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Asymmetric Adaptation to Heat and Energy Poverty*

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Abstract

We study the responses of household electricity consumption to temperature changes, focusing on asymmetries between welfare deciles. Our analysis exploits a unique panel dataset for Peru that links household survey microdata with repeated administrative records on energy use and local temperature. Using fixed-effects models, we estimate how electricity consumption varies with temperature, highlighting the unequal capacity of households across income deciles to adapt to climate change. Based on this evidence, we propose and implement a novel measure of *adaptive energy poverty*, which captures households' ability to respond to rising ambient temperatures through increased electricity consumption.

JEL Codes: I31, Q41, Q54

Keywords: electricity, temperature, energy poverty, Peru

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1 Introduction

Electricity consumption is central to households' capacity to adapt to weather conditions (Deschênes, 2014).[1] Yet, this adaptive capacity is unequally distributed: income and other socioeconomic characteristics shape both households' access to cooling and heating technologies and their patterns of energy use. In this context, understanding how electricity consumption responds to temperature changes —and how these responses vary across socioeconomic groups— is crucial for informing energy, social, and climate policies.

This paper contributes to the growing literature on the relationship between temperature and electricity consumption, with a particular focus on distributional asymmetries. To that end, we study the case of Peru. Although electricity access in that Latin American developing country is widespread, substantial disparities persist in usage intensity, affordability, and vulnerability to climate-related risks (Tornarolli & Puig, 2023).

We exploit a novel dataset that combines three sources of information: nationally representative household survey data, administrative records on electricity consumption, and high-frequency temperature information. This integration enables the construction of a monthly panel at the household level, covering the period 2015 to 2023. The richness of the dataset allows for identification of heterogeneous consumption responses to temperature changes across the well-being distribution. Methodologically, we rely on an econometric approach based on semi-parametric fixed effects models, allowing a flexible specification that captures nonlinear temperature effects while controlling for unobserved heterogeneity across time and space (Davis & Gertler, 2015; Harish *et al.*, 2020; Zhang *et al.*, 2022).

The econometric results confirm that electricity consumption in Peru responds non-linearly to temperature: it remains stable between mean monthly temperature levels of 16°C and 19°C, and rises sharply beyond that threshold, reaching increases of up to 25 kWh per month when temperatures approach 30°C. The analysis by welfare level reveals substantial heterogeneity: while low-income households show almost no increase in consumption even

[1] Adaptation, according to the Intergovernmental Panel on Climate Change (IPCC), is defined as "adjustment in natural or human systems in response to actual or expected climatic stimuli or their effects, which moderates harm or exploits beneficial opportunities" (Barreca *et al.*, 2016).

under extreme heat, higher-income households react much more strongly once temperatures exceed 19°C, widening the energy gap across deciles. For instance, when monthly average temperatures reach 25ºC, electricity consumption in the bottom decile shows no response, whereas households in the top decile increase their usage by about 15 kWh. At 30ºC, the top decile adapts with an increase of nearly 30 kWh, while the bottom decile raises consumption by only around 4 kWh. The robustness of these findings is confirmed by alternative specifications and different measures of temperature exposure, underscoring both the asymmetric nature of the temperature–electricity relationship and the unequal adaptive capacity across socioeconomic groups.

A natural extension of our analysis is to examine the implications of temperature shocks through the lens of energy poverty. Energy poverty broadly refers to households' inability to secure adequate energy services for basic needs and well-being. We begin by applying conventional approaches to its measurement, focusing on both unidimensional and multidimensional indicators: the Ten Percent Rule Index (TPRI) and the Multidimensional Energy Poverty Index (MEPI). The TPRI remained relatively stable at around 3–4% of households between 2015 and 2019, but more than doubled in 2020 as household incomes fell sharply during the pandemic, while real energy expenditures remained broadly unchanged. Since then, it has stabilized at a higher level of 6–7%. The MEPI shows a smoother trajectory: energy poverty incidence gradually declined from 27% in 2015 to 23% in 2019, then rose again to almost 28% during the pandemic and has remained at that level since.

We propose a novel measure of energy poverty that complements existing access and expenditure-based indicators by capturing households' limited capacity to increase electricity use in response to higher temperatures. The idea behind this behaviorally grounded concept of "adaptive energy poverty" is that energy deprivation arises not only from lack of access or affordability, but also from limited ability to adjust energy consumption when environmental conditions become more demanding. Households that fail to increase their consumption in response to heat exposure may face hidden vulnerabilities, even if they are formally connected to the grid. Applying this measure to Peru, we find that around 21% of households can be classified as energy poor under our benchmark parameters. The incidence is strongly graded by welfare: nearly 60% in the bottom welfare decile versus only 12% in the top decile. Substantial regional disparities also emerge, with the prevalence of adaptive energy poverty ranging from 8% in Arequipa to over 30% in La Libertad. Moreover, even among households with electricity access, 17% remain energy poor, reflecting constraints linked to low appliance ownership or financial limitations. Comparisons with standard metrics show moderate overlap with income poverty and the MEPI, but virtually no correlation with the Ten Percent Rule Index, underscoring the added value of this behavioral approach in uncovering forms of deprivation that remain invisible to conventional measures.

As a byproduct, this paper underscores the importance of using administrative data on energy consumption. First, it corroborates the well-documented issue of substantial underreporting in national household surveys, which introduces substantial biases in estimating both the relationship between electricity use and temperature and the incidence of energy poverty. These distortions undermine the basis for sound policy design. Second, administrative records offer repeated observations of the same households over time, enabling panel data analysis. By contrast, survey-based data—even in a country like Peru with a short-panel structure—provide very few repeated observations per household, often restricted to the same month of the year, which severely limits the ability to study household responses to temperature variation.

Our paper is related to at least three strands of literature. First, we speak to a growing body of work at the intersection of energy demand, climate change, and environmental economics that examines how households adjust electricity usage in response to temperature changes. Several studies have documented significant short-run responses of electricity consumption to temperatures, particularly in high-income countries with widespread access to cooling and heating technologies (Bessec & Fouquau, 2008; Auffhammer & Aroonruengsawat, 2011; Deschênes & Greenstone, 2011; Lee & Chiu, 2011; Kang & Reiner, 2022). More recent work has begun to explore these dynamics in developing countries, where behavioral and infrastructural constraints may limit households' adaptive responses (Davis & Gertler, 2015; Li *et al.*, 2018; Du *et al.*, 2020; Harish *et al.*, 2020; Zhang *et al.*, 2022). Methodologically, this literature has employed a range of econometric strategies to test the asymmetric nature of the temperature–electricity relationship. Early studies often relied on parametric specifications—such as quadratic forms—that impose symmetric responses and strong functional assumptions. In contrast, more recent work has favored semi-parametric and non-parametric models that allow for flexible estimation without imposing such restrictions (Bessec & Fouquau, 2008; Deschênes & Greenstone, 2011; Gupta, 2012; Auffhammer, 2022). Within that body of work, evidence from high-income settings typically finds U-shaped or strongly asymmetric responses, with sharp increases in electricity use on very hot (and, in some contexts, very cold) days.[2] Panel and smooth-transition approaches across the US and Europe reveal temperature thresholds and growing sensitivity to summer heat.[3] adopt panel smooth transition models to estimate temperature thresholds across European and OECD countries, revealing substantial regional heterogeneity and a growing sensitivity to summer temperatures over time. Specifically Bessec & Fouquau (2008) identified a clear heating effect in the European Union, whereas the cooling effect is less important. Bessec & Fouquau (2008) distinguish between Northern and Southern countries and show that the non-linear pattern is more pronounced in warmer countries (i.e., U-shaped relationship) than in the cold ones.

In developing countries, where adaptation capacity is shaped by infrastructure gaps and income inequality, studies from Mexico, China, and India show muted reactions to cold, pronounced increases on hot days, and "hockey-stick" patterns concentrated among higher-income or better-equipped households—pointing to a central role for appliance ownership, housing quality, and related constraints.[4] Our analysis contributes new evidence from Peru,

[2]For example, Deschênes & Greenstone (2011) use a semi-parametric panel approach for strong consumption responses to temperature extremes in the United States: annual residential energy consumption increases by approximately 0.4% for days with temperatures above 32ºC (90ºF), and by 0.3% for days below -12ºC (10ºF).

[3]Bessec & Fouquau (2008) and Lee & Chiu (2011)

[4]In Mexico, Davis & Gertler (2015) finds virtually no response to cold days —consistent with the absence of electric heating— but estimates that for days with temperatures above 32ºC (90ºF), monthly electricity consumption increases by 3.2%, with stronger effects in regions with greater air conditioning prevalence. In China, several studies report asymmetric patterns: electricity use rises significantly on hot days but shows muted or no response to cold days due to the widespread use of centralized heating in the north of the country (Li *et al.*, 2018; Du *et al.*, 2020; Zhang *et al.*, 2022). For instance, Zhang *et al.* (2022) find that each additional day above 32ºC raises annual electricity consumption by 8.9%, with a disproportionately smaller effect among rural and low-income households. These differences reflect variations in air conditioning ownership and usage, which are strongly correlated with income and location. Similar heterogeneity is documented in India by Harish *et al.* (2020), who show that electricity demand in Delhi increases by 30–43%

a setting with marked climatic and socioeconomic heterogeneity.[5]

Second, our analysis contributes to the literature on economic inequality in developing countries—and in Peru, in particular. A large body of research has highlighted how inequalities in income, geography, and access to public goods shape household well-being and resilience to shocks (Escobal & Torero, 2005; Gasparini *et al.*, 2013; Tornarolli & Puig, 2023). By documenting how well-being groups differ in their ability to adjust electricity consumption in response to climate events, we uncover a less explored yet critical dimension of inequality: differential adaptive capacity. Our approach complements traditional inequality metrics by using behavioral responses to exogenous variation as a window into the structural constraints faced by disadvantaged households.

Finally, we offer new insights into the concept of energy poverty, broadly understood as the inability to obtain adequate energy services for basic needs and well-being (Boardman, 1991; Foster *et al.*, 2000; Bouzarovski & Petrova, 2015). While most empirical work on the relationship between energy poverty and temperature variation has focused on access, affordability, or energy expenditures,[6] we argue that the limited responsiveness of electricity consumption to extreme temperatures may also signal energy poverty—reflecting constraints in the ability to increase usage when needs rise due to heat or cold. This behavioral perspective, grounded in observed reactions to climate variation, complements existing static indicators and may be particularly valuable in identifying hidden vulnerabilities among formally connected but underserved households.

The remainder of the paper is organized as follows. Section 2 describes the main data sources used in the analysis. Section 3 presents a descriptive analysis of electricity consumption at the household level, exploiting matched data from national household surveys and administrative

on days between 30ºC and 39ºC among high-income households. In contrast, low-income groups show little to no increase, constrained by limited appliance ownership and poorer housing conditions.

[5] Miranda Montero & Contreras (2025) evaluate the impact of higher temperatures in Peru, not on electricity consumption but on a different outcome: learning. Their results suggest that one degree above 20°C is equivalent to 7 and 6% of a standard deviation of what a student learns in a year for math and reading tests, respectively.

[6] Most studies in this line of research estimate the impact of temperature anomalies on conventional measures of energy poverty—such as the 10% income threshold rule proposed by Boardman (1991), the Multidimensional Energy Poverty Index (MEPI), or the Low Income–High Cost (LIHC) indicator (e.g. Feeny *et al.* (2021), Awaworyi Churchill *et al.* (2022), and Li *et al.* (2023)).

records. Section 4 expands the analysis using an econometric approach, presenting the main results together with heterogeneity analyses and extensions. The next two sections address the issue of energy poverty. Section 5 presents estimates of two traditional measures: the Ten Percent Rule Index and the Multidimensional Energy Poverty Index. Section 6 introduces and implements a novel measure of adaptive energy poverty, which reflects households' ability to cope with rising temperatures through increased electricity consumption. Finally, Section 7 provides a summary of the results and a concluding discussion. Additional materials are provided in the Appendix.

2 Data

We draw information from three main sources. First, we use Peru's national household survey (ENAHO), which, in addition to providing standard socioeconomic information on households, includes detailed questions on expenditures, including electricity consumption. Second, we have access to unique administrative data that matches households in ENAHO with records of residential electricity meters. Finally, we exploit information on climate changes (mostly temperature) mapped at the household's Primary Sampling Unit (PSU) level. The remainder of this section provides more details on each of these data sources.

2.1 National household survey

The ENAHO is Peru's primary nationally representative household survey, conducted continuously by the Instituto Nacional de Estadística e Informática (INEI). It collects detailed information on demographic characteristics, income, labor market outcomes, housing conditions, and household expenditures. The survey covers both urban and rural areas across all 24 departments and the Constitutional Province of Callao. Each year, ENAHO interviews over 35,000 households, which, when weighted, represent approximately 10 million households nationwide. For this study, we use the waves from 2015 to 2023. ENAHO's stratified probabilistic sampling design ensures representativeness at the national, regional, and urban/rural levels, making it well-suited for distributional analysis and for linkage with external sources at the PSU level. Although ENAHO has a rotating short-panel structure, most of the analysis in this paper exploits it as a series of repeated cross-sections. The short-panel dimension is used only for selected robustness exercises. Our main source of variation over time comes from administrative records on electricity consumption, which we describe in the following subsection.

2.2 Electricity consumption

We use administrative records from the Organismo Supervisor de la Inversión en Energía y Minería (OSINERGMIN), which provide monthly data on residential electricity consumption, billing amounts, tariff codes, and supply characteristics for the period 2015–2023. This dataset contains over 11 million observations at the household-meter level, and includes key variables such as energy consumption in kilowatt-hours (kWh), total billing in Peruvian soles, and collective supply factors.

To incorporate this information into our analysis, the National Statistical Institute of Peru (INEI) matched the OSINERGMIN records with the ENAHO household sample (over 200 thousand observations). The primary linkage was performed using household addresses, leveraging fields such as street name, lot number, and door number. When available, national ID numbers (DNI) of the account holder were utilized. The matching process involved multiple stages: an exact match on addresses where possible, followed by approximate string matching techniques (Bigram similarity >0.85 and Jaro-Winkler>0.9) to identify additional matches based on the textual similarity of street names. At later stages, unmatched households were assigned average electricity consumption at the block (manzana) or district level using verified geospatial identifiers (UBIGEO codes).

