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# The effect of temperature on household hourly electricity consumption: Evidence from South Africa

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ABSTRACT

Climate change is expected to negatively affect Africa, possibly leading to increased energy needs. However, meeting that need could prove problematic; more than a decade of load-shedding in South Africa is suggestive in that regard. In this research we examine the effect of temperature on electricity consumption, focusing on mainly rural households in South Africa. We apply a series of fixed effects panel models to hourly temperature and electricity consumption data across eight months and twelve locations in the country. We find limited evidence that increased temperatures drive increased electricity use; rather, electricity use increases as temperatures decline, although at temperatures below 10 °C, the gradient is approximately level. Given that few of our study's households own cooling or heating appliances, the result is not entirely surprising. However, without such appliances, poor rural households will not be able to cope with rising temperatures.

## 1. Introduction

A growing literature following Deschênes and Greenstone [1] applies residential user-level panel data models to examine the effect of weather (mainly temperature) on residential electricity consumption to uncover insight into the energy-climate relationship (e.g. [2–5], amongst others). For the most part, this research supports the supposition that rising temperatures will increase energy demand [6]. In this research, we extend the literature by focusing on rural, relatively poor, South African households. We examine an eight-month period in 2014, the most recent data available. We estimate the short-term causal effect of hourly temperature on hourly household electricity consumption, combining meter data with household survey data to address potential heterogeneities in this effect.

Although South Africa is blessed with mild weather – the yearly average temperature is about 18.3 °C over the period 1960 to 2003, while the mean minimum and maximum temperature were 6.8 °C and 29.6 °C between 1962 to 2009, respectively [7,8] – global warming could lead to a 2 °C average temperature increase over the next few decades and considerable climate change challenges for the country [9]. South Africa is already facing electricity supply challenges associated with rolling blackouts (load-shedding to South Africans) that have negatively affected economic performance [10] and could worsen, especially, the rural–urban divide [11]. Thus, there is a need to develop an improved understanding of temperature responses in both rural and urban areas of the country.

Furthermore, Statistics South Africa [12] suggests that the majority of South Africans use electricity for cooking, lighting and heating, with the percentage of households cooking with electricity increasing from 57.5% in 2002 to 76.5% in 2022. Still, approximately 24% of the households rely on non-clean energy sources for cooking. It also suggests that few own air conditioners, despite the relatively warm temperatures. In 2022, 7.4% of households own at least one air conditioner (excluding fans), and air conditioning adoption rates differ by province [12]. Admittedly, Davis et al. [13] argue that air conditioning penetration for the lowest-income groups in South Africa will remain below 4% even in 2050, when global warming temperature increases could reach or even exceed the previously mentioned 2 °C. Given these electricity usage and appliance ownership patterns, relatively poorer and mainly rural households in the country are likely to respond differently to temperature change than either households in developed countries or households in developed areas within developing countries.

Literature from the developed world suggests that high temperatures lead to increased electricity usage [1,5,14,15] or increased electricity bills and the potential for disconnections [16]. The same literature also finds relatively higher usage at low temperatures. Similar findings are uncovered in the developing world, based on data aggregated at the city, state or province level [17–20]. In other words,

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the literature from a wide range of countries points to a $U$−shape relationship – higher at both cold and hot temperatures – between temperature and electricity consumption.

The early literature is underpinned by monthly electricity billing data and binned temperature data (aggregated to a monthly measure). As the literature has progressed, the electricity data has become increasingly disaggregated, including high-resolution meter data for 396 homes in Italy [3], 4,000 homes in Ireland [4] and nearly 6,000 homes in one of the wealthiest regions of South Africa [21]. Although Alberini et al. [3] find support for increased electricity consumption when temperatures rise, they find little evidence that it also rises when temperatures are low. Kang and Reiner [4] find a negative relationship between consumption and temperature. Berkouwer [21] uncovers a similar negative relationship, as well as some evidence of an increase at extremely high temperatures. Thus, with less aggregated data, the previous literature's findings of a $U$ pattern may not be the defining feature of the relationship.

