour productivity of the outdoor workers are significantly more impacted than the labour productivity of the indoor workers during times of extreme temperature. Similarly, the results obtained by Fishman et al. (2019) focusing on the labour market in Ecuador from 1950 to 1990 shows the link between labour productivity and income is significant. This is to say that the reduced labour productivity would then reduce incomes, affecting the household's means to pay for energy (Fishman et al., 2019).

Furthermore, extreme temperatures have an effect on the energy demand and energy consumption (Feeny et al., 2021). This is because extreme temperatures cause thermal discomfort which would then increase the demand for cooling solutions that usually have higher energy requirements such as air conditioners (Feeny et al., 2021). In this case, the higher temperatures in Indonesia meant that households would increase their energy demand through the use of air conditioners which widens the gap of energy poverty between households of different income groups (Feeny et al., 2021; Pavanello et al., 2021). The study by Pavanello et al. (2021), focuses on multiple countries such as Brazil, India, Mexico, and Indonesia. The main results obtained from the study by Pavanello et al. (2021), are that households in the high income group are more likely to have the means to obtain air conditioners and to maintain the higher energy demand of it (Pavanello et al., 2021).

The method used by Feeny et al. (2021) is to estimate the causal effect of temperature shocks on energy poverty. It specifies energy poverty using the MEPI measure as the dependent variable on temperature shocks, household and district characteristics, province fixed effects, time fixed effects and the interaction term between province fixed effects and time fixed effects. The temperature shock is defined as the difference between the average value of temperature in the district in the preceding year and the average value of long run district temperature which is divided by the long run standard deviation (Feeny et al., 2021). Hence two standard deviations from the average long run value is considered as a temperature shock (Feeny et al., 2021).

Another method used by Rofiq Nur Rizal et al. (2024) is to use factors to predict the likelihood of energy poverty using the MEPI as a measure for energy poverty. Rofiq Nur Rizal et al. (2024) then used both multivariate probit and logit models to determine energy poverty as a dependent variable using various factors such as geographic factors and household characteristics. The energy poverty takes the value one if the household is determined to be in energy poverty and zero otherwise. The MEPI is calculated first before being regressed using the other factors and it is determined by the cutoff if a household is deprived in more than one dimension in the MEPI.

Furthermore, there is a method used by climate scientists to measure energy demand needed to provide indoor comfortable temperature due to the external temperatures which may exceed a certain threshold, and it is known as Heating Degree Days (HDD) and Cooling Degree Days (CDD) (Petri & Caldeira, 2015). The degree days are defined as “the sum of the annual or monthly difference between the base temperature and the daily mean outdoor temperature” (Mistry, 2019). Hence, the days in which the outdoor temperature exceeds the base level are known as CDD as it requires the use of cooling devices to maintain a comfortable indoor temperature (Petri & Caldeira, 2015). In the case of HDD it is when the outdoor temperature is lower than the base temperature and it requires the use of heating devices to maintain a comfortable temperature (Petri & Caldeira, 2015). Therefore, the higher the values of the CDD or HDD, would imply that there will be a higher energy demand (Petri & Caldeira, 2015). In this paper, the CDD values are only considered as the climate in Indonesia is mostly hot and humid.

3 The geographical context

3.1 Indonesian Geography & Climate

Indonesia is an archipelagic country, which lies along the equator line. It comprises five main islands and some smaller island groups (Britannica, 2019a). The five main islands in Indonesia are the Sumatra Island, the Java Island, the Kalimantan Island, the Western New Guinea Island and the Sulawesi Island (Wee, 2019). The smaller island groups are the Maluku Islands and the Lesser Sunda islands (Gorlinski, 2019). The climate is generally hot and humid all year round and there are mainly two seasons which characterised Indonesia's climate, that is the wet season and dry season (Britannica, 2019a). The average mean temperatures in Indonesia are approximately between 25 degrees celsius and 26 degrees celsius all year round (Asian Development Bank & The World Bank Group, 2021). The wet season of Indonesia is between November and April whilst the dry season is between May and October. Moreover, the climate is highly influenced by the El Niño Southern Oscillation (ENSO), which meant that it would be drier than the norm during El Niño events and wetter than the norm during La Nina events (Asian Development Bank & The World Bank Group, 2021).

The Sumatra island is divided into seven provinces which are North Sumatra, South Sumatra, West Sumatra, Jambi, Riau, Bengkulu, Lampung and Aceh (Britannica, 2019b). The Java island is divided into five provinces which are West Java, Central Java, East Java, Greater Jakarta, and Yogyakarta (Elyazar et al., 2011). The Kalimantan island is divided into five provinces which are North Kalimantan, South Kalimantan, East Kalimantan, West Kalimantan and Central Kalimantan (Elyazar et al., 2011). The Western New Guinea Island is divided into six provinces which are Central Papua, Highland Papua, Papua, South Papua, Southwest Papua and West Papua (Elyazar et al., 2011). The Sulawesi Island is divided into six provinces which are North Sulawesi, Gorontalo, Central Sulawesi, West Sulawesi, South Sulawesi and Southeast Sulawesi (Elyazar et al., 2011). The Lesser Sunda Island commonly known as Nusa Tenggara and it has three provinces which are Bali, West Nusa Tenggara and East Nusa Tenggara (Elyazar et al., 2011).

Moreover, the population density in Indonesia is mainly concentrated in a few islands (Beta Paramita et al., 2023). This can be seen with about 60% of the Indonesian population are residing in Java Island, 20% in the Sumatra Island, 7% in the Kalimantan Island, 1.5% in the Sulawesi Island, 1.2% in the Papua Island and the remaining 10.3% are in the other Indonesian islands (Beta Paramita et al., 2023).

3.2 Indonesia's Energy Supply

Indonesia's demographic primarily relies on petroleum and coal as its main source of energy to fuel its economic activities (Kurniawan et al., 2020). According to the IEA website, the total energy supply of Indonesia is mainly supplied by coal and oil comprising 30% and 29% of it respectively in 2021. Moreover, the availability and accessibility of the energy in Indonesia varies significantly, which depends on the sources of the energy used, the international supplies of the source of energy, the energy subsidies for the people, and the energy infrastructure in the country (Wayan Ngarayana et al., 2021).

Firstly, the sources of energy used impacts the availability of energy in Indonesia as some of the energy sources are imported (Wayan Ngarayana et al., 2021). This is because in 2004, Indonesia's consumption level of fossil fuel energy exceeded the local production level, which meant that it had to import fossil energy to meet the demand (Wayan Ngarayana et al., 2021). Hence, it is dependent on international supplies and the geopolitics of the international fossil fuel supplies. Moreover, the accessibility of the energy supply is not evenly distributed across Indonesia's provinces due to the differences in geographic and demographic nature of the country (Retnanestri & Outhred, 2021). Hence, it is easier for some provinces to have access to electricity than other provinces and some fossil fuel resources are concentrated in a region (Retnanestri & Outhred, 2021). For example, the fossil fuel resources are mainly concentrated in Sumatera, Kalimantan and Papua (Retnanestri & Outhred, 2021).

Furthermore, the accessibility of energy also depends on fossil fuel subsidies to the general population. This is mainly due to the volatile nature of oil prices which means that the Indonesian government has to subsidise the price of oil to maintain the general public's accessibility to it (Wayan Ngarayana et al., 2021). However, in recent years, the Indonesian government has been reducing the subsidies in an attempt to reduce the dependency on oil for its economy (Rahman et al., 2021).

Moreover, the reliability of the energy infrastructure of the country is an important factor as it provides accessibility to electricity. In Indonesia, the electrification rate in each province is not homogeneous, but generally most of the provinces have access to electricity (Retnanestri & Outhred, 2021). Despite Indonesia's recent achievement of an electrification ratio of 99% in 2020 according to World Bank (2021), the reliability of it still remains a problem in most provinces (Muyasyaroh, 2023). In particular, it was found by Muyasyaroh (2023) that the energy infrastructure in the rural areas are least reliable as compared to urban areas. The parts of Indonesia which have the lowest electrification rate and reliability are located in the rural areas and remote islands (Wayan Ngarayana et al., 2021; Setyowati, 2021).