Overall, this procedure allowed us to successfully link approximately 65% (average for the period 2015-2023) of ENAHO surveyed dwellings to administrative electricity consumption records. The quality of the linkage varies across years and matching levels. On average, about 31% of dwellings were matched at the exact household level (same dwelling), around 4% at the block level, and close to 63% at the district level. Table A1 in the Appendix provides the annual breakdown of matches by level of precision. To ensure internal consistency, we performed additional data cleaning steps: we excluded households that reported having access to electricity in ENAHO but registered zero consumption in the administrative data, and we truncated extreme or implausible values. For reference, the highest monthly residential consumption reported in the Encuesta Residencial de Consumo y Usos de Energía (ERCUE) conducted by OSINERGMIN is around 1,100 kWh; we dropped a small number of outliers that exceeded this threshold.

2.3 Temperature changes

Temperature data is sourced from the Climate Hazards Center InfraRed Temperature with Stations – daily (CHIRTS-daily) dataset, developed by the Climate Hazards Center at the University of California, Santa Barbara.[7] CHIRTS-daily is a quasi-global (60°S–70°N), high-resolution dataset (0.05° × 0.05°, approximately 5 km) that combines satellite infrared data with ground station observations and ERA5 reanalysis fields. The dataset was developed to address the scarcity of reliable temperature data in regions with limited station coverage, and is particularly suited for evaluating climate-related risks in areas vulnerable to food insecurity and extreme weather events. To assign temperature values to each household, geospatial buffers are constructed around the centroid of each PSU.[8] Each buffer represents a 10-kilometer radius around the PSU centroid, and is used to extract localized climate conditions from the CHIRTS-daily gridded surface. A separate shapefile with approximately 5,000 PSU-level polygons is used for each year in the dataset. These buffers allow us to match temperature data with sufficient spatial precision, reflecting meaningful variation in climatic exposure across the Peruvian territory.

For simplicity, most of the analysis relies on monthly averages of daily minimum and maximum temperatures for each location. For robustness, we also consider alternative measures based on daily temperature data, such as the number of days per month exceeding a given threshold. Figure A1 in the Appendix (Panel A) shows the histogram of the monthly mean of the daily average temperature —calculated as the mean between the daily minimum and maximum—for each location, expressed in degrees Celsius (°C). In most locations, mean

[7] https://www.chc.ucsb.edu/data/chirtsdaily

[8] We also have data on precipitation, although it is not the focus of our analysis and is used only as a control variable.

temperatures fall between 10°C and 30°C. For this reason, we restrict the sample to that range in parts of our analysis. Most locations exhibit mean daily minimum temperatures between 0°C and 26°C (Panel B), and mean daily maximum temperatures between 19°C and 29°C (Panel C). Figure A2 displays a map of Peru showing mean monthly temperatures, in degrees Celsius by location.

2.4 Data integration and structure

To construct our dataset, we first append all available waves of the ENAHO survey from 2015 to 2023. Each household is then matched with OSINERGMIN administrative records of electricity consumption, billing amounts, and tariff structure, as described in the previous subsections. The resulting dataset is reshaped into a panel format, where the unit of observation is a household–month. This structure allows us to track the monthly electricity use for each surveyed household over time. Finally, we merge high-frequency weather data using the geographic location of the household's PSU, which captures localized temperature variation.

This integrated panel allows us to exploit within-household temporal variation in both electricity consumption and temperature exposure. In addition, the richness of the ENAHO survey enables us to capture substantial heterogeneity in regional conditions and socioeconomic characteristics. In particular, we classify households into well-being strata based on per capita household total expenditure.[9] To ensure comparability over time, these monetary variables are deflated using the Consumer Price Index (CPI, base year 2023), yielding real, time-consistent measures of household welfare. We then construct expenditure deciles for the full sample, which serve as key stratification variables in our empirical analysis.

3 Descriptive evidence

In this section, we present descriptive evidence on electricity consumption in Peru over the period of study, highlighting changes associated with temperature changes, as well as

[9] Throughout most of the analysis, we use per capita household total expenditures as a proxy for well-being. Results are robust to the use of per capita income as an alternative well-being measure.

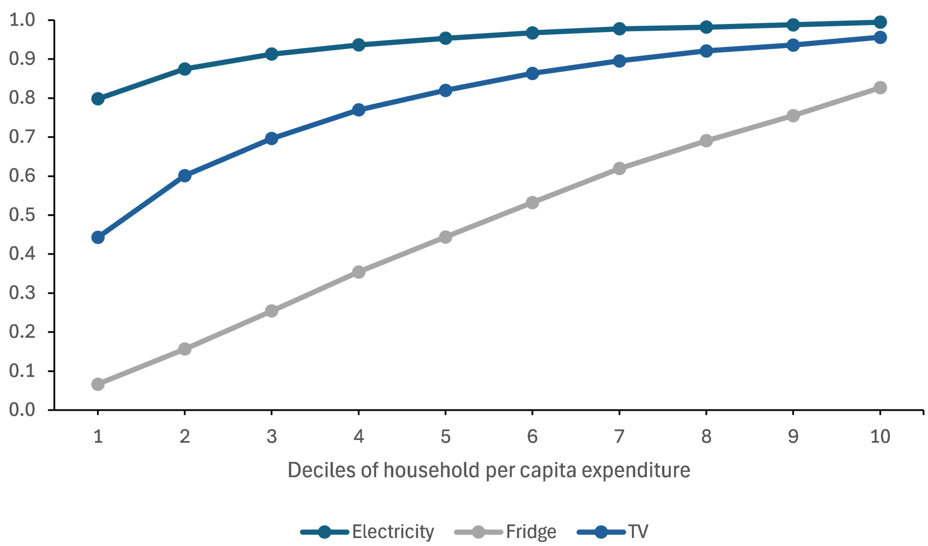
asymmetric responses across the household per capita expenditure distribution. The evidence provided here offers suggestive insights into patterns that will be examined in greater detail in the following section. For simplicity, the evidence in this section is constructed using pooled data for the period 2015–2023. All monetary values are expressed in soles at constant 2023 prices.

Figure 1 shows the access to electricity and to two appliances that require electricity to operate—a TV and a refrigerator—across the distribution of per capita household expenditures.[10] As expected, the gradient is positive in all cases, especially for the appliances. This is relevant to our discussion because it suggests that vulnerable population may have access to electricity (one of the traditional indicators of energy poverty) but may lack very basic appliances, such as a TV and a fridge, to fully benefit from that service.This suggests a form of hidden energy deprivation: households technically connected to the grid but lacking appliances to utilize electricity for cooling or food preservation. This evidence is consistent with the findings of Tornarolli & Puig (2023), who document large inequalities in the quality and intensity of electricity use across income groups in Peru, even among households formally connected to the grid.

The matched ENAHO-OSINERGMIN data enables a more detailed and precise analysis of electricity consumption. Figure 2 shows the average monthly consumption in kWh by deciles. On average for the matched sample, mean monthly electricity consumption is 126.5 kWh. To validate this result, we compare it with those obtained from the ERCUE. The last edition (2023) shows that the monthly average consumption of electricity was 133 kWh at the national level. These similarities persist when the sample is restricted to specific regions or areas. For example, the average consumption reported in urban (rural) areas is 151 kWh (40 kWh) in the matched data and 145 kWh (40 kWh) in ERCUE. The case of the metropolitan area of Lima is also illustrative: although the average consumption reported in the matched data is higher than that reported in ERCUE (181 vs. 235 kWh), both surveys are able to capture the higher consumption in this region. The consistency between the consumption data from both sources provides reassurance for our analysis. Figure 2

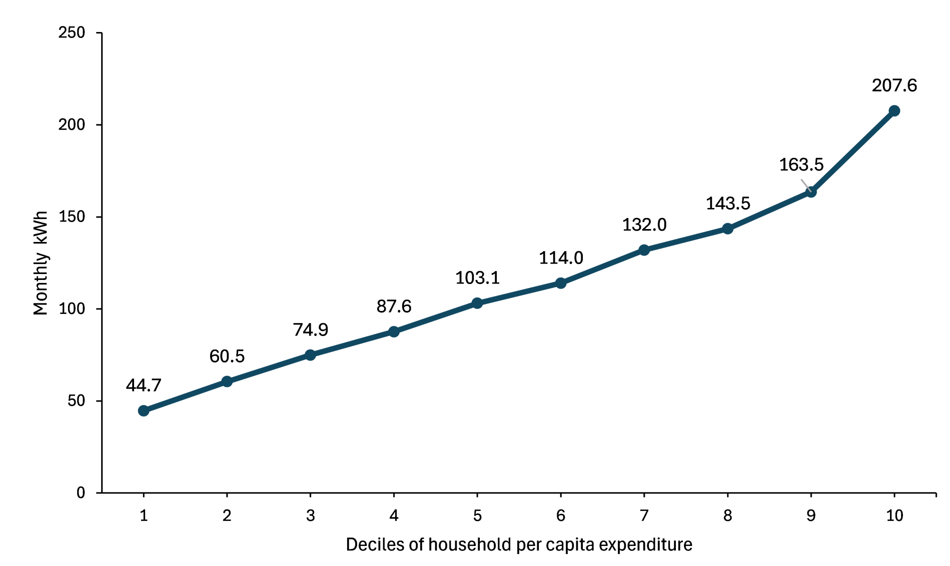
[10] Regarding appliances, we use TV and refrigerator, given that the survey does not include specific devices to control temperatures, such as fan or air conditioning.

Figure 1: Access to electricity, refrigerator, and TV (%)



Source: own calculations based on a pool dataset from ENAHO 2015-2023 (Panel A). *Notes*: All values are weighted using the population expansion factor. Deciles constructed from household per capita expenditure.

Figure 2: Monthly electricity consumption (kWh)



Source: own calculations based on a pool dataset from matched ENAHO–OSINERGMIN data. *Notes*: All values are weighted using the population expansion factor. Deciles constructed from household per capita expenditure.

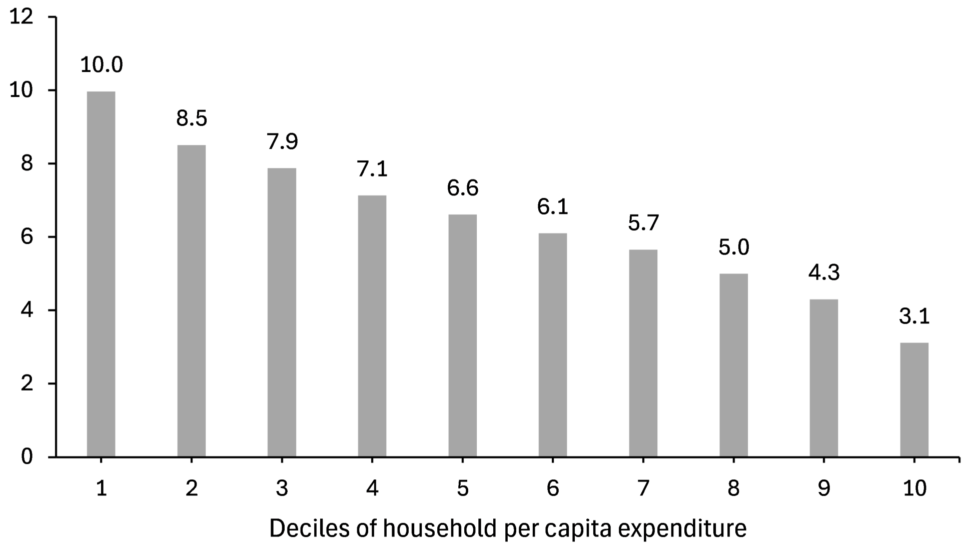
confirms that electricity consumption is clearly increasing in household well-being. The slope is rather constant: electricity consumption increases around 15 kWh when moving to the next decile. The slope becomes much steeper between deciles 9 and 10 as it increases to 44.1 kWh.

The matched ENAHO–OSINERGMIN data allow us to compare administrative billing records with electricity expenditures self-reported in the household survey. While survey-based expenditure data are widely used in empirical research, a large literature documents substantial measurement error in household surveys, particularly for income and recurrent expenditures (Bound *et al.*, 2001; Meyer *et al.*, 2015). Figure 3 shows sizable discrepancies between administrative billing amounts and survey self-reports. On average, administrative records exceed survey-reported expenditures by a factor of 4.6. The gap is larger at the bottom of the expenditure distribution and declines monotonically toward the top decile, a pattern consistent with systematic reporting differences across the welfare distribution, in line with the broader literature on survey measurement error. Importantly, our core estimations rely exclusively on administrative electricity consumption data (kWh). Therefore, reporting error in survey expenditures does not affect the main temperature–consumption results nor the construction of the adaptive energy poverty indicator.

Once again, we use the ERCUE data to validate our results. The average reported expenditure in this survey is 87 soles (S/), which is very close to the 91 S/ observed in the administrative records. This similarity suggests that a specialized survey is less prone to measurement error and underreporting than a general expenditure survey. As with consumption, there are notable regional disparities: average expenditure is 94 S/ in urban areas and 119 S/ in metropolitan Lima.