A wider range of micro-level data is increasingly available in developing – mostly middle income – countries [22–25]. With the exception of Cui et al. [22] and Zhang et al. [26], which are estimated for daily intervals, these analyses are focused on the average response of monthly consumption to various measures of temperature during the month. For daily estimates from 723 households in Zhejiang Province, China, there is strong evidence of the $U$ observed in other studies, even for rural households without air conditioners [22]. For households in a northwest province in China, urban households follow the $U$, but electricity consumption increases with temperature for rural households [26]. With billing data, electricity increases at moderate to high temperatures for 7,000 households across China [25], increases with temperature for households in Anhui province, China [24], and follows a range of possibilities (including flat, increasing and $U$) depending on the area in Delhi from which the data are collected [23].

As the above highlights, there is a literature examining temperature effects in developing countries; however, that literature does not find consistent results, presumably due to differing features of the locations under consideration. A fair share of the literature focuses on China, primarily within developed areas of the country, although there are studies from Brazil and India, as well as South Africa. Of the two studies examining South Africa, one focuses its attention on Sandton [21], one of the wealthiest areas of the country, while the other uses data aggregated for the entire domestic sector each day [17]. Thus, there is a need for further developing country studies, as well as studies examining different subsets of the population.

Our study contributes to the literature through its examination of rural households in South Africa that are more representative of the population of the country, as well as more recent data, than is available from previous South African studies. The detailed, high-resolution micro data capturing household hourly electricity usage across larger geographic areas allows for a better understanding of temperature responses in a developing context. Furthermore, the meter and temperature data is merged with household survey data, allowing for an analysis of temperature response heterogeneity, which has received less attention in the broader literature. Our results are unusual, with respect to the literature: we find increasing electricity consumption at very low temperatures (below 0 °C), as well as very weak evidence that the negative relationship might be starting to reverse at very high temperatures (34 °C and up); there is a mostly negative relationship in-between. This relationship is robust to the inclusion of a variety of fixed effects, as well as other differences across households.

## 2. Data

### 2.1. Hourly electricity usage data

The hourly electricity consumption data are sourced from the South Africa Domestic Electrical Load (DEL) study, which was conducted from 1994 until 2014, although we limit our attention to 2014, incorporating just over three million hourly observations. Although the data is approximately 10 years old, similar data covering similar households is, unfortunately, not available. Despite that, economic growth in South Africa since 2014 has been between 0 and 2% per annum, not counting the COVID recession (−6%) and recovery (+4.7%). To place that into context, real gross domestic product (GDP) per capita stood at USD 6,965 for 2014, falling to USD 6253 by the end of 2023.[1] Thus, despite the time elapsed, the types of households under consideration for this analysis are likely quite similar to households that might be considered with more recent data.

DEL aimed to inform South Africa's electrification strategy, providing inputs towards policy development and technical design guidelines for domestic electricity distribution [27]. Over the twenty years, the programme collected electricity meter readings and conducted an annual socio-demographic survey of metered households throughout South Africa. Therefore, DEL contains domestic hourly electricity meter data [28] and household survey data [29] for each year. The meter data can be merged with the household survey data via household identifiers.

Geographically, DEL included twelve different sites across seven provinces in 2014 inclusive of inland and coastal regions; see Fig. 1. Given the different locations, and, therefore, differences in climatic conditions, differences in the relationship between temperature and residential electricity consumption are likely. Unfortunately, DEL did not capture price information. However, all surveyed and metered households were supplied directly by Eskom, whose tariff follows a standard two-block structure with a threshold at 350 kWh per month — price increases happen once per year as per the regulator's approval. For our data, that increase occurred on April 1. It was near 6% for households whose monthly consumption was no more than 350 kWh and 8%, for those whose monthly consumption was higher than 350 kWh [30]. According to Auffhammer [5], price responses are negligible, when estimating the effect of temperature on energy demand. Furthermore, our modelling approach includes monthly fixed effects, which should capture within-month time invariant factors affecting electricity consumption. Given that prices are fixed (for each block level) in the months before April and fixed at different levels in the months after, we do not consider price effects in the analysis. Previous hourly temperature-electricity consumption research in the country has also ignored price [21].