3.3 Current State of Energy Poverty in Indonesia

The topic of energy poverty in Indonesia is a significant topic that has been continuously addressed by the Indonesian government throughout the years (Setyowati, 2021). For example, the Indonesian government has been attempting to mitigate energy poverty and achieving the transition towards carbon neutrality through programs such as the energy justice program (LISDES), Indonesia Just Transition Partnership (JETP), and solar powered lamps program (LTSHE) (Setyowati, 2021). Although the efforts from the Indonesian government were commendable in the past years in reducing energy poverty, the problem of accessibility, affordability and reliability of energy still remains in certain parts of the country (Setyowati, 2021; Ambarsari Dwi Cahyani et al., 2022).

Firstly, in Indonesia the accessibility of energy is easier in urban areas rather than rural areas in 2018 (Ambarsari Dwi Cahyani et al., 2022). The energy accessibility is typically measured through the household energy expenditure and energy consumption (Hartono et al., 2020; Ambarsari Dwi Cahyani et al., 2022). This is mainly due to the hypothesis that the increase in energy accessibility would increase both the energy expenditure and energy consumption (Hartono et al., 2020; Ambarsari Dwi Cahyani et al., 2022). It was found by Hartono et al. (2020), the accessibility of energy has significantly improved in the rural areas through the significant increase in energy expenditure but this remains relatively low compared to urban areas. In addition, the accessibility of energy is important in the context of improving living standards (Rao & Pachauri, 2017). This is because the improved energy accessibility has an effect of improving other factors related to human development and health such as an increase in the use of cleaner cooking fuels, all of which contributes to alleviating poverty in the long term (Rao & Pachauri, 2017).

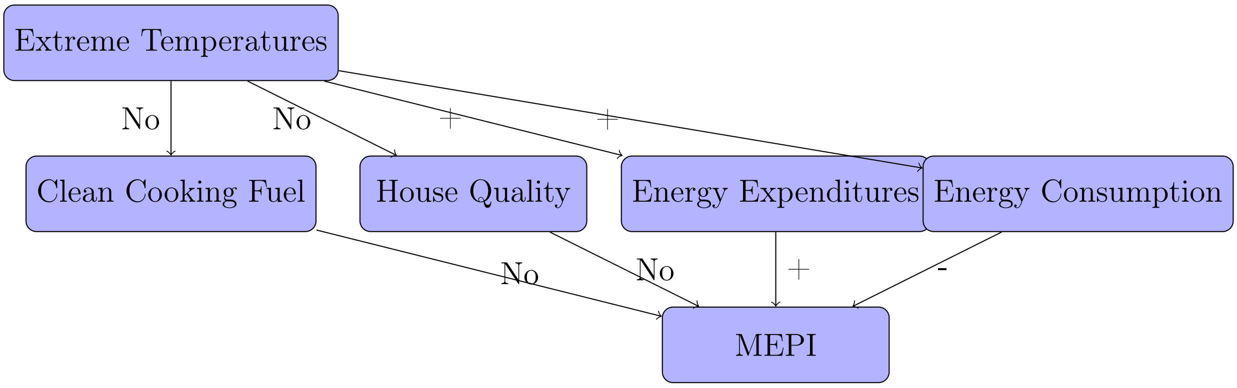
Moreover, the reliability of the energy infrastructure is a factor that should be considered in Indonesia due to its geography and the distribution network of energy (Setyowati, 2021). The archipelagic geography of Indonesia led to a fragmented distribution of the energy network, which meant providing access to energy is expensive in geographically isolated parts and remote islands of Indonesia (Setyowati, 2021). Hence, this would affect the reliability of the energy network which meant that the rural and remote areas would experience frequent power outages due to the high cost of maintaining the electric infrastructure in these areas (Setyowati, 2021). It is also important to note that the electrification ratio does not take into account the reliability of electricity, and hence the ratio could not be used to measure the reliability of electricity (Handayani et al., 2023). This could explain the results found by Hartono et al. (2020) where the accessibility to electricity has increased but the electricity consumption remains low in rural areas. The current methods used to measure reliability are through the geographical distance between the village and the power station or the frequencies of power outages or through the use of indices such as the System Average Interruption Duration Index (SAIDI) and System Average Interruption Frequency Index (SAIFI) (Kunaifi & Reinders, 2018; Handayani et al., 2023). It was found by Kunaifi & Reinders (2018) that the provinces in Riau and Papua had the worst reliability of energy supply in 2018.

Furthermore, the affordability of energy needs to be taken into account when considering energy poverty, as access to energy is limited when the price of energy is too high (Ambarsari Dwi Cahyani et al., 2022). Hence, this will discriminate against those from the lower income group from accessing energy and these groups will not have enough access to energy to support their daily activities (Ambarsari Dwi Cahyani et al., 2022). The efforts made by the government of Indonesia to increase the affordability are mainly done by providing financial support to the State Electrical Company (PLN), differentiated price for electricity based on consumer groups, and electricity subsidies tariffs (Hartono et al., 2020). However, these efforts to increase the affordability of energy to the lower income households in Indonesia are not efficient since it is found by Hartono et al. (2020) that only about 8% of the energy subsidies reached the low-income groups. The current methods to measure the affordability of energy is usually done through the ratio of monthly electricity bill to the minimum wage in each province or if a household spends more than ten percent of their income on energy bills (Retnanestri & Outhred, 2021).

4 A new empirical analysis for Indonesia

4.1 Conceptual framework

The framework below shows how the extreme temperatures affect each component of the MEPI.



First, it has been established by Jaime et al. (2020) and, Hanna and Oliva (2015) that the choice of cooking fuel among households depend on income, fuel prices, and wealth. The paper by Hanna and Oliva (2015) on the low income households in India shows that despite an increase in economic growth and income, the households within this income bracket did not switch away from traditional biomass as their cooking fuel instead, there was an increase in the use of traditional biomass. It was posited by Hanna and Oliva (2015), that this may have been due to the lack of information on the negative health effects of traditional biomass and the fixed cost of acquiring a stove that uses different type of fuel. Moreover, the paper by Jaime et al. (2020) on urban households in Chile has shown that the choice of cooking fuel was influenced by the household's income and housing conditions. The results obtained by Jaime et al. (2020) shows that households that have better dwelling conditions would use more cleaner fuels and higher income is also associated with the increased use of clean fuels. The link between the choice of fuel and temperatures was also explored by Jaime et al. (2020) and it was suggested that the Chilean households uses more traditional fuels when temperatures are colder and less when the temperatures are warmer. However, the same type of relationship in the Indonesian context cannot be said the same, as Indonesian temperatures do not vary much and are warm throughout the year with some variation between regions. Hence, the expectation is that there is no relationship between extreme temperatures and cooking fuels used and the house quality of the households.

Mainly, the decision to use a type of cooking fuel in a household is not tied to extreme temperatures. However, it is included in the formation of MEPI, as it aims to capture the lack of access of the households to clean and modern energy services. Moreover, the house quality of the household is postulated to have no relationship with extreme temperatures as not all households have the capabilities to modify houses to adapt to extreme temperatures in a short amount of time. Hence, this is included in the formation of MEPI as it is a form of deprivation for the households to live in a comfortable state.

Then, it is postulated that both the energy consumption and energy expenditures have a positive relationship with extreme temperatures. This is because with the higher temperatures faced by households, there is a need to increase the usage of cooling devices in the house to regulate the temperature. Hence, this will increase both the energy consumption and energy expenditures of the households. However, the effect on the formation of the MEPI will have opposing effects. First, the increase in energy expenditures of the households might exceed the ten-percent-rule which will then make the households more likely to be classified as energy poor in the MEPI. Then, the increase in energy consumption of the households might exceed the minimum threshold of energy consumption, which meant that households would be more likely to be classified as not energy poor in the MEPI.

4.2 Empirical approach

This section will develop a new empirical analysis of energy poverty and extreme high temperatures in Indonesia. In order to measure high temperatures, CDDs were used. CDDs were mainly used to estimate energy demand and consumption, and its associated carbon emissions in buildings (Mistry, 2019). It is defined by Mistry (2019), as "the monthly or annual sum of the difference between the base temperature T_b and the daily mean outdoor air temperature T_d", where the base temperature is the comfortable temperature for humans which do not require the use of cooling systems (Mistry, 2019). The following equation is the equation that is used to calculate the annual CDD used in this paper.

$$\text{CDD} = \sum_{i=1}^{n} (T_{d,i} - T_b)^+$$

This equation indicates that only days where $T_{d,i}$ is higher than T_b are summed over an n-day period.