Finally, Figure 4 presents the unconditional relationship between electricity consumption and average monthly temperatures. For the overall population, consumption gradually increases from about 42 kWh at 10ºC to 66 kWh at 18ºC. The most significant increase occurs between 18°C and 22°C, where the mean consumption increases from 66 kWh to 160 kWh, remaining at elevated levels beyond that range. Notable differences emerge between welfare groups. In particular, for households in deciles 1 through 3, consumption remains relatively flat at

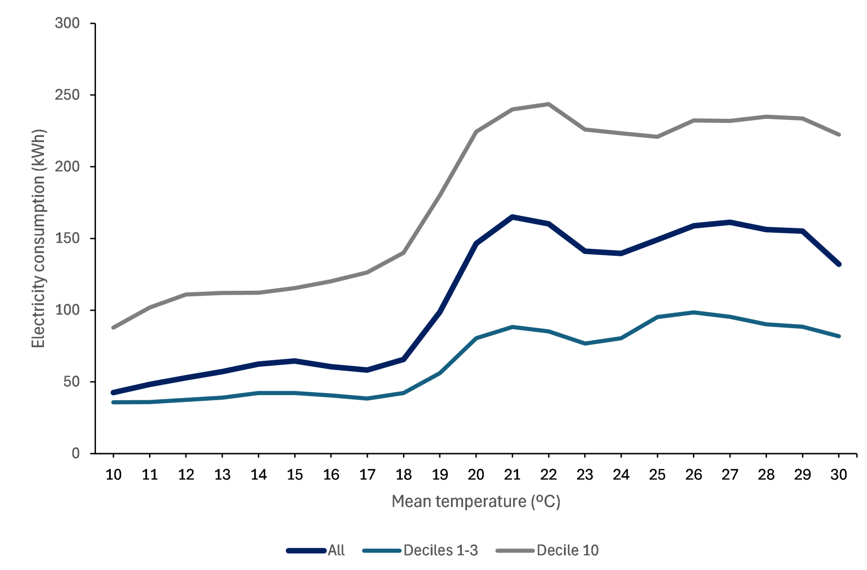
Figure 3: Ratio of electricity spending— administrative records vs. self-reported in ENAHO



Source: Own calculations based on matched data ENAHO-OSINERGMIN. Pooled data 2015-2023. *Notes*: All values are weighted using the population expansion factor. Deciles constructed from household per capita expenditure.

lower and moderate temperatures, and the sharp increase around 18°C is less pronounced. Panels A and B in Figure A4 (Appendix), which plot the relationship using maximum and minimum temperatures, respectively, display similar patterns. However, these trends reflect an unconditional analysis, where other factors may confound the observed relationship between temperature and electricity use. The next section addresses this issue through a conditional analysis.

Figure 4: Electricity consumption (kWh) by temperature (ºC) exposure. Monthly, by average temperature



Source: Own calculations based on matched ENAHO–OSINERGMIN data. Pooled sample, 2015–2023.

Notes: All values are weighted using the population expansion factor.

4 Model and estimations

In this section, we lay out the main model to be estimated and present the results, along with some extensions.

4.1 The model

Since we have administrative records of household electricity consumption over multiple months, we can estimate a regression model that includes household fixed effects. The baseline specification is:

$$E_{hlt} = \beta_0 + \beta_1 \cdot F(T_{lt}) + \psi_h + \gamma_t + \varepsilon_{hlt} \tag{1}$$

where E_{hlt} denotes electricity consumption (in kWh per month) by household h, in location l, and at time t. Locations l correspond to PSUs, time t refers to a given month within the 2015–2023 period, $F(T_{lt})$ represents a flexible function capturing the temperature in location

l at time t, measured as the monthly average of daily temperature; ψ_h captures household fixed effects, γ_t captures month fixed effects and ε_{hlt} is the error term. The function $F(T_{lt})$ allows for a flexible relationship between temperature and electricity consumption.

In the benchmark model, monthly household electricity consumption is modeled as a function of the monthly mean temperature at the household's location. In the extensions, we explore alternative temperature measures, such as the number of days in a month exceeding a given threshold, or the number of days at a specific temperature level.

Given that we have household-level panel data, we include household fixed effects in the model to control for all time-invariant characteristics specific to each household—such as location, household composition, and dwelling features like housing quality, appliance ownership, or consumption preferences—that may affect electricity use. This allows us to exploit within-household variation over time to identify the effect of temperature on electricity consumption. We also include time fixed effects (γ_t) to account for common shocks and seasonal trends that affect all households in a given month. Together, these fixed effects help ensure that the estimated relationship between temperature and electricity use is not confounded by unobserved heterogeneity at the household, temporal, or locational level. Since the source of identifying variation in temperature operates at the location level, standard errors are clustered at the PSU to allow for correlation of the error term within locations over time.

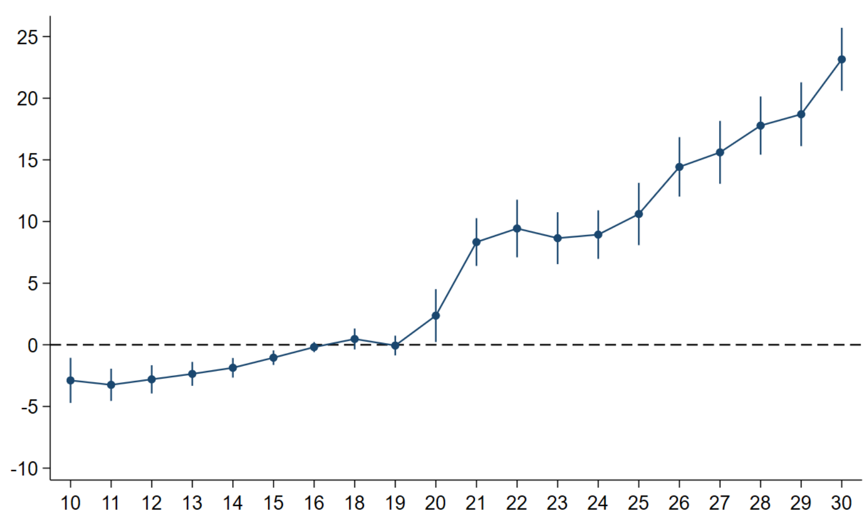
4.2 Results

We explored a variety of parametric and non-parametric models to assess the relationship between electricity consumption and temperature. While parametric models—such as linear and quadratic specifications—provide a useful starting point, they impose strong functional form assumptions that may not capture the complexity of the underlying relationship. In any case, we report these additional estimates in Appendix 2, where the results further support the non-linear relationship between temperature and electricity consumption. Given the large number of observations in our dataset and preliminary evidence suggesting the presence of non-linearities, we opt for a more flexible approach in the remainder of this section. Specifically, we focus on a fully non-parametric model that allows the effect of temperature to vary freely across different values by including a set of temperature-level dummy variables. This approach enables us to capture potential threshold effects or asymmetric responses that may be obscured in simpler models.

The main estimation results are presented in Table 1. Column (1) reports estimates from a simple regression without controls. In Column (2), we add household fixed effects, while the third column incorporates month fixed effects. The dummy variable for a temperature of 17ºC is omitted as the baseline category, so all reported coefficients represent differences in monthly electricity consumption (measured in kWh) relative to that baseline. The inclusion of household-fixed effects is key for the identification of the results. In contrast, the inclusion of time fixed effects does not alter the results significantly.

Figure 5 displays the estimated coefficients for the full sample. After a mild increase between 10º and 16º, electricity consumption remains relatively stable for average monthly temperatures between 16ºC and 19ºC. Beyond 19ºC, consumption rises sharply. The increase amounts to approximately 10 kWh at a mean temperature of 23ºC and reaches around 25 kWh when temperatures climb to a monthly 30ºC.

Figure 5: Coefficients of temperature dummies in the model of electricity consumption



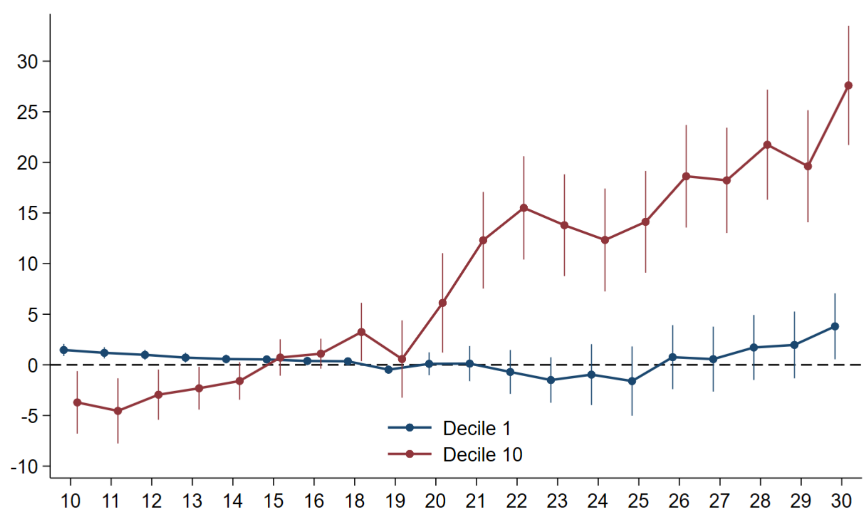
Source: own calculations based on matched data ENAHO-OSINERGMIN. 95% confidence intervals.

These findings align with several results reported in the existing literature. In particular, most studies document a plateau in electricity consumption at mild temperatures, followed by a sharp increase as temperatures rise. This surge is typically attributed to the use of air conditioning, electric fans, and refrigerators to manage heat. Unlike many of those studies, however, we do not observe an upward trend in electricity consumption as temperatures drop. This divergence may be partly explained by two factors. First, weather conditions in most parts of Peru tend to be relatively mild, with few instances of extreme cold that would drive up electricity use for heating. Second, in colder periods, households often rely on alternative sources of heating, such as gas or firewood, rather than electricity.

4.3 Heterogeneities

We are particularly interested in the potential differences in how households of different socio-economic status respond to temperature changes. We begin by dividing households into deciles based on their level of per capita expenditures. Table 2 presents the estimates obtained by splitting the sample by deciles. Figure 6 displays the coefficients for deciles 1 and 10.

Figure 6: Coefficients of temperature dummies in model of electricity consumption - Deciles 1 and 10

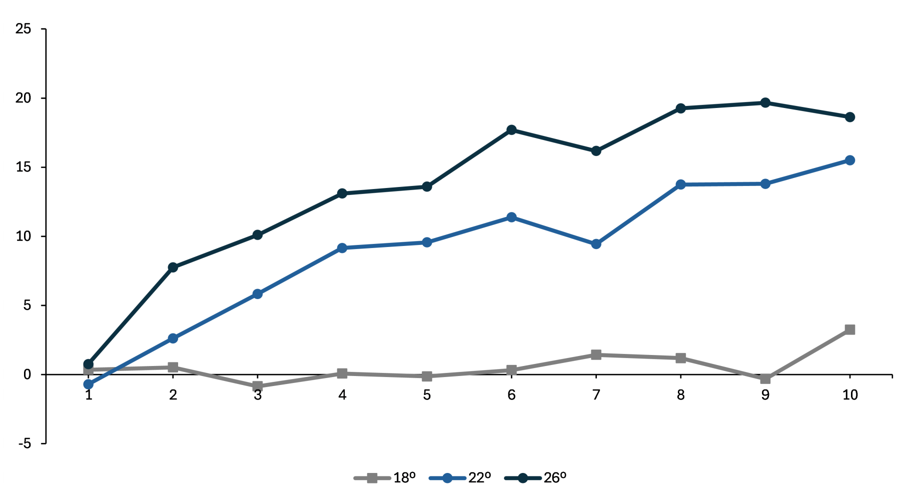


Source: own calculations based on matched data ENAHO-OSINERGMIN. 95% confidence intervals.

Interestingly, the coefficients for low-income households are close to zero across most of the temperature range, increasing only at very high levels. Even then, the effect is modest: electricity consumption rises by just 4 kWh when temperatures reach extreme levels (30ºC). In contrast, the response of households in decile 10 is strong once monthly temperatures exceed 19ºC. Electricity consumption increases by around 15 kWh when the temperature reaches 22ºC, and by an additional 13 kWh when it reaches 30ºC.

Figure 7 summarizes the results by showing the regression coefficients for all deciles at three different temperature levels. Coefficients at 18ºC are close to zero across the entire distribution. At 22ºC, responses vary significantly by socio-economic status: while households in decile 1 show no increase, electricity consumption increases from 3 kWh in decile 2 to 15 kWh in decile 10. When temperatures become high (26ºC), the income gradient in electricity consumption becomes steeper, ranging from almost zero in decile 1 to more than 19 kWh in deciles 8 to 10.

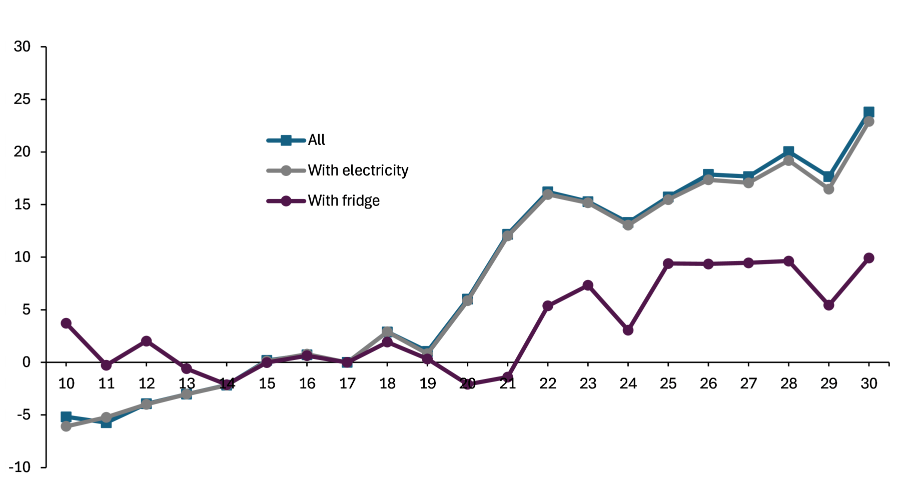
Figure 7: Coefficients of temperature dummies by deciles



Source: own calculations based on matched data ENAHO-OSINERGMIN.

In Figure 8, we further explore the results by showing the gap between decile 10 and decile 1 in the coefficients of the temperature dummies. When considering the whole population (blue line), the gap departs from zero at a temperature level of 19º. When restricting the sample to households with electricity (grey line), the results remain largely unchanged. This is likely due to two factors. First, as discussed in the previous section, the share of households without access to electricity in Peru is small. Second, even among bottom-decile households with electricity, the response to higher temperatures in terms of increased electricity consumption is minimal and only becomes noticeable at very high temperature levels. In contrast, the decile gap in the response to temperature changes becomes substantially smaller when the comparison is restricted to households with a refrigerator (violet line), suggesting that part of the gap in the asymmetric adjustments is due to the lack of appliances among the poor.

Figure 8: Gap between decile 10 and decile 1 in coefficients of temperature dummies



Source: own calculations based on matched data ENAHO-OSINERGMIN.

The asymmetric responses documented above are likely to depend not only on households' financial capacity to afford higher energy consumption, but also on a set of mediating factors that shape their behavioral adjustments. One important factor is the type of labor activity: households with a greater prevalence of work-from-home arrangements are more likely to exhibit stronger consumption responses (Figure A3). Housing characteristics also play a relevant role. Dwellings built with more thermally efficient materials may reduce the need for additional energy use during heat waves. Unfortunately, the available survey data do not provide sufficiently detailed information to explore these mechanisms in depth. In any case, a comprehensive analysis of the drivers behind consumption asymmetries across welfare deciles lies beyond the scope of this paper.