I model a linear relationship between energy poverty and CDDs as described in the equation below:

$$\text{Energy Poverty Status}_i = \beta_0 + \beta_1\text{Sector}_i + \beta_2\text{Sex}_i + \beta_3\text{Literacy}_i + \beta_4\text{Education}_i$$
$$+ \beta_5\text{Occupation}_i + \beta_6\text{House Quality}_i + \beta_7 \log(\text{Total Expenditures})_i$$
$$+ \beta_8\text{Mean CDD}_{d(i)} + \beta_9\text{State}_{s(i)} + \epsilon_i$$

for $i = Household$, $d = district$, $s = state$

where:

- Energy Poverty Status is a binary indicator of the energy poverty indicator with value one if the household is energy poor and zero if the household is not energy poor
- Sector is a binary indicator which indicates the sector in which the head of the household works in. It takes the value one if the head of the household works in agricultural sector and zero otherwise.
- Sex is a binary indicator which indicates the sex of the head of the household. It takes the value one when the household head is male and two if it is female
- Literacy is a binary indicator which indicates the literacy of the household head. It takes the value one when the household head is literate and zero if it is not literate
- Education is a categorical variable which indicates the education level completed by the household head. It takes four values that are, no education = 0, primary =1, secondary =2, above =3.
- Occupation is the categorical variable which indicates the occupation type of the household. It takes six values that are, inactive=0, unemployed=1, self-employed=2, regular wage/salary earning=3, casual worker=4, other=5
- House Quality is the categorical variable which indicates the quality of the house in which the household lives in. It takes three values that are, High =3, Decent =2, Low = 1
- Total Expenditures is a continuous variable which is the annual total expenditures of a household

- Mean CDD is a continuous variable which is the mean of the CDD in the past ten years at the district level

The model specified here shows the energy poverty indicator as the dependent variable which takes the value either one or zero, where one indicates that the household is energy poor and zero if the household is not energy poor.

It is dependent on the following variables; the sector in which the head of the household works, the sex of the head of the household, the literacy of the head of the household, the education level completed by the head of the household, the occupation status of the head of the household, the quality of the house, the CDDs at the district level, the log total expenditures of the household and the state of the households. All the independent variables are categorical variables, except for the CDD variable and the total expenditures variable.

The fixed effects of the model are controlled for by including the state fixed effects in the regression. The robust standard errors are clustered at the state and district level. These are done to account for the differences between households in different states and districts. The error term is represented by ϵ_{it}.

A logistic (logit) regression is used here to predict the outcome of the household being in energy poverty, which is a binary variable using the logistic function. The equation of the logit model is shown in the equation below:

$$P(EnergyPoverty = 1|X) = \frac{1}{1 + e^{-(\beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_k X_k)}}$$

where:

- EnergyPoverty is the dependent variable that is a binary variable
- β_0 is the intercept
- $\beta_1 X_1, \beta_2 X_2, \ldots, \beta_k X_k$ are the coefficients of the independent variables

The logit model assumes the following conditions must be satisfied;

- The errors are independent
- The relationship between the dependent variable and the independent variables are linear
- There is no multicollinearity between the independent variables
- There should not be the presence of outliers

4.3 Data

The dataset used here are cross sectional datasets from the Indonesian Household Survey known as National Socio-Economic Survey (SUSENAS) from 2012 and 2017 (BPS Statistics Indonesia, 2012; BPS Statistics Indonesia, 2017). It is a large-scale annual survey compiled by the Indonesian Central Agency of Statistics (BPS) on its population and it samples about 200 000 households from different states and districts. It collects detailed information on the households such as sex, age, education level and marital status for all the members of the household which also includes the breakdown of the household's expenditures and their energy usage. It also includes information about the household's nutrition, healthcare, and their labour experience. The households interviewed in the survey were classified into districts and states in order to be representative of the population. There are 31 states present in this dataset which comprises of 71 districts in it. The households are classed into both states and districts. After cleaning the dataset from missing values and extreme values, the following dataset is used throughout the paper with the summary statistics as seen in table 1. The summary statistics of household characteristics are complied into the table 2. Moreover, the CDD are measured at the district level over the years and complied into the map as seen in figure 1.

Table 1: Dataset Summary

Year	Observations	Proportion
2012	224,050	53.02
2017	198,539	46.98
Total	422,589	100

4.3.1 Housing Index

First, the housing index to determine the quality of the house inhabited by each household is calculated. It is a measure using the following variables: urban, number of members in the house, ownership of the house, size of the house, material of the house walls, material of the house roof, electricity access, type of access to drinking water, type of toilet present in the house and the number of appliances available in the household (e.g: TV, radio, phone, computer, fridge, AC, Internet). The ratio of the size in square meters per person is determined by dividing the size of the house by the number of members in the house.

The score sheet for computing the housing index is based on the paper by Rao and Min (2017). It defines having a minimum floor space between 30 and 10 sqrm

Table 2: Summary Statistics of Household's Characteristics

Sector of the Household Head	Observations	Proportion
Other Sectors	236511	55.97
Agricultural	186078	44.03
Sex of the Household Head	**Observations**	**Proportion**
Male	368788	87.27
Female	53801	12.73
Literacy of the Household Head	**Observations**	**Proportion**
Not Literate	31833	7.533
Literate	390756	92.47
Occupation of the Household Head	**Observations**	**Proportion**
Inactive	24043	5.689
Unemployed	2275	0.538
Self-employed	231209	54.71
Regular wage/Salary earning	121280	28.70
Casual worker	40209	9.515
Other	3573	0.846
Education Level Completed of the Household Head	**Observations**	**Proportion**
No Education	76607	18.13
Primary Education	130603	30.91
Secondary Education	157073	37.17
Completed Education Above Secondary	58306	13.80
House Quality	**Observations**	**Proportion**
Low	23432	5.545
Decent	343315	81.24
High	55842	13.21
Year	**Observations**	**Proportion**
2012	224050	53.02
2017	198539	46.98
Total	422589	100.00

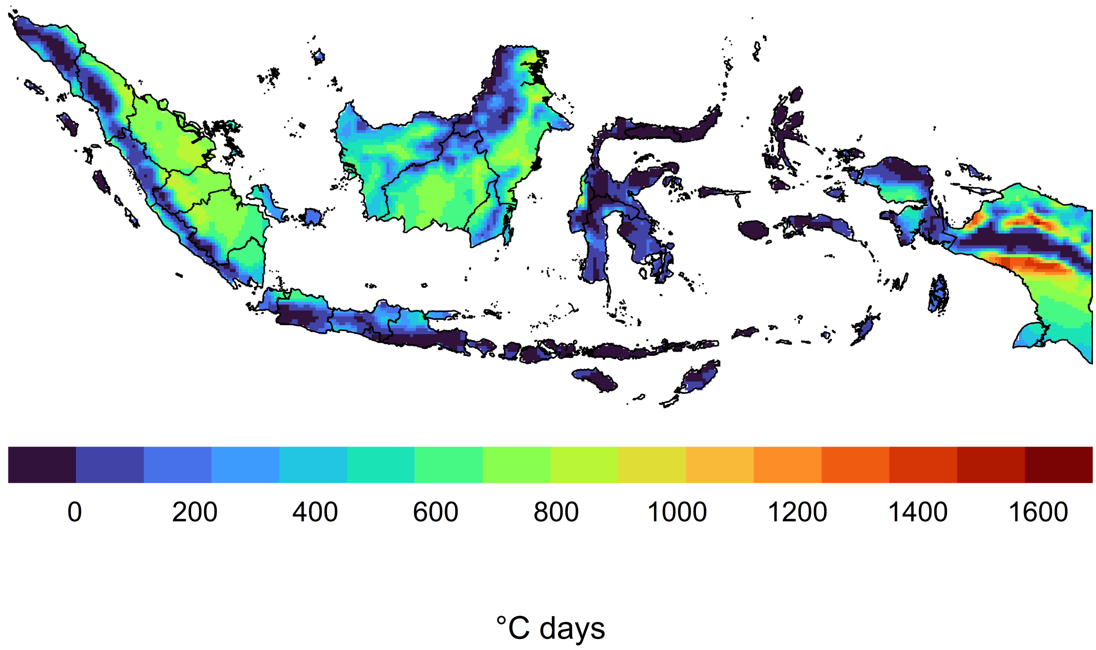


Figure 1: Map of Indonesia with Mean CDD (Pavanello et al., 2021)

per person as the minimum floor space and a set of requirements that a house must fulfill to be considered as a decent living conditions (Rao & Min, 2017). A house is considered to be decent if it has solid walls that are made out of concrete and solid roofing that is made out of metal and tiles (Rao & Min, 2017). Since the climate in Indonesia is tropical, roofing made out of tiles is better than metal and asbestos in maintaining a comfortable room temperature (Budi Priyanto & Romi Nur Hafittuloh, 2019). Then, in comparison to metal and asbestos roofing with concrete roofing, the concrete roofing performs better in keeping the heat out (Yuliani et al., 2020). Then the rank for the roof materials are as follows: tiles, concrete, metal and asbestos, wood, earth and others. The following table 3 shows the score sheet used to compute the housing index.

Table 3: Score Sheet for the Housing Index

Variables	Description	Scores
Urban	Household is living in urban area or not urban area	Urban = 1, otherwise = 0
Ownership	Household owns the house or not	Ownership = 1, No ownership = 0
Electricity Access	House has electricity access or not	Electricity access = 1, No access = 0
Ratio	Minimum floor space in a household per person	Ratio $>$ 30 = 2, 10 $<$ Ratio $<$ 30 = 1, Ratio $<$ 10 = 0
Walls	The material of the house walls	Masonry = 2, Woods = 1, otherwise = 0
Roof	The material of the house roof	Tiles = 3, Concrete = 2, Metal, asbestos, wood = 1, earth and others = 0
Water	The main water source for the households	Piped Water = 3, Bottled Water = 2, Wells and springs = 1, others = 0
Toilet	The type of toilet present in the household	Flush = 2, Pit and latrine = 1, No toilet = 0
Appliances	The presence of the following appliances in the household: 1. TV 2. Radio 3. Phone 4. Computer 5. Refrigerator 6. AC 7. Internet	The presence of each appliance = 1, Not present = 0

4.3.2 The MEPI

The MEPI is calculated for each household with the dimensions of energy poverty as defined by Nussbaumer et al. (2012). The dimensions of energy poverty in this case are availability, affordability, energy consumption, and access to energy services.

The dimension of availability is measured by the following indicators of the type of fuel used for cooking. This is to measure the availability of clean cooking fuel since the availability of electricity is measured by the quality of the house. Hence, cooking variables that are traditional cooking fuels such as coal and firewood are considered as energy deprived and cooking fuels from kerosene, gas sources and electricity are considered as clean cooking fuels. Since, the dataset also includes households which do not have cooking arrangements and other sources of cooking fuel, then these will be classified as energy deprived. The following table 4 summarises the classification used for cooking fuels.

Table 4: Classification for cooking fuels

Type of Cooking Fuel	Classification	Score
Coal, firewood, others, no cooking arrangement	Not clean cooking fuel	1
Kerosene, gas, electricity	Clean cooking fuel	0

The dimension of affordability is measured using the indicator of the percentage of the electrical energy expenditures and generator fuel expenditures over the total expenditures of the household, as the variable of total income of the household is missing. Hence, the variable total expenditures is used as an approximation of the household's income. Moreover, the focus of this paper is on the energy poverty related to cooling solution, then only the energy consumption related to electricity and for the residential use will be considered and the energy consumption related to cooking and other activities such as transportation will not be included. Since, there are some households without electricity, then the ratio will be calculated using their main sources of energy. The percentage of the energy expenditures that exceeds 10% will be considered as energy deprived.

The dimension of energy consumption is measured by using the indicator of electricity quantity used by households. Since, there is no fixed consensus on the minimum energy requirement (Pereira et al., 2011; Simões & Leder, 2022). Then using the requirement fixed by Novani Karina Saputri et al. (2024) on Indonesia from the years 2015 - 2019, which defined energy poor households as households which consume less than 32.4 kilowatt-hour (kWh) per month in terms of electricity. Moreover, it has been defined by IEA (2020) that the minimum energy consumption required by households is 1250 kWh per year. Hence, following the definition used by Novani Karina Saputri et al. (2024), the minimum sufficient energy consumption is 388.8kWh per year and households consuming below this level are considered to be energy poor. This is because the dataset used by Novani Karina Saputri et al. (2024) is in Indonesia so it is customised to fit the energy needs of the Indonesian population whilst the requirement set by the IEA is more generalised to the international community. Since, the minimum energy consumption determined in the paper by Novani Karina Saputri et al. (2024) only relates to residential energy. Hence, we only consider the residential energy consumption such as the electricity, LPG, city gas and generator fuel consumption of the households.

Since the LPG, city gas and generator fuel consumed by the households are in different units of measurement, it will be converted to kWh. The conversion of LPG from a kg is equivalent to 15.75kWh (Rubio et al., 2023) . The conversion of city gas from a kg is equivalent to 15.75kWh (Rubio et al., 2023). The conversion of diesel from a litre is equivalent to 10.26 kWh (Rubio et al., 2023).

The dimension of energy services will be measured by the indicator of the quality of the house. In this case, the house quality which has been defined as low quality means that the household is considered energy poor in this dimension. The summary statistics for the MEPI will be shown in the following table 6 with the other energy poverty indicators.

4.3.3 The Ten Percent Rule (TPR)

The TPR is an energy poverty indicator developed by Boardman in 1991 to define households that spend more than ten percent of their income on energy expenditures are considered to be energy poor (Feeny et al., 2021). Given that the income of households is missing in this dataset, then we consider the total energy expenditures over the total expenditures of the households. The summary statistics for the TPR indicator is summarised in the table 6.

4.3.4 Quantity Based Electricity Poverty Indicator (QBP)

The quantity based electricity poverty indicator was proposed by Coelho and Goldemberg (2013) which sets a threshold of 100kWh per year on a household's consumption of electricity, as it seeks to measure energy poverty based on a household's consumption (Feeny et al., 2021). This threshold was defined based on the Brazilian program for increasing access to electricity in the city of San Paulo to meet the basic human needs in 2010 (Coelho & Goldemberg, 2013). The basic human needs defined by Coelho and Goldemberg (2013) comprises of cooking, lighting and heating. It does not include the use of modern appliances or domestic activities (Coelho & Goldemberg, 2013).

At the same time, a study by Novani Karina Saputri et al. (2024) on Indoensian households from 2015 to 2017 defined the minimum threshold as 388.8kWh per year, as it was derived from the "Presidential Regulation of Republic Indonesia No. 47", which regulates lighting by solar power for households without access to electricity in 2017. This threshold only includes the use of electricity related to lighting in a household. In spite of that, the threshold defined by Novani Karina Saputri et al. (2024) will be used here since it is most suited to the Indonesian household and it defines the energy poverty as households who consume electricity below 388.8kWh per year. However, the use of such indicator is subjective due to the arbitrary setting of the threshold. In this dataset, the average energy consumed by a household in 2017 is higher than the average of energy consumed by a household in 2012 which can be seen in the summary statistics in table 5. It was found by Hartono et al. (2020) that due to the extensive transformation of the accessibility and availability of electricity since 2008 meant that there is an increase in total energy consumption. The summary statistics for the QBP indicator is summarised in the table 6.

Table 5: Summary Statistics for Energy Quantity

Total Energy Consumed (kWh)	Statistics for				Percentiles		
	Mean	Std. Dev.	Min	Max	P25	P50	P75
Energy 2012 & 2017	1870.732	7091.078	0	1188123	517.2	1449	2538
Energy 2012	1558.142	9551.391	0	1188123	300	876	2007
Energy 2017	2223.488	1960.091	0	115800	1092.6	1962	2922

Table 6: Summary Statistics of Energy Poverty Indicators

MEPI	Obs.	Proportion
Not Energy Poor	321364	76.05
Energy Poor	101225	23.95
Ten Percent Rule Energy Poverty Indicator	Obs.	Proportion
Not Energy Poor	300048	71.00
Energy Poor	122541	29.00
Quantity Based Energy Poverty Indicator	Obs.	Proportion
Not Energy Poor	333257	78.86
Energy Poor	89332	21.14
Total	422589	100.00

4.3.5 Cooling Degree Days (CDD)

The data available for CDD were available on a district level annually and it is available from the year 1970 to the year 2016 from De Cian et al. (2019) project and it is merged with the SUSENAS dataset. Then, the average of the last ten years and thirty years for the CDD were taken at the district level for the year 2012 and 2017. Moreover, the summary statistics of the CDD shows that the mean of the averages of CDD in 2012 is higher than the mean of the averages of CDD in 2017 in the table 7. This can be explained by the intensity and frequency of El Nino events from 2002 to 2009 compared to 2012 to 2016 (Anugrah et al., 2020; Nurdiati et al., 2021). The El Nino events are known to be climate events that affects the sea surface temperature and rainfall in Indonesia, which are characterised by the increase in sea surface temperature and lower rainfalls (Anugrah et al., 2020). Thus, when the El Nino event is longer and more intense, there will be an increase in the CDD. Figure 2 shows the average CDD in Indonesia throughout the years, which confirms the presence and the intensity of the El Nino events from 2002 to 2009.