4.4 Robustness analysis

To assess the robustness of our findings, we perform a series of complementary exercises that test the sensitivity of the results to alternative specifications and sample restrictions.

First, Figures 10 and 11 show that the estimated effects remain consistent when using temperature bins instead of a continuous temperature measure. Second, we re-estimate the models with daily data rather than monthly averages, to assess whether aggregation obscures short-run dynamics. Figures 12 and 13 confirm the robustness of the results under this alternative specification. Third, we run a model with a different explanatory variable: the number of days with temperatures above 25ºC. Once again, the results are consistent with our main findings (Figure 14).

Fourth, we exclude Lima to verify that the results are not driven by the distinctive economic and climatic conditions of the capital. Figures 15 and 16 replicate the analysis excluding the Lima area. The results closely mirror those for the country as a whole. In fact, the coefficients are estimated with greater precision, and the patterns appear smoother once Lima is omitted. This improvement likely reflects Lima's unique characteristics: (i) its climate is unusually stable, with limited temperature variability, which provides little identifying variation while adding noise; and (ii) measurement issues may arise because electricity use is recorded at the household level, and in highly dense urban areas like Lima, housing problems introduce additional noise in consumption data.

Fifth, we confirm the robustness of our results when running regressions by deciles of household per capita income instead of expenditure (Figure 17).

Finally, Figures 18 and 19 replicate the analysis using only data from the national household survey, exploiting the rotating panel structure of ENAHO. The results are broadly consistent with those obtained from administrative data, but are substantially less precise. This loss of precision reflects several limitations of the survey data, including the smaller number of observations, reliance on expenditure rather than consumption measures, and the underreporting of expenditure discussed in previous sections.[11]

[11] To avoid unduly extending this section, we do not report additional exercises we conducted. For instance, we replicate the analysis at the district level instead of the household level, and we also estimate the results

5 Energy poverty: traditional measures

Energy Poverty (EP) refers to the inability of households to adequately meet their energy needs, reflecting deprivation in essential energy resources (Awaworyi Churchill *et al.*, 2022). Typically, EP has two core dimensions: affordability and access to modern energy services. These dimensions give rise to two main measurement approaches: unidimensional and multidimensional.

The unidimensional approach assesses energy poverty (EP) based on households' energy budget shares. Its most widely used variant is the Ten Percent Rule Index (TPRI), introduced by Boardman (1991), which classifies a household as energy poor when its energy expenditure exceeds 10% of total income.

The multidimensional approach captures deprivations that extend beyond energy expenditure alone. The most widely adopted measure is the Multidimensional Energy Poverty Index (MEPI) (Nussbaumer *et al.*, 2012), which includes three equally weighted dimensions ($d = 3$): (i) Physical access (acc), defined by the use of modern cooking fuels and reliable access to electricity; (ii) Ownership of appliances (own), referring to possession of communication devices (e.g., mobile phones, landlines), information assets (e.g., TV, computer), and food preservation appliances (e.g., refrigerator, freezer); and (iii) Affordability (aff), measured using the TPRI. Each indicator is binary (1 = deprived, 0 = not deprived) and equally weighted within its dimension.[12] For household i, the weighted deprivation score is:

$$c_i = \sum_{j=1}^{d} w_j x_{ij}, \qquad \sum_{j=1}^{d} w_j = 1,$$

where x_{ij} is the deprivation in dimension j. A household is multidimensionally energy poor

for different groups within the matching procedure (see Section 2.2). The findings remain largely unchanged across these exercises. We further assess a potential concern arising from the presence of a gas subsidy program (Bono Gas), which may affect beneficiaries' electricity consumption. Our results are not significantly altered when excluding the (few) households that receive this subsidy.

[12] Our estimation includes six binary indicators grouped into three equally weighted dimensions: (i) physical access, measured by lack of connection to the public electricity grid and reliance on traditional fuels for cooking; (ii) ownership of appliances, measured by the absence of refrigeration devices, information devices (TV, radio, computer), and communication devices (telephone, mobile phone); and (iii) affordability, measured by whether household energy expenditure exceeds 10% of income. We use microdata from the ENAHO for the period 2015–2023 to estimate energy poverty indicators.

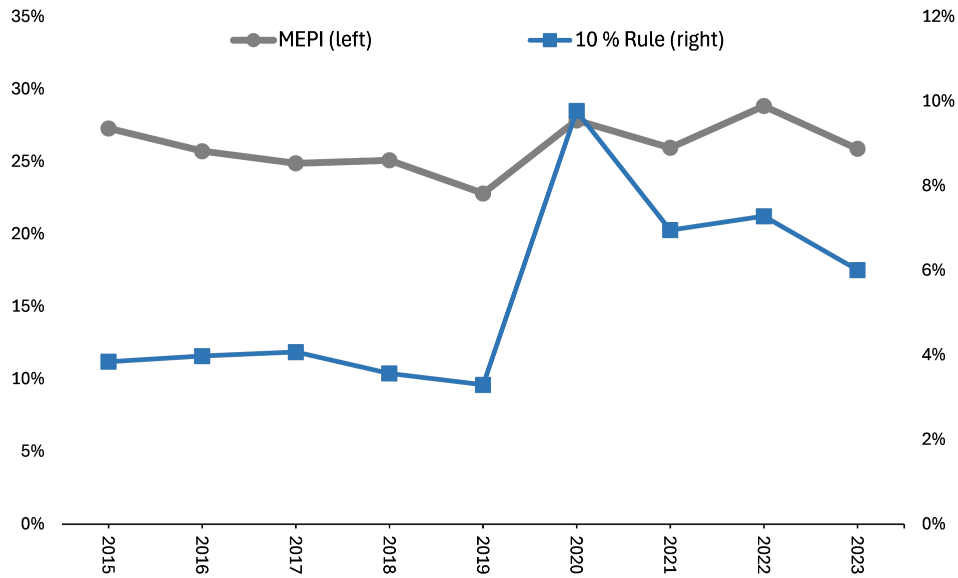
if $c_i > k$, with $0 < k < 1$. Following Bezerra *et al.* (2022), we adopt $k = 1/6$, meaning that a single deprivation in access suffices to classify a household as energy poor.

Despite their widespread use, both the unidimensional and multidimensional approaches present important limitations. First, the TPRI (as with other threshold-based indicators) is inherently arbitrary, since the 10% cutoff lacks a solid theoretical foundation. Second, and relatedly, this measure is prone to misclassifications. It may identify high-income households with large dwellings and elevated energy consumption as energy poor (Boardman, 1991; Pachauri & Spreng, 2011). More critically for our purposes, the TPRI can label a low-income household that spends very little on energy—precisely because it cannot afford higher consumption—as energy non-poor. Third, the TPRI is highly volatile, as it depends on cyclical variables such as household income and energy prices: small variations in either the numerator (energy expenditure) or the denominator (income) can substantially alter classification, even in the absence of structural changes in access to energy services.

For its part, the MEPI is closely inspired by the general Multidimensional Poverty Index (MPI), raising concerns about whether it truly captures energy-specific deprivations or merely proxies overall poverty (Pelz *et al.*, 2018). In addition, MEPI indicators are typically binary and limited in scope, overlooking relevant dimensions such as reliability, service quality, thermal comfort, and intra-household inequalities. The omission of these aspects may result in either under- or overestimation of energy poverty (Ssennono *et al.*, 2021). Finally, most MEPI-based applications focus on incidence and intensity while neglecting severity and inequality among the energy poor, despite evidence that energy deprivation is unevenly distributed across population subgroups (Aristondo & Onaindia, 2018). More generally, a common critique of both indices (TPRI and MEPI) is that they tend to overlook the complexity of energy poverty, as social relationships, norms, and behaviors shape how households actually benefit from access to energy services (Day *et al.*, 2016).

After acknowledging these limitations, we proceed to present estimates based on conventional measures of energy poverty in Figure 9. The unidimensional indicator based on the TPRI remained relatively stable at around 3-4% of households between 2015 and 2019. In 2020, it almost tripled to 9.8%, reflecting the sharp decline of nearly 20% in household incomes during the pandemic, while real energy expenditures remained broadly unchanged. Since income levels did not return to their pre-2020 trajectory, the share of households above the 10% threshold has stabilized at a higher level, fluctuating between 6% and 7% in 2021-2023.

Figure 9: Evolution of energy poverty in Peru, 2015–2023.



Source: Own calculations based on ENAHO. *Notes*: All values are weighted using the population expansion factor.

The MEPI shows a smoother pattern. Energy poverty incidence decreased gradually from 27% in 2015 to 23% in 2019, before rising again during the pandemic to nearly 28% and remaining elevated thereafter. These figures are consistent with previous cross-country estimates. Santillán *et al.* (2020) report a MEPI of 0.27 for Peru in 2014. Unlike the TPRI, the impact of the income shock is diluted across dimensions of access and ownership, which evolve more slowly over time. As a result, the MEPI captures both the medium-term progress in infrastructure and appliances and the temporary setback caused by the affordability shock, yielding a trajectory that is more stable but still responsive to the crisis.

6 A measure of adaptive energy poverty

As discussed in the previous section, traditional measures of energy poverty typically rely on static indicators such as access to electricity or the share of income spent on energy. While these dimensions are crucial, they fail to capture whether households can adjust their energy use in response to environmental changes. In this section, we propose a novel, behaviorally grounded measure of energy poverty that reflects households' capacity to adapt to climate shocks—specifically, to increased ambient temperatures—through increased electricity consumption.

The core idea is simple: when temperatures rise beyond a certain point, most households increase their electricity usage, typically due to higher demand for cooling. Households that do not exhibit such increases may face constraints—financial, infrastructural, or behavioral—that limit their ability to respond, placing them at risk of adverse health or productivity outcomes. These households can be considered energy poor, not necessarily because of low access, but because they cannot adjust their energy use when it matters most.

To operationalize this idea, we define a household-level binary indicator of *adaptive energy poverty*, denoted by AEP_h. The construction involves three main steps:

1. **Baseline temperature (t_0):** Choose a reference temperature t_0 (e.g., a moderate mean monthly temperature such as 17 °C) at which electricity consumption is measured as a baseline.

2. **Response temperature (t_τ):** Identify a temperature $t_\tau > t_0$ such that p percent of households increase their electricity consumption C by more than x absolute units (kWh/day) relative to t_0. For that, first define the function:

$$P(t, x) = \frac{1}{N} \sum_{h=1}^{N} \mathbf{1}\big(C_h(t) - C_h(t_0) > x\big)$$

where 1(.) is an indicator function. This expression captures the proportion of households that increase their electricity consumption by more than x. Then set:

$$t_\tau = \min\{t \in \mathcal{T} : P(t, x) \geq p\}$$

where $\mathcal{T}$ is the set of observed temperature values.

3. **Energy poverty indicator:** A household h is classified as adaptive energy poor if its change in electricity consumption between t_0 and t_τ is smaller than a threshold $z < x$. That is,

$$AEP_h = \begin{cases} 1 & \text{if } C_h(t_\tau) - C_h(t_0) < z \\ 0 & \text{otherwise} \end{cases}$$

This approach yields a dynamic and context-sensitive measure of energy poverty that is grounded in observed behavior. It captures not just who lacks energy, but who cannot use it adaptively when environmental conditions demand it. The measure is especially relevant in the context of climate change, where exposure to temperature extremes is increasing, and the ability to adapt through energy use is becoming a critical dimension of well-being.

As with any poverty measure—whether based on income, energy, or multidimensional criteria-the construction of our adaptive energy poverty indicator inevitably involves decisions about thresholds. In our case, the choice of parameters such as the reference percentile p, the benchmark increase in electricity consumption x, and the minimum adaptive response z reflects an effort to operationalize meaningful behavioral differences in the data. However, as in all poverty measurement exercises, these thresholds are ultimately arbitrary to some extent, and their selection can affect the resulting classification. In the empirical analysis, we report how the incidence of adaptive energy poverty varies when we adjust some of these parameters within plausible ranges.

A potential limitation of our approach arises from the behavioral interpretation of adaptive responses. We classify a household as energy poor when its electricity consumption does not increase sufficiently in the face of rising temperatures, interpreting this as an inability to cope with higher cooling needs. However, in principle, some households may deliberately choose not to intensify electricity use because they have a higher tolerance for heat or a lower preference for air conditioning. This type of misclassification is conceptually similar to that present in standard income-based poverty measures: households are deemed poor when their income falls below a threshold, even though some may voluntarily supply little labor because they place a high value on leisure. In both cases, the classification captures observed outcomes rather than underlying preferences. We do not downplay this limitation; rather, it calls for a cautious interpretation of our estimates, which may be better understood as an upper bound of adaptive energy poverty. It also highlights the need for further work—by us and by other researchers who find this framework useful—to refine the concept and develop empirical strategies capable of more clearly disentangling choice from constraint in households' adaptive behavior. While this limitation is inherent to outcome-based poverty metrics, we consider it less severe than the structural bias affecting conventional expenditure-based indicators, which systematically fail to identify households that under-consume energy due to binding affordability constraints.

6.1 Implementation and results

We apply the measure of adaptive energy poverty using high-frequency matched data on household electricity consumption, weather conditions, and socioeconomic characteristics in Peru. In this section, we present the results of a benchmark case; the next section discusses extensions and robustness analysis. In this benchmark case, we set p=0.7, x=6 kWh, and z=$x/3$.[13] For simplicity, we apply the same parameters to all households, regardless of their geographical location or other characteristics. In the following section, we show that our results are only marginally affected by introducing heterogeneity in these parameters. Moreover, it is not obvious that, conceptually, geographical differences should necessarily be reflected in the parameter settings.[14]

[13]As discussed above, the underlying intuition is that a "large" proportion of households should increase their electricity consumption by a "non-negligible" amount when temperatures rise. Naturally, both notions—"large" and "non-negligible"—are inherently arbitrary, as is common in poverty measurement. We set our baseline value for x based on the empirical fact that the mean increase in electricity consumption associated with a one-degree rise in temperature is approximately 6 kWh. We select $p = 0.7$ to represent a sizable behavioral response and also for practical reasons, since for this value (together with $x = 6$) the implied temperature-response bin aligns almost exactly with a bin defined by integer temperature values (the 23º–25º interval), which facilitates interpretation and simplifies both the empirical analysis and the presentation of results.