Table 7: Summary Statistics of the CDD in 2012 and 2017

Variable	Obs	Mean	Std. Dev.	Min	Max	P25	P50	P75
MeanCDD_2012	422589	691.599	419.691	0	1472	305	686	1075
MeanCDD_2017	422589	605.414	292.636	0	1201	386	582	868

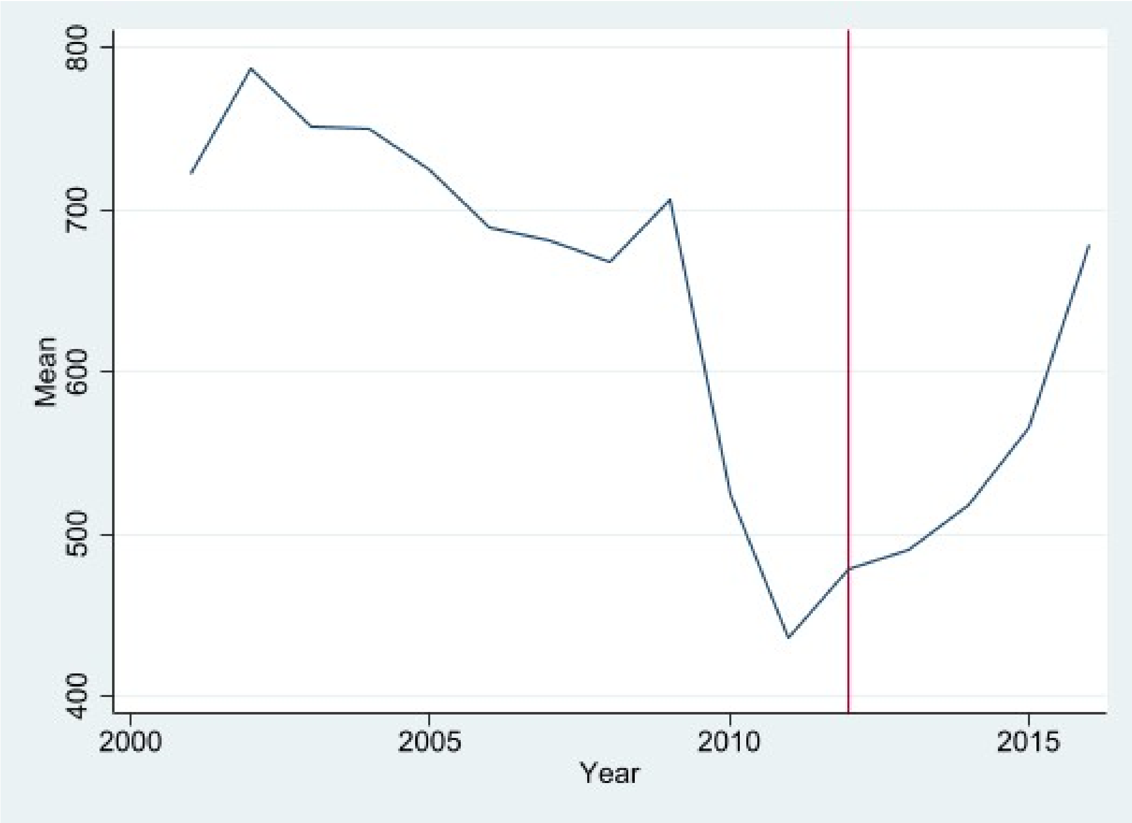


Figure 2: Graph of CDD over the years

4.4 Results

The first section will present the preliminary results of the logistic regression of the CDD on the MEPI. The second section focuses on explaining the results of the CDD on each sub component of the MEPI. The following section will present the robustness of the results with respect to different definitions of the CDD on the MEPI.

4.4.1 Preliminary Results

First, the logistic regression were done separately each year and hence it is treated as a cross-sectional dataset. Moreover, the reference category for occupation of the household head is "inactive" for the year 2012 and "unemployed" for the year 2017 as the category "inactive" is unavailable in the year 2017. The reference category "inactive" in 2012 refers to household head that are unemployed in the labour market and are not looking for employment in that period, while the reference category in 2017 is "unemployed" which refers to the household head that are unemployed in the labour market. The results are shown in the table 10 below and the results from the state variables are excluded. This is because the main variable of interest is the CDD.

The matrix shown in table 8 shows the correlation matrix between the independent variables that will be used in the regression. This is to understand the relationship between the independent variables and to observe if there is a potential problem of multicollinearity. Mainly, it is postulated that there will be a correlation between education level completed, literacy of the household head, occupation of the household head, the sector in which the household head works in, and the house quality of the household. This is because an individual who is literate is most likely to have higher education levels completed and this in turn could affect the job prospects of the individual and the quality of the house in which they will live in. Despite the possible high correlation between the variables, the table 8 shows that the correlation are low with all the variables as the values are all below $|0.5|$.

Table 10 presents the empirical results from the logistic regression. The results here suggests that the higher the number of CDD would meant that households are less likely to be energy poor. Moreover, it also suggests that the effect of higher number of CDD on energy poverty is very minimal given the size of the coefficients.

Furthermore, the signs on the other variables except for the occupation of the household head are as expected in both models. First, the household head who works in the agricultural sector are more likely to be in energy poverty as their main source of income are more vulnerable to climatic change. These households are also most likely to be located in rural areas where the accessibility to electricity is more limited than urban areas. This result is also supported by Feeny et al. (2021), where similar results have been obtained in Vietnam. The findings by Feeny et al. (2021), are similar as they postulated that rural households are more likely to be in the agricultural sector which makes the household more vulnerable in experiencing energy poverty.

Moreover, the signs on the literacy of the household head and the highest education level completed by the household head are negative in both years, which are as expected. It is possible that the household head that are literate and have completed some level of education are more likely to work in the other sectors than the agricultural sector. Hence, this would mean that they are less likely to be in energy poverty. The results obtained here are similar to the results obtained by Hartono et al. (2020) on a similar dataset in Indonesia from 2008 to 2018. Furthermore, the negative sign when the sex of the household head is female is as expected since it was found by Hartono et al. (2020) that female household heads are more likely to spend and consume more on energy thereby making them less likely to be classified as experiencing energy poverty. At the same time, the negative signs on the house quality is as expected since the higher quality of the house would mean that the households are more likely to have better socioeconomic conditions and quality access to energy, and hence less likely to be in energy poverty. The magnitudes for the house quality is as expected with more negative values as the house quality improves from decent to high quality. On a similar vein, the negative sign of the total expenditures is as expected since the households with higher expenditures would have higher income which meant that they are less likely to be experiencing energy poverty.

The results that were unexpected was on the variable related to the occupation of the household head. In 2012, it was negative and significant but in 2017 it was positive and not significant. This might be due to multicollinearity problem as the occupation of the household head might be correlated with the variables such as total expenditures, house quality, literacy, education level completed and the sector where the household head works in.

Table 8: Correlation Matrix

Variables	sector	sex	literacy	occup	edu	HouseQ	exp	CDD17	CDD12
sector	1								
sex	-0.0639	1							
literacy	-0.1329	-0.1869	1						
occup	-0.0331	-0.1926	0.1293	1					
edu	-0.2171	-0.0268	-0.219	0.0452	1				
HouseQ	-0.3109	0.0059	0.177	0.0356	0.183	1			
exp	-0.2248	-0.2209	0.2455	0.104	0.2244	0.3299	1		
CDD17	-0.0724	-0.0161	0.082	0.0415	-0.0189	0.1536	0.0689	1	
CDD12	-0.0502	-0.0166	0.0667	0.0364	-0.0018	0.1031	0.0952	0.9049	1

The results from the variance inflation factor (VIF) from the table 9 shows that there exists multicollinearity problem in this model. The values of VIF that are above five are considered to have a problem of multicollinearity whilst values above 10 are considered to have a serious problem of multicollinearity. Hence, the variables with values above 10 are removed, and the regressions are run again. The results of the VIF improved with reduction of the VIF values in all the remaining variables as seen in the table 9. The results from the regressions with the removed variables are the models 2012A and 2017A in table 10. The results shows that the coefficients of the variables are slightly inflated and do not greatly vary from the initial results, with the exception of the variable sex of the household head, which has a reversal of signs.