[14]For example, if we observe that p percent of the national population increases electricity consumption by more than x kWh when the temperature rises from t_0 to t_τ, but in a given region r, this share is lower than p, there are at least two possible interpretations. One is that many households in that region are unable to increase energy consumption, even if they would like to, due to constraints such as limited access or financial difficulties. Another is that, for cultural or other reasons, people in region r simply do not respond to such a temperature increase by consuming more energy, and therefore may not perceive the absence of a reaction as a sign of deprivation. By using the same parameters for all regions in this section, we prioritize the first interpretation. In the next section, we allow parameters to vary by region and other household

As previously discussed, an important limitation of our analysis is that Peru generally does not experience extreme temperatures requiring cooling. For this reason, we work with temperature bins rather than specific values. In particular, we take the 17º–19º bin as the baseline temperature, t_0. We find that the response temperature t_τ for parameters $p = 0.7$ and $x = 6$ kWh corresponds to the 23º–25º bin. In sum, when monthly mean temperature increases from 17-19º to 23-25º, 70% of Peruvian households raise their monthly electricity consumption by more than 6 kWh. We define as energy poor those households that, under the same temperature increase, raise their electricity consumption by less than 2 kWh.

Even when working with temperature bins rather than exact temperature values, the limitation of having few observations remains. In fact, we are able to compute energy poverty only for a subset of 15,368 households—those in our sample that have at least one monthly observation with temperatures in the 17º–19º bin and at least one observation in the 23º–25º bin.[15]

With the parameters of the benchmark case, the incidence of energy poverty is 20.9%. In our framework, this means that 20.9 % of households in the sample fail to increase their electricity consumption by at least 2 kWh in a situation where 70 % of households increase it by more than 6 kWh.

Table 3 reports the incidence of energy poverty across households grouped by welfare level, region, and age. As expected, the share of energy-poor households declines steadily with welfare: 59.8 % in the bottom decile, compared with 19.2 % in the fifth decile and 12.5 % in the top decile. In light of the previous discussion, the non-negligible incidence of adaptive energy poverty observed in upper welfare deciles may partly reflect behavioral choices rather than financial constraints. Some higher-income households may choose not to increase electricity consumption in response to rising temperatures because of greater heat tolerance, different comfort preferences, or lower reliance on air conditioning. In the extreme, the adaptive energy poverty rate estimated for the top decile could be interpreted

characteristics.

[15] The analysis would be unfeasible if we relied solely on data from the national household survey (even disregarding the issue of underreporting of electricity expenditures). The ENAHO panel for the study period comprises approximately 31,000 households, but only 1% have at least one observation in the 17–19 range and another in the 23–25 range.

as an approximation to the potential misclassification driven by preferences rather than binding constraints. At this stage, however, we refrain from pursuing this adjustment, as disentangling voluntary under-consumption from true adaptive limitations would require additional behavioral or technological information beyond the scope of the present data.

In contrast to the marked differences by income, disparities by the age of the household head are less pronounced. Energy poverty is most prevalent among households headed by individuals younger than 30 (24.5%), while it is lowest among those aged 45–60 (20.2%). Only a few regions have a sufficient number of observations to compute representative energy-poverty statistics. Among these regions, heterogeneity is substantial. The last panel of Table 3 shows that energy poverty is highest in La Libertad (33.3%) and lowest in Arequipa (8.2%).

By definition, all households without access to electricity are classified as energy poor, since they cannot adjust their electricity consumption when temperatures rise. Among households with electricity, 17.1% are still classified as energy poor because their consumption response is insufficient. Among energy-poor households, 22.1% have no electricity access at all. An additional 46.1% are connected to the grid but lack a refrigerator (even if they have other basic appliances). The remaining 31.8% do have both electricity and a fridge, yet still fall into adaptive energy poverty due to low usage.

We compare traditional measures of monetary poverty with our estimates of adaptive energy poverty (Table 4). For simplicity, we set a monetary poverty line that replicates the average headcount ratio of Peru over the study period, using the USD 6.85 PPP international line. This threshold, equivalent to 440 soles, implies a poverty rate of 33% in our complete dataset. The rate decreases to 24% when restricting the sample to the smaller panel used for the energy poverty analysis in this section.[16] Among households classified as monetary poor, 34.9% are also energy-poor, while the share drops to 16.5% among those that are non-poor in terms of a monetary measure of deprivation.

Finally, we compare our adaptive measure of energy poverty with the more traditional approaches discussed in the previous section. Its correlation with the MEPI index is similar to

[16] Recall that to implement the idea of adaptive energy poverty, we need to observe a household in two specific temperature bins.

that with income poverty: among households classified as energy-poor according to MEPI, 36.3% are also energy-poor under our definition, while the share falls to 16.7% among those classified as non-poor. The correlation increases when ignoring the affordability factor in the MEPI (labeled as MEPI 2 in Table 4). By contrast, the correlation virtually disappears when using the 10% rule. In fact, the proportion of energy-poor households is slightly higher among the non-poor group defined by this rule, this pattern suggests serious shortcomings in the 10% rule as a measure of energy deprivation.

While the Pearson correlation coefficient between our measure of adaptive energy poverty and both monetary poverty and the MEPI is positive and highly significant (0.31 and 0.35, respectively), its correlation with energy poverty measured by the 10% rule is small and negative (-0.03) (Table 5). The correlation with the MEPI increases to 0.39 when ignoring the affordability variable in that multidimensional indicator. When using tetrachoric correlations—which are designed for binary variables under the assumption that they stem from underlying continuous latent traits—the associations are even stronger. For instance, the correlations with monetary poverty and the MEPI reach 0.49 and 0.56, respectively, and rise to 0.63 when the affordability component is excluded.

We further examine the characteristics of households classified as energy poor under our adaptive methodology, but not under alternative approaches. The number of such cases is relatively small, which limits the scope for a detailed characterization. For example, only 2,087 households are identified as energy poor by the adaptive approach but not by the MEPI-2 criterion (which excludes the affordability dimension from the multidimensional index). Interestingly, these households are disproportionately concentrated in the middle of the per capita expenditure distribution. Many middle-class households own enough appliances to avoid being classified as energy poor by MEPI-2, yet still face constraints in increasing their energy consumption when temperatures rise. By contrast, both the poorest and the richest households are underrepresented in this group: only 5.37% belong to the bottom decile and 6.33% to the top decile. The reasons differ—most poor households are already considered energy poor under MEPI, while most rich households are not classified as poor by the behavioral criterion.

The situation looks somewhat different when considering households classified as energy poor by the adaptive approach but not by the energy expenditure share criterion. In this case, low-income households are overrepresented: 15% of them belong to the bottom decile of the per capita expenditure distribution. These households have very limited resources and spend less than 10% of their total income on energy, likely because they must prioritize more pressing needs. As a result, they are excluded from energy poverty under the affordability criterion, yet they are classified as energy poor under our adaptive measure. In fact, a significant share of these households—more than 60%—lack access to electricity altogether.

6.2 Extensions and sensitivity

In this section, we explore the sensitivity of the results with respect to alternative parameter values and methodological choices. Table 6 presents the incidence of energy poverty for different values of z. In the benchmark case, where $z = 2$, the incidence is 20.9. As expected, higher values of z lead to higher poverty rates, although the increase is moderate: from 16.2 when the poverty line z is close to 0, to 28.4 when $z = 5$ (i.e., close to the value of x). Importantly, the relative ranking of groups and regions remains largely unchanged when alternative poverty lines are considered.

In Table 7, we perform a different sensitivity exercise: we fix the initial temperature bin at 17–19ºC (bin 1), consider alternative values of p and x, identify the corresponding bin of the comparison maximum temperatures (bin 2), and compute the energy-poverty headcount ratio. The results are not highly sensitive to these parameter changes.

As mentioned above, our preferred approach would be to compute energy poverty by exploiting changes in electricity consumption between two specific temperature levels (e.g., from 18º to 24º). However, due to limitations in the number of observations, we instead group temperatures into bins (e.g., 17–19º and 23–25º in the benchmark case). Table 8 reports the results for different bin sizes. While the number of observations varies substantially with the choice of bin size, the poverty estimates remain broadly stable.

As explained above, in the benchmark exercise, we use the same parameters across all regions. As a simple robustness check, we keep the same value of p and the same temperature bins for all regions, but allow the resulting values of x (and hence z) to vary by region. As previously discussed, the number of observations is too small to replicate this analysis for every region, so we restrict the sample to the set of regions reported in Table 3. Within this group, the incidence of energy poverty using the benchmark parameters is 17.4% (a bit lower than the national figure of 20.9%). When allowing for regional differences in parameters, the poverty incidence increases only modestly, to 20.3%.

Finally, we consider the robustness of the results to differences in household size. For simplicity, we divide households into three groups: Group 1 includes those with 1 or 2 members, Group 2 those with 3 or 4 members, and Group 3 the more numerous households. Interestingly, there are no significant differences in responses to temperature changes across these groups, likely reflecting offsetting factors associated with household size. The share of households that increase electricity consumption by more than 6 kWh is very similar: 67.1% in Group 1, 71.2% in Group 2, and 70.3% in Group 3. To carry out a simple sensitivity analysis, we keep the value of p=0.7 and the reference temperature bins constant, but adjust the values of x (and hence z) for each group. The incidence of energy poverty shows only a negligible change: from 20.9% in the benchmark case to 21.0% in this robustness exercise. Also, the relative ranking of groups and regions remains largely unchanged.

7 Concluding remarks

This paper has examined household electricity consumption responses to temperature changes in Peru, with particular attention to heterogeneity across the welfare distribution. Exploiting a unique dataset that combines administrative consumption records with household survey data and high-frequency temperature information, we documented a non-linear relationship between electricity use and heat exposure: consumption remains stable at moderate temperatures, but rises sharply once monthly averages exceed 19°C. Crucially, these responses are highly unequal. While wealthier households significantly increase their consumption at higher temperatures, poorer households display little or no adjustment, even under conditions where cooling needs are expected to intensify.

Building on these findings, we introduced a novel indicator of adaptive energy poverty, which captures households' inability to raise electricity use when temperatures rise. Unlike conventional indicators—such as the Ten Percent Rule Index or the Multidimensional Energy Poverty Index—our measure highlights a hidden form of deprivation that is not necessarily linked to grid access or reported expenditures, but rather to the limited capacity to adapt energy use in the face of climatic stress.

A further contribution of the paper is to illustrate the value of using administrative data. Compared with survey self-reports, administrative records offer more accurate consumption information, reduce underreporting biases, and enable panel analyses of household responses to temperature shocks. These features are particularly important in contexts like Peru, where short survey panels provide few repeated observations.

Overall, our results underscore that energy poverty is not only about affordability or physical access, but also about adaptive capacity. In sum, poorer households in Peru face a dual burden: they are less able to cool down as temperatures rise, which our adaptive poverty measure captures as a form of latent energy deprivation. In the context of climate change, policies aimed at reducing energy poverty should therefore go beyond subsidies and connections, and also address barriers to adaptation—such as limited appliance ownership and liquidity constraints. Strengthening households' resilience through targeted programs can help mitigate the unequal impacts of rising temperatures and support more inclusive adaptation strategies.

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Table 1: Regression by temperature bin

	(1)	(2)	(3)
10 °C	-14.57**	0.980	-2.886***
	(6.398)	(0.702)	(0.933)
11 °C	-9.821	0.0271	-3.246***
	(6.128)	(0.399)	(0.667)
12 °C	-4.814	0.172	-2.800***
	(5.566)	(0.324)	(0.584)
13 °C	0.367	-0.0640	-2.357***
	(5.599)	(0.302)	(0.495)
14 °C	5.931	-0.340	-1.862***
	(5.486)	(0.291)	(0.406)
15 °C	7.967	-0.371	-1.044***
	(5.024)	(0.251)	(0.300)
16 °C	3.038	-0.0311	-0.188
	(3.439)	(0.182)	(0.207)
18 °C	7.581*	0.523	0.473
	(4.440)	(0.416)	(0.432)
19 °C	35.86***	-0.0908	-0.0583
	(8.333)	(0.322)	(0.408)
20 °C	80.98***	2.376**	2.370**
	(9.638)	(1.096)	(1.094)
21 °C	99.70***	8.096***	8.334***
	(9.743)	(0.935)	(0.987)
22 °C	93.88***	9.128***	9.433***
	(9.603)	(1.095)	(1.191)
23 °C	74.79***	7.650***	8.649***
	(9.352)	(0.919)	(1.073)
24 °C	73.81***	8.844***	8.938***
	(9.279)	(0.885)	(1.004)
25 °C	83.94***	9.788***	10.61***
	(9.345)	(1.124)	(1.287)
26 °C	92.44***	13.23***	14.43***
	(9.929)	(1.071)	(1.229)
27 °C	95.10***	14.26***	15.61***
	(9.375)	(1.153)	(1.300)
28 °C	88.68***	15.63***	17.78***
	(9.136)	(1.054)	(1.203)
29 °C	87.53***	16.08***	18.70***
	(9.736)	(1.184)	(1.319)
30 °C	66.03***	19.90***	23.15***
	(9.946)	(1.112)	(1.302)
Constant	53.90***	103.3***	104.2***
	(5.137)	(0.520)	(0.635)
Observations	2,217,915	2,217,915	2,217,915
# Household IDs		241,059	241,059
Household fixed effects	No	Yes	Yes
Month fixed effects	No	No	Yes

Notes: Robust standard errors clustered at the district level in parentheses. The omitted category is 17 °C. Robust standard errors clustered at the district level in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 2: Model of electricity consumption by deciles of per capita expenditure

	All	Decile 1	Decile 2	Decile 3	Decile 4	Decile 5	Decile 6	Decile 7	Decile 8	Decile 9	Decile 10
10 °C	-2.886***	1.472***	-0.506	-1.677	0.449	-6.146***	-4.817***	-5.134***	-3.734	-6.787***	-3.710*
	(0.933)	(0.562)	(0.795)	(1.198)	(2.930)	(1.403)	(0.982)	(1.154)	(2.793)	(2.149)	(2.077)
11 °C	-3.246***	1.189**	-0.940	-2.045**	-3.415***	-4.998***	-4.989***	-3.819***	-6.037***	-4.861***	-4.545**
	(0.667)	(0.490)	(0.673)	(0.884)	(1.309)	(1.255)	(0.971)	(0.959)	(1.543)	(1.163)	(1.962)
12 °C	-2.800***	0.991**	-1.069*	-1.420*	-2.080**	-5.012***	-4.551***	-3.869***	-5.144***	-4.870***	-2.946*
	(0.584)	(0.423)	(0.593)	(0.779)	(0.873)	(1.258)	(0.829)	(0.948)	(1.316)	(1.079)	(1.558)
13 °C	-2.357***	0.714**	-1.026**	-1.288*	-1.645**	-4.135***	-3.708***	-3.689***	-4.041***	-3.668***	-2.312
	(0.495)	(0.339)	(0.502)	(0.672)	(0.685)	(1.135)	(0.758)	(0.798)	(1.151)	(0.824)	(1.417)
14 °C	-1.862***	0.575**	-0.896**	-1.054*	-1.236**	-3.609***	-2.522***	-2.694***	-3.514***	-2.934***	-1.591
	(0.406)	(0.285)	(0.401)	(0.557)	(0.577)	(1.056)	(0.645)	(0.680)	(0.946)	(0.830)	(1.262)
15 °C	-1.044***	0.536**	-0.685**	-0.798*	-0.606	-2.030**	-1.849***	-1.763***	-1.851***	-2.328***	0.728
	(0.300)	(0.233)	(0.284)	(0.429)	(0.501)	(0.931)	(0.572)	(0.582)	(0.653)	(0.634)	(1.430)
16 °C	-0.188	0.385**	-0.143	-0.707*	0.0652	-1.208**	0.425	-0.452	-0.569	-0.310	1.102
	(0.207)	(0.178)	(0.210)	(0.383)	(0.278)	(0.549)	(0.470)	(0.487)	(0.610)	(0.525)	(1.115)
18 °C	0.473	0.352	0.527	-0.847	0.0765	-0.125	0.319	1.428	1.194	-0.311	3.246
	(0.432)	(0.313)	(0.409)	(0.742)	(0.375)	(0.741)	(0.649)	(1.053)	(0.958)	(1.476)	(2.822)
19 °C	-0.0583	-0.474	-1.121	-1.570*	1.441	0.529	1.715*	0.0217	0.545	0.706	0.575
	(0.408)	(0.322)	(0.692)	(0.803)	(0.895)	(0.888)	(0.954)	(0.928)	(0.995)	(1.160)	(1.590)
20 °C	2.370**	0.104	1.323	1.826	1.751	2.198*	4.079***	1.841*	5.032***	4.452**	6.122***
	(1.094)	(0.865)	(1.818)	(1.776)	(1.103)	(1.142)	(1.283)	(1.085)	(1.283)	(2.205)	(2.249)
21 °C	8.334***	0.125	2.734*	7.607***	10.81***	8.498***	10.65***	9.188***	10.94***	11.71***	12.31***
	(0.987)	(1.836)	(1.617)	(1.365)	(1.698)	(1.257)	(1.377)	(1.355)	(1.271)	(1.923)	(2.082)
22 °C	9.433***	-0.700	2.623	5.843***	9.158***	9.567***	11.38***	9.440***	13.75***	13.81***	15.51***
	(1.191)	(1.729)	(1.694)	(1.605)	(1.587)	(1.739)	(1.488)	(1.776)	(1.650)	(2.027)	(2.432)
23 °C	8.649***	-1.500	3.533**	4.823***	7.617***	8.498***	10.67***	9.789***	12.79***	14.29***	13.79***
	(1.073)	(1.820)	(1.790)	(1.211)	(1.368)	(1.513)	(1.253)	(1.366)	(1.382)	(2.227)	(2.476)
24 °C	8.938***	-0.964	3.362**	6.475***	7.442***	9.432***	11.49***	9.661***	12.80***	13.38***	12.33***
	(1.004)	(2.031)	(1.653)	(1.483)	(1.571)	(1.718)	(1.405)	(1.506)	(1.498)	(2.145)	(2.272)
25 °C	10.61***	-1.602	5.015***	7.407***	10.17***	10.11***	12.82***	12.26***	15.22***	15.47***	14.13***
	(1.287)	(2.367)	(1.747)	(1.553)	(1.432)	(1.501)	(1.652)	(1.395)	(1.833)	(2.645)	(2.496)
26 °C	14.43***	0.761	7.757***	10.10***	13.10***	13.59***	17.70***	16.19***	19.26***	19.68***	18.63***
	(1.229)	(1.934)	(1.690)	(1.933)	(1.523)	(1.405)	(1.627)	(1.551)	(1.760)	(2.489)	(2.625)
27 °C	15.61***	0.564	8.041***	10.35***	14.63***	14.63***	18.24***	17.28***	21.47***	21.78***	18.23***
	(1.300)	(2.092)	(1.513)	(1.650)	(1.601)	(1.303)	(1.799)	(1.766)	(1.891)	(2.294)	(2.790)
28 °C	17.78***	1.718	9.879***	11.61***	16.09***	16.94***	20.65***	19.20***	23.24***	24.74***	21.74***
	(1.203)	(2.145)	(1.623)	(1.716)	(1.581)	(1.619)	(1.655)	(1.698)	(1.745)	(2.298)	(2.729)
29 °C	18.70***	1.969	10.69***	14.14***	18.11***	19.35***	21.63***	20.25***	24.50***	25.67***	19.62***
	(1.319)	(2.177)	(1.631)	(1.752)	(1.783)	(1.872)	(1.741)	(1.976)	(1.996)	(2.345)	(3.241)
30 °C	23.15***	3.806*	13.20***	17.00***	21.03***	24.40***	26.64***	24.98***	28.09***	30.10***	27.60***
	(1.302)	(2.272)	(1.588)	(1.640)	(1.656)	(1.954)	(1.822)	(2.050)	(2.136)	(2.638)	(3.236)
Observations	2,217,915	276,121	253,100	236,297	222,516	214,602	205,032	203,286	200,660	199,571	206,730
# Household IDs	241,059	29,308	27,031	25,587	24,288	23,467	22,417	22,266	22,010	21,854	22,839
Household fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Dependent variable: monthly electricity consumption (kWh). Robust standard errors clustered at the district level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 3: Incidence of energy poverty by expenditure decile, age group, and region

	Energy poverty
All	20.9
By deciles of expenditure	
1	59.8
2	30.8
3	24.8
4	23.3
5	19.2
6	18.2
7	15.3
8	13.8
9	16.2
10	12.5
By age	
Less than 30	24.5
30–45	21.3
45–60	20.2
More than 60	20.4
By region	
Arequipa	8.2
Callao	18.1
Ica	10.9
La Libertad	33.3
Lima	13.5

Source: Own calculations based on matched ENAHO–OSINERGMIN data. Pooled sample, 2015–2023.

Table 4: Adaptive energy poverty levels by groups of monetary poverty and energy poverty measured with traditional methods

	Value
Total	20.9
Monetary poverty	
Poor	34.9
Non poor	16.5
Energy poverty - MEPI	
Poor	36.3
Non poor	16.7
Energy poverty - MEPI 2	
Poor	46.0
Non poor	16.6
Energy poverty - 10% rule	
Poor	17.5
Non poor	21.2

Table 5: Correlation coefficients between poverty indicators.

	Pearson	Tetrachoric
Monetary poverty	0.3009***	0.4907***
Energy poverty		
MEPI	0.3484***	0.5581***
MEPI 2	0.3887***	0.6253***
10% rule	-0.029	-0.082

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 6: Energy-poverty - sensitivity to values of z

z	H
0.01	16.2
1	18.9
2	20.9
3	23.3
4	25.9
5	28.4

Table 7: Energy poverty - sensitivity to different combinations of p and x

bin1	p	x	bin2	Observations	H
17–19°	0.7	6	23–25°	15,368	20.9
17–19°	0.7	5	23–24°	14,892	21.3
17–19°	0.6	5	22–23°	18,502	26.9
17–19°	0.6	6	22–24°	19,151	25.4

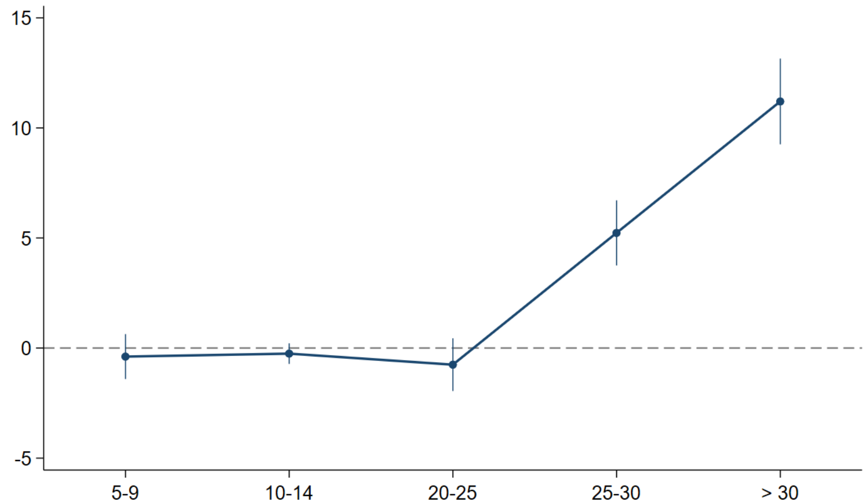
Source: Own calculations based on matched ENAHO–OSINERGMIN data. Pooled sample, 2015–2023

Table 8: Energy poverty – different bins of temperature

Bins of temperature			
minimum	maximum	Observations	H
17–19º	23–25º	15,368	20.9
16–20º	23–27º	30,030	19.4
15–21º	22–28º	49,788	23.3
18–19º	24–25º	14,112	20.4

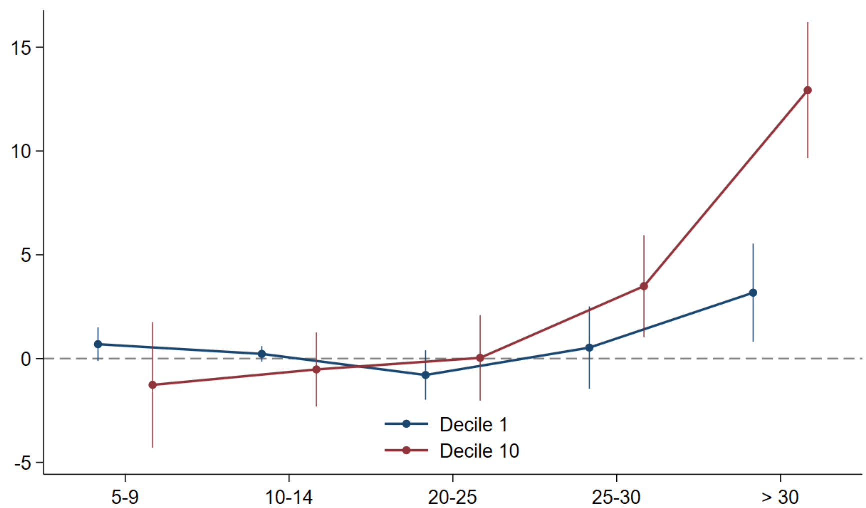
Source: Own calculations based on matched ENAHO–OSINERGMIN data. Pooled sample, 2015–2023.

Figure 10: Coefficients of temperature bins in model of electricity consumption



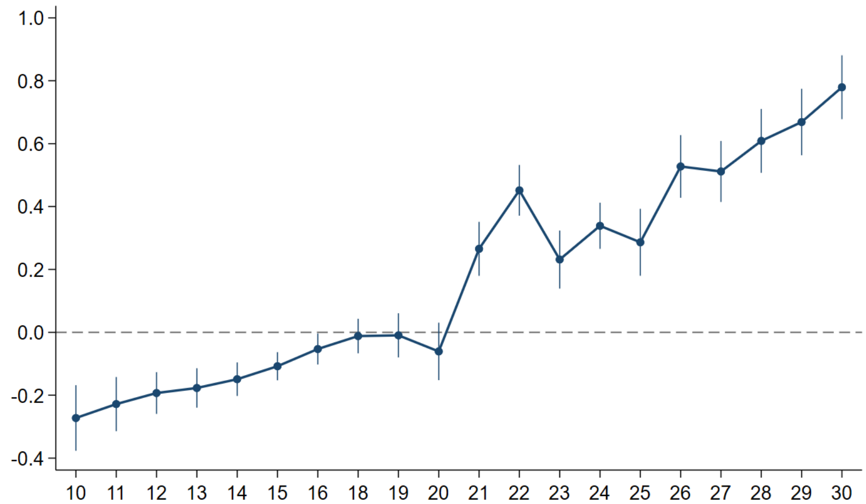
Source: own calculations based on matched data ENAHO-OSINERGMIN. 95% confidence intervals. The omitted category is bin 15-19.

Figure 11: Coefficients of temperature bins in model of electricity consumption - Deciles 1 and 10



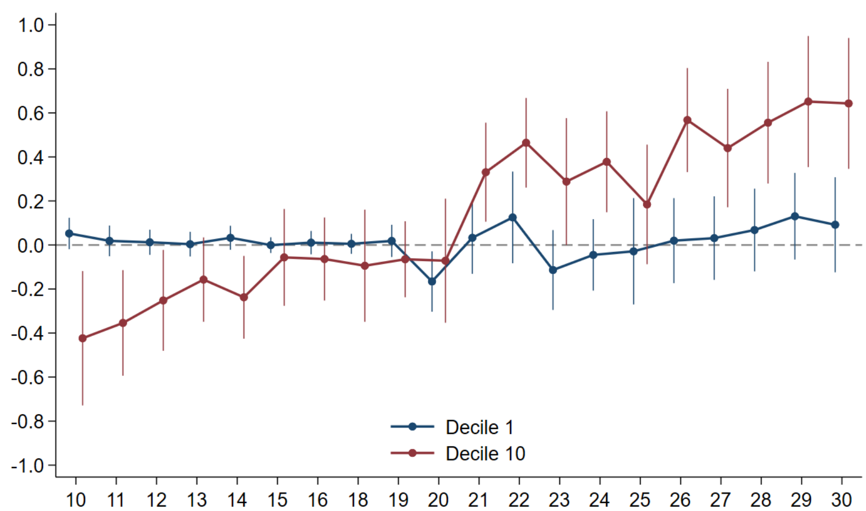
Source: own calculations based on matched data ENAHO-OSINERGMIN. 95% confidence intervals. The omitted category is bin 15-19.