Despite the improvement on the VIF values, the problem of multicollinearity affects the standard errors of the model by inflating it but it will not affect the coefficients. However, the problem of omitted variable bias affects the value of coefficients and the estimated coefficients will be unreliable. Hence, despite the problem of multicollinearity, the variables will still be included in the regressions.

Table 9: VIF Results

Variable	VIF (2012)	VIF (2017)	VIF (2012A)	VIF (2017A)
Sector_h~d	2.57	2.51	1.86	1.97
Sex_head	1.36	1.17	1.2	1.14
Literacy~d	18.96	26.97	-	-
Edu_head				
Primary	2.65	3.04	2.3	2.59
Secondary	3.2	3.78	2.6	3.01
Above	2.43	2.24	1.69	1.67
Occupation~d				
Unemployed	1.03	-	-	-
Self-employed	7.8	68.2	-	-
Regular wage	4.18	37.05	-	-
Casual worker	2.22	11.44	-	-
Others	1.07	2.26	-	-
HouseQuality			-	-
Decent	17.61	23.61	-	-
High	4.65	5.17	-	-
logtotal_exp	76.71	185.99	-	-
MeanCDD_2012	5.77	-	4.91	-
MeanCDD_2017	-	10.6	-	9.14

VARIABLES	(1) Model 2012	(2) Model 2017	(3) Model 2012A	(4) Model 2017A
Sector Head				
Agriculture	0.738***	0.787***	1.181***	1.439***
	(0.0259)	(0.0342)	(0.0329)	(0.0527)
Sex Head				
female	-0.187***	-0.292***	0.458***	0.318***
	(0.0237)	(0.0311)	(0.0207)	(0.0284)
Literacy Head				
yes	-0.476***	-0.254***		
	(0.0327)	(0.0484)		
Edu Head				
primary	-0.125***	-0.142***	-0.313***	-0.279***
	(0.0210)	(0.0306)	(0.0209)	(0.0283)
secondary	-0.474***	-0.518***	-0.922***	-0.881***
	(0.0254)	(0.0359)	(0.0277)	(0.0372)
above	-0.119***	0.0394	-0.209***	-0.113**
	(0.0374)	(0.0521)	(0.0390)	(0.0532)
Occupation Head				
unemployed	-0.187			
	(0.120)			
self-employed	-0.164***	0.105		
	(0.0315)	(0.115)		
regular wage/salary earning	-0.388***	-0.135		
	(0.0327)	(0.116)		
casual worker	-0.168***	0.0128		
	(0.0389)	(0.120)		
other	-0.125*	0.110		
	(0.0706)	(0.152)		
House Quality				
Decent	-3.379***	-3.124***		
	(0.127)	(0.0734)		
High	-3.980***	-4.457***		
	(0.149)	(0.121)		
logtotal_exp	-1.222***	-1.448***		
	(0.0347)	(0.0397)		
MeanCDD_2012	-0.000613***		-0.000706***	
	(0.000109)		(0.000106)	
MeanCDD_2017		-0.00142***		-0.00160***
		(0.000203)		(0.000219)
Constant	23.57***	25.36***	-0.931***	-2.782***
	(0.615)	(0.683)	(0.147)	(0.190)
Observations	224,050	198,539	224,050	198,539

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 10: Regressions with 10 year Mean CDD

Since the MEPI is composed of different sub components, it is also essential to explore the effect of CDD on each of these sub components individually.

4.4.2 Energy Consumption

VARIABLES	(1) Model 2012	(2) Model 2017
MeanCDD_2012	-0.000405**	
	(0.000206)	
MeanCDD_2017		-0.00152***
		(0.000254)
Constant	14.01***	25.74***
	(1.091)	(0.884)
Observations	224,050	198,539

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Regressed with all other variables

Table 11: Effect of CDD on Energy Consumption

First, the energy consumption component of the MEPI is measured by using the QBP. Hence, using the threshold defined earlier, the results obtained are as expected and shown in the table 11. Both the signs on 2012 and 2017 were negative as the higher the number of CDD, the more likely it is that the household increases its energy consumption for cooling purposes. This increase in energy consumption meant that some households would surpass the threshold and be classified as not in energy poverty. However, the magnitude of this negative sign is very minimal since it has a very small effect in both 2012 and 2017.

4.4.3 Energy Expenditures

The energy expenditures component of the MEPI is measured by using the ten percent rule and the table 12 shows the results obtained. The results obtained here are as expected, with the positive signs on the CDD in both 2012 and 2017. The positive sign might be due to the households increasing their energy consumption due to the higher number of CDD, which will then increase their energy expenditures and consequently some households will spend more than ten percent of their income on energy. Moreover, the magnitude of this positive sign is very minuscule in both 2012 and 2017.

VARIABLES	(1) Model 2012	(2) Model 2017
MeanCDD_2012	0.000175**	
	(8.87e-05)	
MeanCDD_2017		0.000460***
		(0.000123)
Constant	5.248***	6.863***
	(0.480)	(0.414)
Observations	224,050	198,539

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Regressed with all other variables

Table 12: Effect of CDD on Energy Expenditures

4.4.4 House Quality

VARIABLES	(1) Model 2012	(2) Model 2017
MeanCDD_2012	-0.000425**	
	(0.000199)	
state3 = 5, omitted	-	-
MeanCDD_2017		-0.00126***
		(0.000440)
Constant	21.74***	12.45***
	(1.184)	(2.619)
Observations	221,711	196,574

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Regressed with all other variables except HouseQuality

Table 13: Effect of CDD on House Quality

The house quality component of the MEPI is measured by using the housing index that has been constructed. The house quality component of the MEPI is a binary indicator when converted from the housing index, with value one when the house quality has a poor quality and value zero when the house quality has decent or high quality. In this regression, the component house quality variable is removed from the independent variables as the dependent variable is derived from this variable. The results are displayed in the table 13.

The results meant that when there is a higher number of CDD, the less likely households will have poor house quality. Moreover, the magnitude of the coefficients are different between 2012 and 2017, with 2017 having the larger magnitude than 2012.

Then, to ensure that the direction of this effect is the same in two different groups, that is a group with a high proportion of households with decent to high quality houses and a group with low proportion of households with decent to high quality houses. The regression is done for both groups in two years and the results are shown below. The results for the year 2012 are displayed in the table 14 and results for the year 2017 are displayed in the table 15. In both groups and both years, the effect is negative but the magnitude of it differs. Hence, it is possible that there are other factors influencing the negative sign of the CDD on the house quality.

VARIABLES (2012)	(1) High Proportion of Decent House	(2) Low Proportion of Decent House
MeanCDD_2012	-0.000236	-0.000853***
	(0.000246)	(2.52e-05)
1o.occupation_head	-	
5o.occupation_head	-	
Constant	13.56***	18.80***
	(3.174)	(0.314)
Observations	77,675	145,216

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Regressed with all other variables except HouseQuality

Table 14: Effect of CDD on states with different proportion of house quality in 2012

VARIABLES (2017)	(1) High Proportion of Decent House	(2) Low Proportion of Decent House
MeanCDD_2017	-0.00213***	-0.00135***
	(4.34e-05)	(0.000389)
Constant	10.56***	10.04***
	(0.418)	(2.704)
Observations	132,603	65,936

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Regressed with all other variables except HouseQuality

Table 15: Effect of CDD on states with different proportion of house quality in 2017

Hence, another regression is done with two different groups that is a group which has states that have high values of CDD and low proportion of households with decent to high quality houses, and a group which have low values of CDD and high proportion of households with decent to high quality houses. The results for the year 2012 are displayed in the table 16 and the year 2017 in the table 17.

VARIABLES (2012)	(1) High CDD, Low Decent House	(2) Low CDD, High Decent House
MeanCDD_2012	-0.000661***	0.000304
	(2.88e-05)	(0.000363)
1o.occupation_head		-
5o.occupation_head		-
Constant	18.83***	10.30**
	(0.363)	(4.072)
Observations	94,079	21,496

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Regressed with all other variables except HouseQuality

Table 16: States with different proportion of house quality and different proportion of CDD in 2012

VARIABLES (2017)	(1) High CDD, Low Decent House	(2) Low CDD, High Decent House
MeanCDD_2017	-0.00111	-0.00213***
	(0.000750)	(4.84e-05)
5o.occupation_head	-	
Constant	14.92***	8.817***
	(4.541)	(0.478)
Observations	17,901	88,209

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Regressed with all other variables except HouseQuality

Table 17: States with different proportion of house quality and different proportion of CDD in 2017

Based on the results, the signs of the CDD coefficients are negative and significant everywhere except for the group which has low values of CDD and high proportion of households with decent to high quality houses in 2012. Hence, in general there is a negative effect of the CDD on the house quality of the household. The negative effect might be due to other factors that could not be observed using this dataset. A possible explanation for this negative effect of CDD on the house quality, might be due to the improvement of house quality over time. This might be due to the Indonesian government's housing development plan for affordable livable housing conditions since 2015 by constructing a million houses each year (Perdamaian &

Zhai, 2024). Hence, there is a possibility that the households are experiencing an improvement in their house quality.

Table 18: T-test Results for House Quality
diff = mean(2012) - mean(2017)
H0: diff = 0

Alternative Hypothesis	P-Values
Ha: diff <0	0.0009
Ha: diff != 0	0.0018
Ha: diff >0	0.9991

A t-test was performed to check if the means of the house quality scores between the two years are different. The results shown in the table 18 indicates that there is difference between the means of the house quality scores between the two years and it is very significant that the mean of the house quality score in 2012 is lower than the mean of the house quality score in 2017. Hence, there is evidence that there are more higher quality housing in 2017 than 2012. However, it is not possible to check if there is a change in the household's behaviour as the dataset used is not panel data and the regressions are done such that it is treated as a cross sectional dataset.

4.4.5 Cooking Fuel

VARIABLES	(1) Model 2012	(2) Model 2017
MeanCDD_2012	-0.000803***	
	(0.000117)	
MeanCDD_2017		-0.00142***
		(0.000190)
Constant	23.36***	20.75***
	(0.507)	(0.556)
Observations	224,050	198,539

Robust standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 19: Effect of CDD on Cooking Fuel

The cooking fuel component of the MEPI is similar to the house quality component which is a binary variable with value one when the cooking fuel used is not clean cooking fuel and zero when the cooking fuel is clean. The results are shown in the table 19 reveals a surprising result since there is no expectation of relationship between cooking fuel and CDD. However, the signs are negative which indicates that the higher number of CDD would mean that the household is less likely to use not clean cooking fuel. Moreover, the magnitude of the signs differs in both years, with a larger magnitude in 2017 than 2012.

Then separating the dataset into two groups by states, that is a group with a high proportion of households with clean cooking fuel and the other group with a low proportion of households with not clean cooking fuel. A regression with the cooking fuel as the dependent variable is run again for each group in each year. The table 20 displays the results for the year 2012 and the table 21 displays the results for the year 2017. Based on the results, the negative sign remains in both groups, which meant that there might be a different source for the negative relationship.

	(1)	(2)
VARIABLES (2012)	High Proportion of Clean Fuel	Low Proportion of Clean Fuel
MeanCDD_2012	-0.000514***	-0.00116***
	(1.43e-05)	(3.90e-05)
Constant	18.90***	25.84***
	(0.188)	(0.434)
Observations	176,619	47,431

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Regressed with all other variables

Table 20: Effect of CDD on states with different proportion of cooking fuels in 2012

	(1)	(2)
VARIABLES (2017)	High Proportion of Clean Fuel	Low Proportion of Clean Fuel
MeanCDD_2017	-0.000647***	-0.000599***
	(2.65e-05)	(6.83e-05)
Constant	20.45***	21.33***
	(0.252)	(0.482)
Observations	160,787	37,752

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Regressed with all other variables

Table 21: Effect of CDD on states with different proportion of cooking fuels in 2017

Another regression is done with two different groups that is a group which has states that have high values of CDD and low proportion of households with clean cooking fuel, and a group which have low values of CDD and high proportion of households with clean cooking fuels. The table 22 below displays the results of the regressions.

VARIABLES	(1) High CDD Low Clean Fuel	(2) Low CDD High Clean Fuel	(3) High CDD Low Clean Fuel	(4) Low CDD High Clean Fuel
MeanCDD_2012	-0.000615***	-0.00110***		
	(1.75e-05)	(5.78e-05)		
MeanCDD_2017			-0.000130**	-0.00143***
			(5.22e-05)	(8.79e-05)
Constant	18.36***	23.93***	24.32***	23.63***
	(0.224)	(0.696)	(0.540)	(0.739)
Observations	121,194	17,489	44,458	19,739

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Regressed with all other variables

Table 22: States with different proportion of cooking fuels and different proportion of CDD

Based on the results in table 22, it is negative and significant on all the groups in both years. Hence, the source of the negative relationship cannot be observed using the existing variable. It is possible that there are some other factors jointly affecting the household's choice on cooking fuels and the number of CDD. A possible explanation for this might be due to the Indonesian government program that encourages households to change to clean cooking fuels that started in 2012 (World Bank, 2014). Thus, the change in households behaviour to use less traditional cooking fuels might affect the coefficient of the CDD in both years.

Table 23: T-test Results for Cooking Score
diff = mean(2012) - mean(2017)
H0: diff = 0

Alternative Hypothesis	P-Values
Ha: diff <0	1.0000
Ha: diff != 0	0.0000
Ha: diff >0	0.0000

A t-test was used to test the difference in means between the cooking scores in both years. The results displayed in table 23 indicates that there is a very significant difference between the means of the cooking score in both years, with the mean of the cooking score in 2012 higher than the mean of the cooking score in 2017. This can be interpreted that more households in 2017 were using clean cooking fuel than households in 2012. However, similar to the section on house quality, it cannot be concluded that households are transitioning towards using more clean cooking fuel as the dataset is treated as a cross sectional dataset.

4.5 The Robustness of the Results

The robustness and the sensitivity of the model is tested using different definitions of CDD, such as one year CDD (CDD 1Y) and the average of the past thirty years CDD (CDD 30Y). The results are shown in the table 25

The results for both CDD 30Y and CDD 1Y in the table 25 are consistent with the main regression results from table 10. Moreover, the coefficient estimates between the different definitions of CDD are similar in signs with little variation in the estimated value of the coefficients. However, the estimated coefficient for the CDDs has different magnitudes, with a larger magnitude when the CDD is defined for a year than the thirty years. The result is unsurprising since a similar study on Vietnamese households by Feeny et al. (2021) yielded similar results, that is temperature shocks that were lagged longer had a lower effect on the MEPI. A possible explanation for the difference in magnitude of the CDD on MEPI might be due to the household's resilience towards extreme temperatures in the long run. The households might be less resilient to the extreme temperatures in the short run than the long run as households can adjust their adaptation strategies more easily in the long run than in the short run.

Table 24: T-test Results for CDD 30Y and CDD 1Y
diff = mean(CDD 30Y - CDD 1Y)
H0: diff = 0

Alternative Hypothesis	P-Values (2012)	P-Values (2017)
Ha: diff <0	1.0000	0.0000
Ha: diff != 0	0.0000	0.0000
Ha: diff >0	0.0000	1.0000

Furthermore, it is also plausible that the difference in magnitude might be due to the higher values of the mean of CDD 1Y than CDD 30Y. Hence, a t-test to test the mean of the difference between CDD 30Y and CDD 1Y is done. The results for the t-test is shown on the table 24. Based on the results, there is a difference in the values of CDD 30Y and CDD 1Y for both years. However, the results show that the CDD 30Y is greater than CDD 1Y in 2012 and the CDD 1Y is greater than CDD 30Y in 2017. These results disprove the possibility that the differences in magnitude between CDD 1Y and CDD 30Y could be due to the higher values of CDD 1Y than CDD 30Y, as the results show significance in 2017 but not in 2012.