Figure 12: Coefficients of temperature bins in the model of electricity consumption



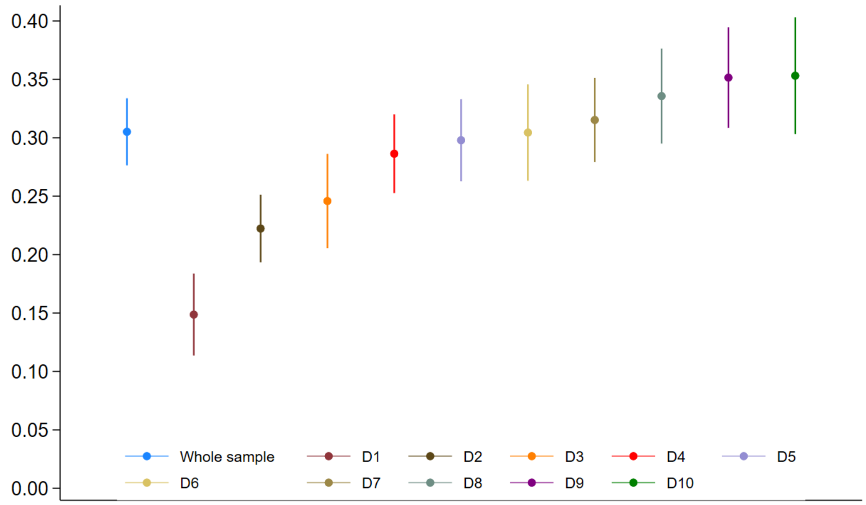
Source: own calculations based on matched data ENAHO-OSINERGMIN. 95% confidence intervals. Each bin represents the number of days with a specific average temperature in a month. The omitted category is bin 17.

Figure 13: Coefficients of temperature bins in model of electricity consumption - Deciles 1 and 10



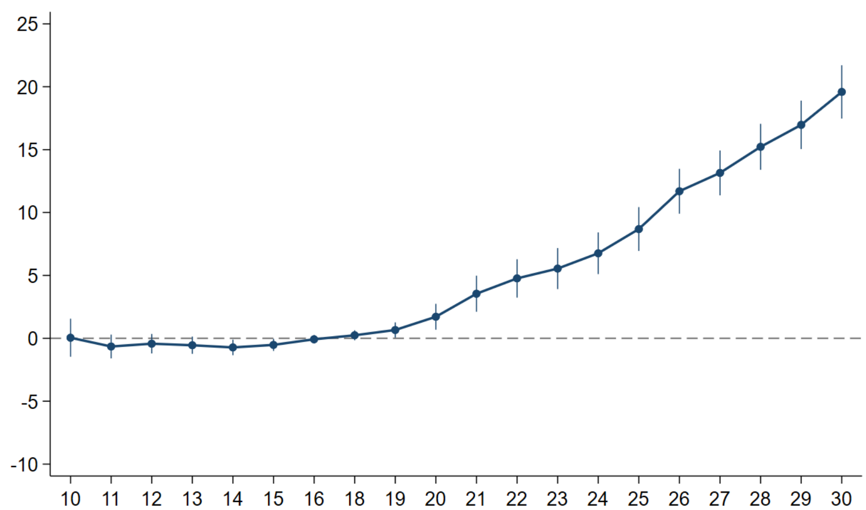
Source: own calculations based on matched data ENAHO-OSINERGMIN. 95% confidence intervals. Each bin represents the number of days with a specific average temperature in a month. The omitted category is bin 17.

Figure 14: Coefficients of number of days above 25ºC in a month in model of electricity consumption



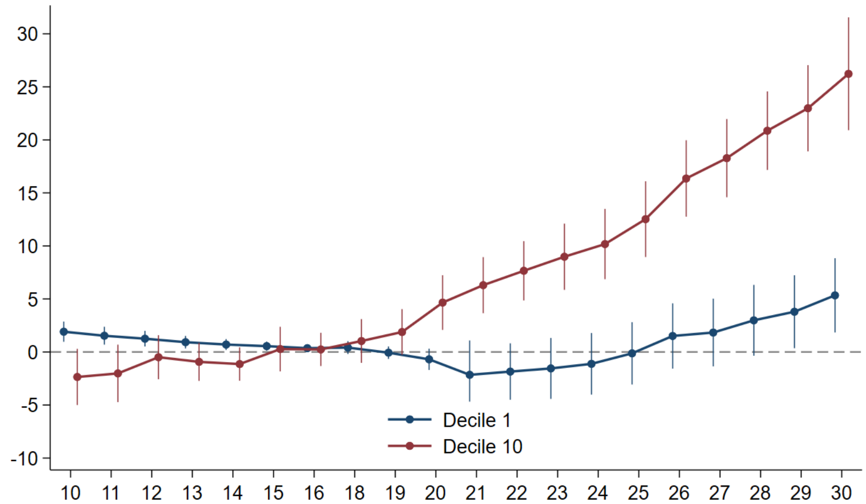
Source: own calculations based on matched data ENAHO-OSINERGMIN. 95% confidence intervals.

Figure 15: Coefficients of temperature dummies in model of electricity consumption - Excluding Lima



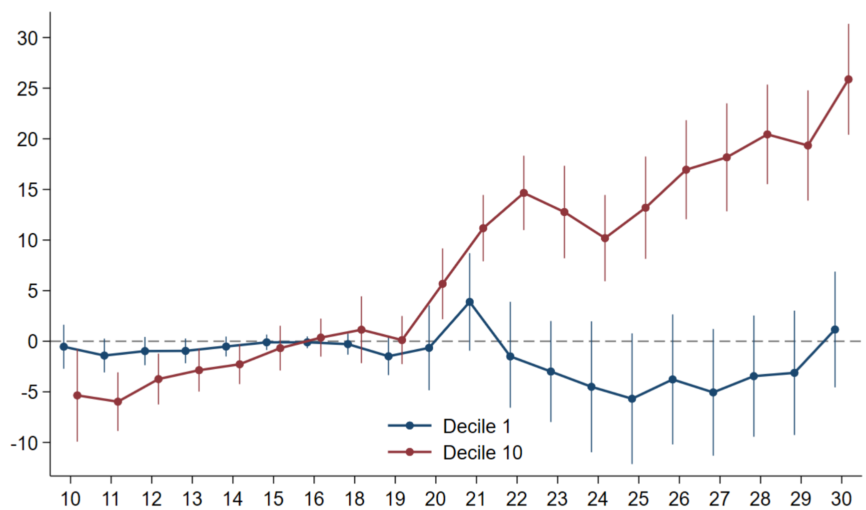
Source: own calculations based on matched data ENAHO-OSINERGMIN. 95% confidence intervals.

Figure 16: Coefficients of temperature dummies in model of electricity consumption - Excluding Lima - Deciles 1 and 10



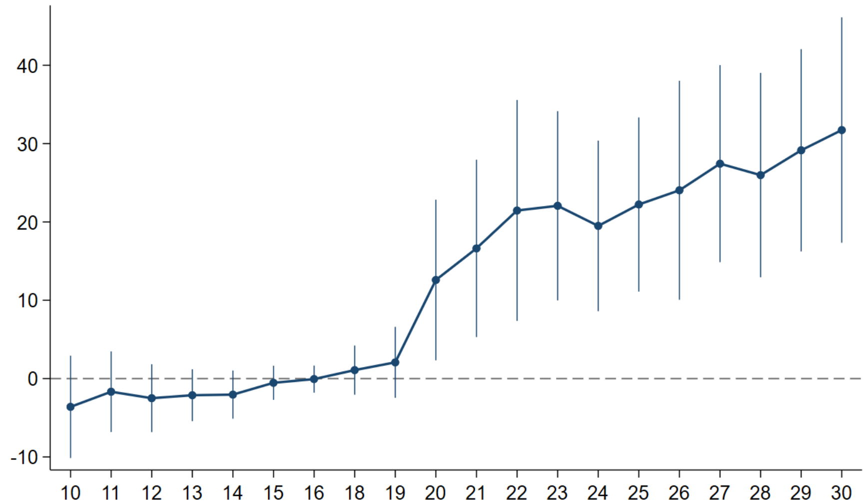
Source: own calculations based on matched data ENAHO-OSINERGMIN. 95% confidence intervals.

Figure 17: Coefficients of temperature dummies in model of electricity consumption - Deciles 1 and 10 (household per capita income)



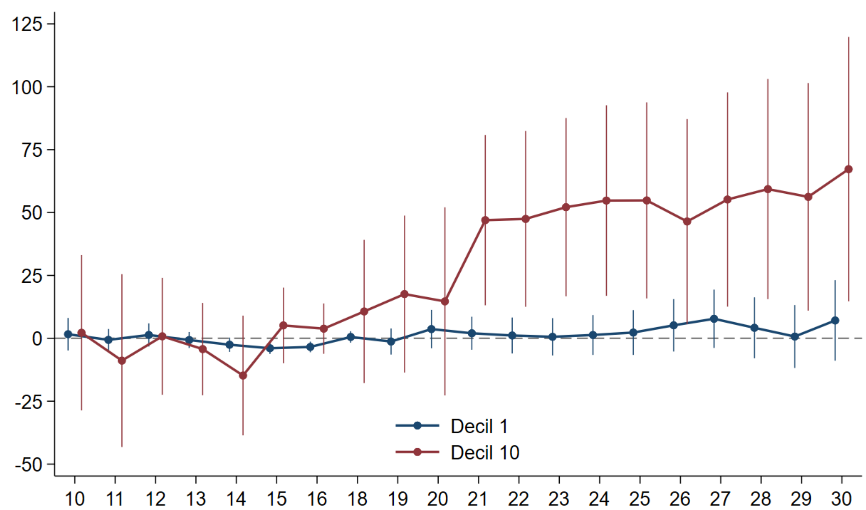
Source: own calculations based on matched data ENAHO-OSINERGMIN. 95% confidence intervals.

Figure 18: Coefficients of temperature dummies in model of electricity consumption - ENAHO rotating panel



Source: own calculations based on matched data ENAHO-OSINERGMIN. 95% confidence intervals.

Figure 19: Coefficients of temperature dummies in model of electricity consumption - ENAHO rotating panel - Deciles 1 and 10

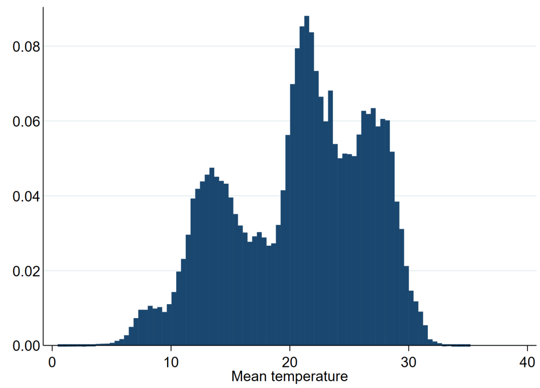


Source: own calculations based on matched data ENAHO-OSINERGMIN. 95% confidence intervals.

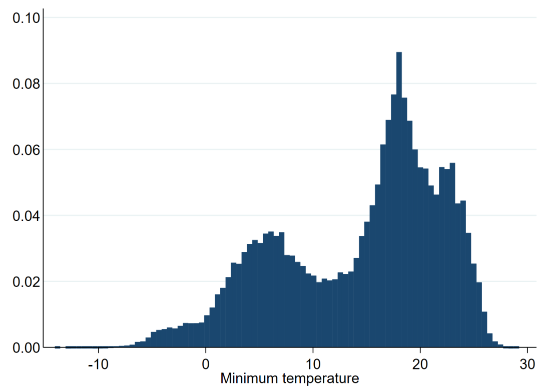
Appendix 1. Additional Figures and Tables