VARIABLES	(1) (30Y) 2012	(2) (30Y) 2017	(3) (1Y) 2012	(4) (1Y) 2017
Sector Head				
Agriculture	0.738***	0.793***	0.733***	0.787***
	(0.0259)	(0.0345)	(0.0260)	(0.0352)
Sex Head				
Female	-0.187***	-0.292***	-0.186***	-0.294***
	(0.0237)	(0.0312)	(0.0238)	(0.0315)
Literacy Head				
yes	-0.476***	-0.264***	-0.454***	-0.236***
	(0.0327)	(0.0483)	(0.0329)	(0.0489)
Edu Head				
primary	-0.126***	-0.144***	-0.122***	-0.145***
	(0.0209)	(0.0307)	(0.0213)	(0.0308)
secondary	-0.474***	-0.523***	-0.460***	-0.512***
	(0.0254)	(0.0361)	(0.0257)	(0.0362)
above	-0.119***	0.0546	-0.121***	0.0284
	(0.0374)	(0.0521)	(0.0370)	(0.0551)
Occupation Head				
unemployed	-0.187		-0.193	
	(0.120)		(0.121)	
self-employed	-0.162***	0.0929	-0.161***	0.132
	(0.0315)	(0.116)	(0.0316)	(0.114)
regular wage/salary earning	-0.388***	-0.146	-0.406***	-0.134
	(0.0327)	(0.116)	(0.0333)	(0.116)
casual worker	-0.167***	0.00921	-0.172***	0.0250
	(0.0389)	(0.120)	(0.0400)	(0.120)
other	-0.125*	0.0956	-0.105	0.157
	(0.0705)	(0.152)	(0.0718)	(0.151)
HouseQuality				
Decent	-3.379***	-3.122***	-3.392***	-3.136***
	(0.127)	(0.0747)	(0.124)	(0.0744)
High	-3.982***	-4.470***	-3.992***	-4.485***
	(0.149)	(0.122)	(0.146)	(0.123)
logtotal_exp	-1.223***	-1.441***	-1.228***	-1.463***
	(0.0347)	(0.0401)	(0.0350)	(0.0400)
CDD12_30Y	-0.000558***			
	(9.98e-05)			
CDD17_30Y		-0.000960***		
		(0.000128)		
CDD_2011			-0.00107***	
			(0.000223)	
CDD_2016				-0.00115***
				(0.000240)
Constant	23.54***	25.26***	23.40***	25.36***
	(0.614)	(0.688)	(0.608)	(0.683)
Observations	224,050	198,539	224,050	198,539

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 25: Robustness and sensitivity regression

5 Conclusion and Discussion

First, the main results show that extreme temperatures do have an effect on the MEPI. However, the effect of that is minimal and negative which can be due to the conflicting effects of the different components of the MEPI and household's behaviour that could not be observed. Moreover, most of the household characteristics are also significant in predicting the household's status in energy poverty. This is unsurprising given the link between household socioeconomic characteristics and access to better living conditions and consequently less likely to be energy poor. Furthermore, a more detailed effect of CDD can be seen through the breakdown of the effect of the CDD on each individual components of the MEPI.

The results are as expected from the component of energy consumption which shows that there is a small negative relationship with CDD. This is because as the CDD increases, the household will then increase their energy consumption such that it would surpass the threshold to be considered as energy poor, which makes the households less likely to be classified as energy poor. In a similar vein, the results are as expected from the component of energy expenditures which is a positive relationship with CDD. In this component, an increase in the CDD meant that household will increase their energy expenditures due to higher energy consumption which similarly makes the household more likely to be classified as energy poor. The results from house quality and cooking fuel component were surprising as there is no expectation of a relationship between those components and CDD. However, both of these components had a small and negative relationship. Upon further investigation, it is possible that there are other factors that are affecting the results that could not be observed by the dataset.

This suggests that there is a need to include more data and information to better capture the effect of extreme temperatures on the multidimensional nature of energy poverty, which was a challenge in this paper. At the same time, the model is robust and sensitive when regressed with different definitions of CDDs. The sensitivity of the model implies that this could be used in countries that have similar weather patterns to Indonesia. However, due to the limitations of the data, it could only be interpreted as a cross sectional dataset. In addition, the time interval between the two dataset could be wider to better observe changes in the effect of the CDD on the MEPI. This could also be further improved through the use of panel data such that the changes in energy poverty among households attributed to behavioural change can be tracked and accounted. This is particularly important as it provides insights on household's response to an increase in CDD through their energy consumption and expenditures which may not be fully reflected using cross-sectional dataset.

Moreover, there are improvements that can be made on the construction of the MEPI. In particular, components related to the energy reliability could be added to improve the analysis. Whilst energy accessibility in Indonesia has greatly improved, the country still has issues with the reliability of its energy structure. This would mean some households would still experience a form of energy deprivation and hence energy poverty, which would not be considered if the component of energy reliability is not included in the MEPI. Hence, the inclusion of the component of energy reliability could provide a more comprehensive understanding of the MEPI. Overall, for policy considerations, it could prove useful for policymakers to consider the breakdown of the effect of extreme temperatures on the MEPI, such that they could intervene by targeting policies to reduce poverty incidence in each component of the MEPI.

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A Appendix

Table 26: Tabulation of States

State	Observations	Proportion
Aceh	18664	4.417
Bali	2365	0.560
Banten	1557	0.368
Bengkulu	8524	2.017
DI Yogyakarta	4304	1.018
Gorontalo	1896	0.449
Jambi	11459	2.712
Jawa Barat	37055	8.769
Jawa Tengah	48926	11.58
Jawa Timur	53295	12.61
Kalimantan Barat	11619	2.749
Kalimantan Selatan	12793	3.027
Kalimantan Tengah	13056	3.090
Kalimantan Timur	9570	2.265
Kepulauan Bangka Belitung	968	0.229
Kepulauan Riau	790	0.187
Lampung	17063	4.038
Maluku	1962	0.464
Maluku Utara	4701	1.112
Nusa Tenggara Timur	9022	2.135
Papua	18472	4.371
Papua Barat	6812	1.612
Riau	13926	3.295
Sulawesi Barat	4907	1.161
Sulawesi Selatan	23860	5.646
Sulawesi Tengah	10798	2.555
Sulawesi Tenggara	9445	2.235
Sulawesi Utara	753	0.178
Sumatera Barat	17480	4.136
Sumatera Selatan	17241	4.080
Sumatera Utara	29306	6.935
Total	422589	100.00

Table 27: State Codes

State	Code
Aceh	1
Bali	2
Banten	3
Bengkulu	4
DI Yogyakarta	5
Gorontalo	6
Jambi	7
Jawa Barat	8
Jawa Tengah	9
Jawa Timur	10
Kalimantan Barat	11
Kalimantan Selatan	12
Kalimantan Tengah	13
Kalimantan Timur	14
Kepulauan Bangka Belitung	15
Kepulauan Riau	16
Lampung	17
Maluku	18
Maluku Utara	19
Nusa Tenggara Timur	20
Papua	21
Papua Barat	22
Riau	23
Sulawesi Barat	24
Sulawesi Selatan	25
Sulawesi Tengah	26
Sulawesi Tenggara	27
Sulawesi Utara	28
Sumatera Barat	29
Sumatera Selatan	30
Sumatera Utara	31

Table 28: Description of the Variables

Variables	Variable Code	Description	Description of the values
House Index	HouseQuality	The quality of the house	High = 3, Decent = 2, Low = 1
Cooking Score	cooking_score	The type of cooking fuels used by the households	clean = 0, deprived = 1
Sector Head	sector_head	The sector in which the head of the household works in	Others = 0, Agricultural including forestry, fishing, livestock = 1
Sex Head	sex_head	The sex of the head of the household	Male = 1, Female = 2
Literacy Head	literacy_head	The literacy of the head of the household	No = 0, Yes = 1
Edu Head	edu_head_2	The education level completed by the head of the household	no edu = 0, primary = 1, secondary = 2, above = 3
Occupation Head	occupation_head	The type of occupation held by the head of the household	inactive = 0, unemployed = 1, self-employed = 2, regular wage/salary earning = 3, casual worker = 4, other = 5
MEPI	MEPI_binary	The multidimensional energy poverty indicator for each household	Not energy poor = 0, energy poor = 1
Ten Percent Rule	TPR	The energy poverty indicator based on the ten percent rule	Not energy poor = 0, energy poor = 2
Quantity Based Poverty	QBP	The energy poverty indicator based on the energy consumed by household	Not energy poor = 0, energy poor = 3
District	district3	The district where the household is located in	There are too many states to describe here; see the table for district tabulation
State	state3	The state where the household is located in	There are too many districts to describe here; see the table for state tabulation
Energy Expenditures	exp_score	The annual energy expenditures of the household in the local currency	It is a continuous variable
Energy Consumption	energy_score	The annual amount of energy consumed by households in kWj	It is a continuous variable
Energy Service	energy_service_score	The recode of the house quality to binary variables	clean = 0, deprived = 1; The House Quality that is High and Decent is classified as clean and Low is classified as deprived
Year	year	The year in which the household was surveyed	There are two values, 2012 and 2017