Figure A1: Monthly temperatures in °C in Peru

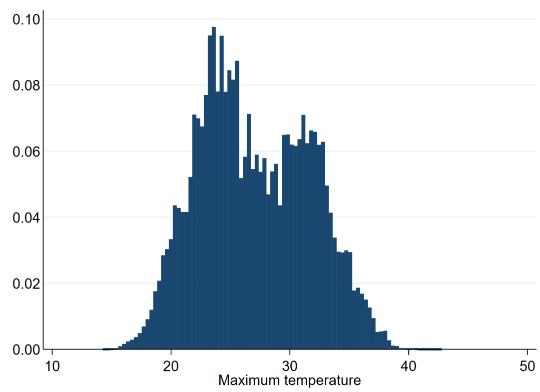
Panel (a) Mean



Panel (b) Min

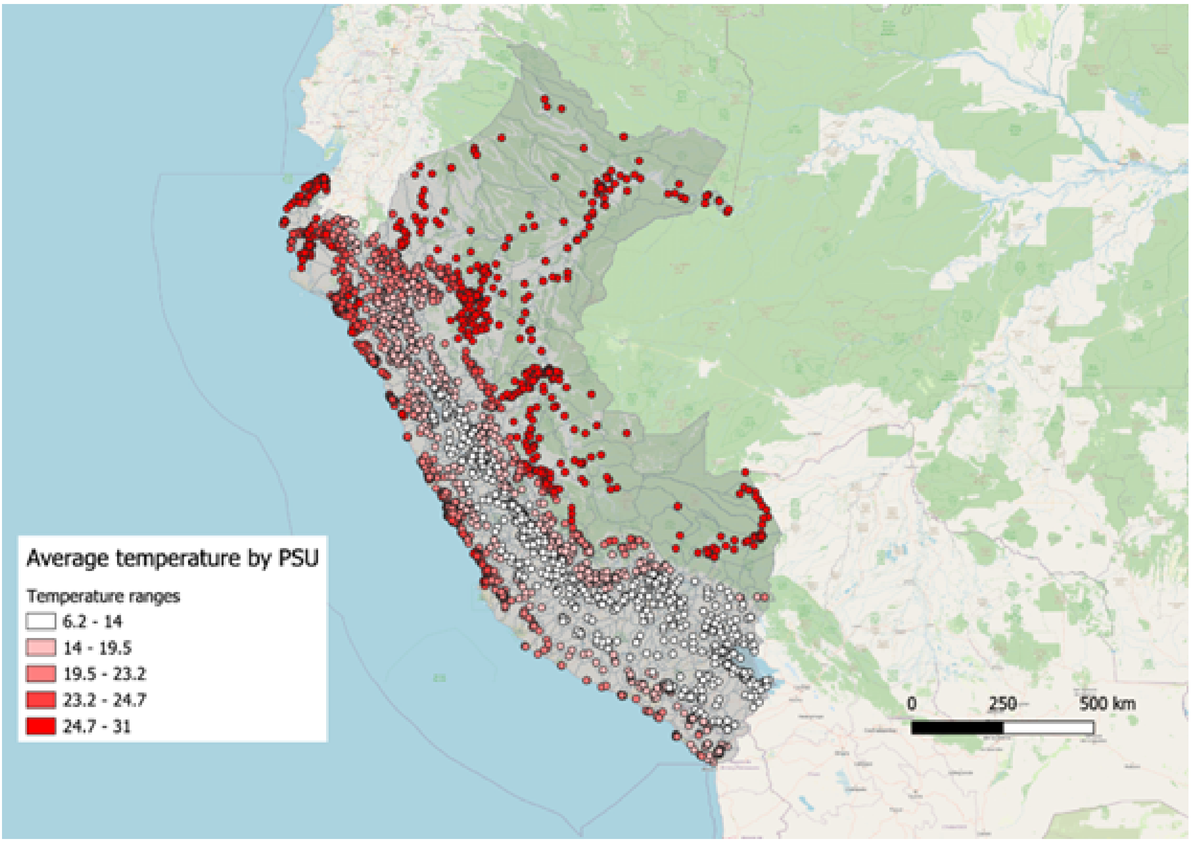


Panel (c) Max



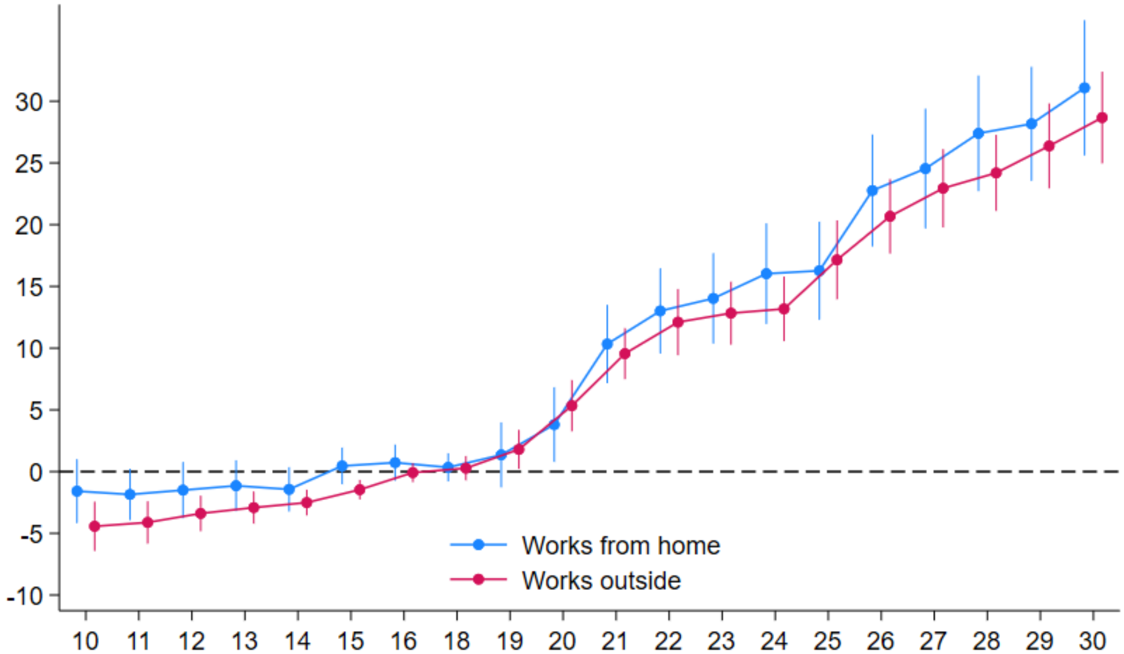
Source: Own elaboration. *Notes*: All values are weighted using the population expansion factor.

Figure A2: Map of mean monthly temperatures by location



Source: Climate Hazards Center at the University of California, Santa Barbara.

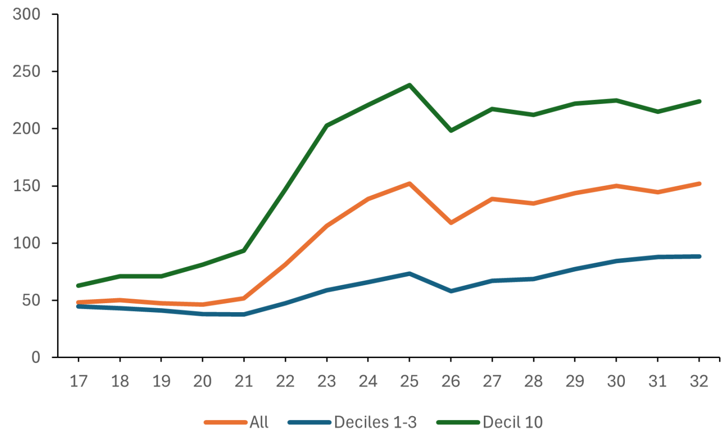
Figure A3: Electricity consumption (kWh) by temperature (ºC) exposure. Work from home and work outside



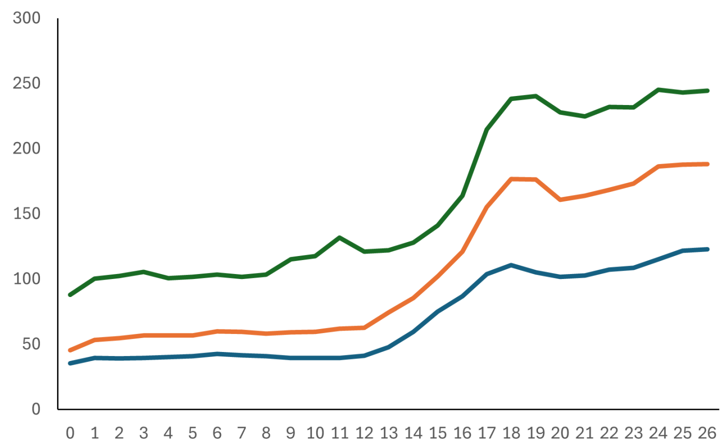
Source: Own calculations based on matched data ENAHO–OSINERGMIN.

Figure A4: Electricity consumption (kWh) by temperature (ºC) exposure. Maximum and minimum temperature

Panel A. Monthly electricity consumption by daily **maximum** temperature



Panel B. Monthly electricity consumption by daily **minimum** temperature



Source: Own calculations based on matched ENAHO–OSINERGMIN data. Pooled sample, 2015–2023.

Notes: All values are weighted using the population expansion factor.

Table A1: Annual household matches between ENAHO and OSINERGMIN records (2015–2023)

	Same dwelling		**Same block**		**Same district**	
Year	**Abs.**	**%**	**Abs.**	**%**	**Abs.**	**%**
2015	9,556	30.0	1,446	4.5	19,872	62.5
2016	11,478	32.4	1,401	4.0	21,567	61.0
2017	10,916	31.9	1,387	4.1	20,959	61.3
2018	10,744	29.0	–	–	–	–
2019	10,972	32.1	1,329	3.9	21,584	63.2
2020	11,004	32.2	1,381	4.0	21,581	63.1
2021	10,582	31.2	1,387	4.1	21,716	64.1
2022	10,620	31.4	1,468	4.3	21,577	63.7
2023	10,501	31.3	0	0.0	22,817	68.1

Source: ENAHO 2015–2023 and OSINERGMIN administrative records (2015–2023). *Notes*: For 2018, no administrative consumption data are available.

Appendix 2 Estimates with paremetric models

This Appendix presents the results of the estimations obtained from basic linear and quadratic specifications, which serve as a benchmark for comparison. Table B1 reports log-log estimates of the relationship between temperature and electricity consumption. The estimates are statistically significant and robust across specifications. In the fully specified model (Column 7), the elasticity of electricity consumption with respect to temperature is approximately 0.16. When disaggregated by income level, the responsiveness is significantly higher for wealthier households (0.204 in deciles 6–10) than for poorer ones (0.094 in deciles 1–5), consistent with the notion that adaptation to heat through electricity-intensive appliances is constrained among low-income households.

Table B2 presents results from a log-linear model using temperature levels instead of logs. While the magnitude of the coefficient is smaller due to the scale of the temperature variable, the pattern of heterogeneity across the income distribution remains. In the fully specified model (Column 7), a 1°C increase in monthly average temperature is associated with a 1.5 kWh increase in monthly electricity consumption, on average. The effect is slightly stronger among poorer households (0.0147 kWh for deciles 1–5) than among richer ones (0.0135 kWh for deciles 6–10), although the absolute differences are small.

To test for non-linearities in the temperature-consumption relationship, Table B3 includes a quadratic term for temperature. The coefficients reveal a U-shaped relationship: electricity consumption decreases with temperature up to a certain point, and then increases at higher levels. This pattern is consistent across specifications and particularly pronounced among low-income households, for whom the turning point occurs at lower temperature values. The significance and stability of the quadratic term across specifications lend further support to the hypothesis that temperature has a non-linear and asymmetric impact on electricity use, shaped by income-driven constraints on adaptation.

Together, these parametric results confirm the key stylized facts suggested by the graphical analysis: electricity consumption responds positively to rising temperatures, but the magnitude and functional form of this response vary across the income distribution.

Table B1: Effect of temperature on electricity consumption (log-log models)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	Dec. 1–5	Dec. 6–10
Log(temperature)	1.295***	0.0951***	0.154***	0.154***	0.154***	0.154***	0.154***	0.0916***	0.199***
	(0.00255)	(0.0144)	(0.0186)	(0.0186)	(0.0186)	(0.0186)	(0.0186)	(0.0185)	(0.0219)
Constant	0.461***	4.041***	3.872***	3.872***	3.872***	3.872***	3.872***	3.641***	4.153***
	(0.00751)	(0.0429)	(0.0562)	(0.0562)	(0.0562)	(0.0562)	(0.0562)	(0.0547)	(0.0681)
Observations	2,314,027	2,314,027	2,314,027	2,314,027	2,314,027	2,313,565	2,313,565	1,276,456	1,037,109
Household fixed effects	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month fixed effects	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Department fixed effects	No	No	No	No	Yes	Yes	Yes	Yes	Yes
Household-level controls	No	No	No	No	No	Yes	Yes	Yes	Yes
Dwelling-level controls	No	No	No	No	No	No	Yes	Yes	Yes
Number of household IDs	251,847	251,847	251,847	251,847	251,847	251,796	251,796	137,860	113,936

Source: Own elaboration. *Notes*: Robust standard errors clustered at the district level in parentheses. All models estimated on monthly household-level panel data (2015–2023). Dependent variable: log of monthly electricity consumption (kWh). Significance level * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, respectively.

Table B2: Effect of mean temperature on electricity consumption (levels)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	Dec. 1–5	Dec. 6–10
Mean temperature	0.0714***	0.00725***	0.0151***	0.0151***	0.0151***	0.0151***	0.0151***	0.0143***	0.0131***
	(0.00458)	(0.000583)	(0.000763)	(0.000763)	(0.000763)	(0.000763)	(0.000763)	(0.000868)	(0.000993)
Constant	2.845***	4.175***	4.006***	4.006***	4.006***	4.005***	4.005***	3.617***	4.464***
	(0.0894)	(0.0121)	(0.0166)	(0.0166)	(0.0166)	(0.0166)	(0.0166)	(0.0177)	(0.0227)
Observations	2,314,027	2,314,027	2,314,027	2,314,027	2,314,027	2,313,565	2,313,565	1,276,456	1,037,109
Household fixed effects	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month fixed effects	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Location fixed effects	No	No	No	No	Yes	Yes	Yes	Yes	Yes
Household-level controls	No	No	No	No	No	Yes	Yes	Yes	Yes
Dwelling-level controls	No	No	No	No	No	No	Yes	Yes	Yes
Number of household IDs	251,847	251,847	251,847	251,847	251,847	251,796	251,796	137,860	113,936

Source: Own elaboration. *Notes*: Robust standard errors clustered at the district level in parentheses. All models estimated on monthly household-level panel data (2015–2023). Dependent variable: monthly electricity consumption (kWh). Significance level * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, respectively.

Table B3: Quadratic effect of temperature on electricity consumption (levels)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	Dec. 1–5	Dec. 6–10
Mean temperature (°C)	0.194***	-0.0210***	-0.0158***	-0.0158***	-0.0158***	-0.0158***	-0.0158***	-0.0226***	-0.00413*
	(0.0328)	(0.00245)	(0.00285)	(0.00285)	(0.00285)	(0.00285)	(0.00285)	(0.00336)	(0.00242)
Mean temperature squared	-0.00312***	0.000623***	0.000665***	0.000665***	0.000665***	0.000665***	0.000665***	0.000850***	0.000355***
	(0.000746)	(5.52e-05)	(6.28e-05)	(6.28e-05)	(6.28e-05)	(6.28e-05)	(6.28e-05)	(7.39e-05)	(5.80e-05)
Constant	1.750***	4.472***	4.343***	4.343***	4.343***	4.343***	4.343***	3.985***	4.664***
	(0.325)	(0.0268)	(0.0327)	(0.0327)	(0.0327)	(0.0327)	(0.0327)	(0.0370)	(0.0284)
Observations	2,314,027	2,314,027	2,314,027	2,314,027	2,314,027	2,313,565	2,313,565	1,276,456	1,037,109
Household fixed effects	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month fixed effects	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Department fixed effects	No	No	No	No	Yes	Yes	Yes	Yes	Yes
Household-level controls	No	No	No	No	No	Yes	Yes	Yes	Yes
Dwelling-level controls	No	No	No	No	No	No	Yes	Yes	Yes
Number of household IDs	251,847	251,847	251,847	251,847	251,847	251,796	251,796	137,860	113,936

Source: Own elaboration. *Notes*: Robust standard errors clustered at the district level in parentheses. All models estimated on monthly household-level panel data (2015–2023). Dependent variable: monthly electricity consumption (kWh). Significance level * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, respectively.