The hourly metering dataset contains the current readings in Amperes (A) aggregated over a 60 min interval defined to start daily at 00:00:00 - 00:59:59. We convert the current (A) readings to energy usage (kWh) using a default value 230 voltage (V) for residential customers: $x_t$ A $\times \frac{230}{1000}$ V $\times$ 1 h $=$ $y_t$ kWh, where $x_t$ refers to the aggregate hourly current readings in the data, and $y_t$ is the electricity consumption in kWh for hour $t$, with $t = 0, \ldots, 23$.[2] When extracting the hourly consumption, observations with missing/invalid meter readings were removed. The data also includes valid meter readings of 0 kWh, which is true for 11.4% of the hourly readings. Since these are valid readings, we keep them for the empirical analysis, although we do consider the sensitivity of the analysis to their exclusion. Most of

[1] See https://www.macrotrends.net/global-metrics/countries/ZAF/south-africa/gdp-growth-rate for these summary statistics, which was accessed on 25 November 2024.

[2] We assume voltage to be consistent at 230, instead of using real readings, because the original DEL datasets are not available for public use. Power quality could vary across households and may not always be stable [28]. However, it is technically crucial to maintain a stable voltage in power supply. Hence, one should not expect large fluctuation in the measured voltage, because large fluctuations would damage appliances and cause other unexpected accidents. In terms of data analysis, the worry that wattage calculations could be "measured with error" is not expected to affect the results, because random measurement error in the dependent variable does not bias estimation.

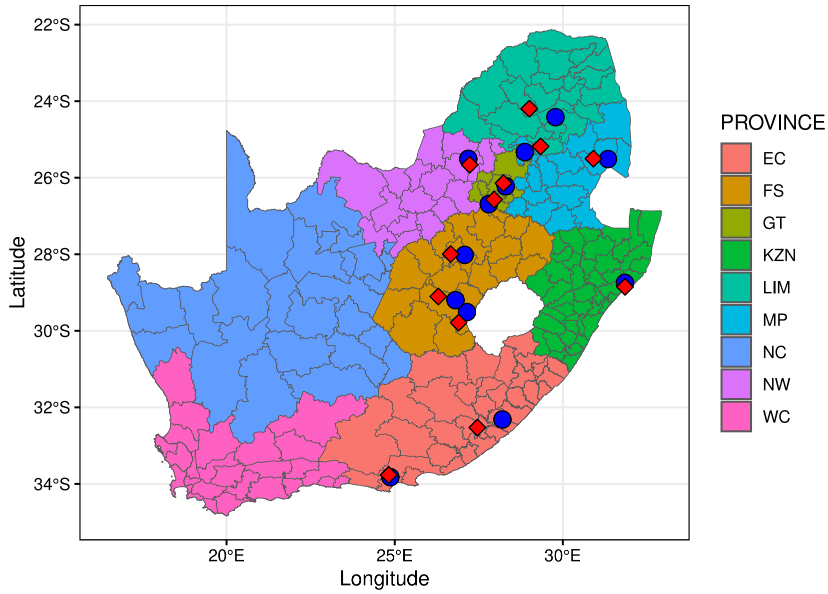


**Fig. 1.** Locations of the data collection sites (circle in blue) and matched weather stations (diamond in red).

the households from which data was collected were equipped with 20 A circuit box; there were nine exceptions, six had 60 A and three 80 A circuits. In order to concentrate on the electricity consumption behaviour of the majority group, we remove these nine households. We also remove the outliers with hourly usage more than 4.6 kWh (230 V × 20 A = 4.6 kWh) because that is the maximum load for the circuit box with size 20 A. Eventually, we are left with 3,358,301 hourly observations from 611 households.

### 2.2. Temperature data

To examine the responsiveness of electricity consumption to temperature, we merged the hourly load with hourly temperature data. Temperature data for the period 1 January to 31 August, 2014, was sourced from the South Africa Weather Service (SAWS). We calculated the centroid distance between each survey site and any South African weather station in the neighbourhood, assigning the temperature of the closest weather station for that survey site. However, SAWS data is not complete. For our study period, there are 5,832 total hours ($= 24 \times (31 \times 5 + 30 \times 2 + 28)$), therefore, there should be 69,984 ($= 5832 \times 12$) hourly temperature records; however, 0.9% of these temperature values (576 out of 69,984) are missing. We linearly interpolated the missing hourly values using the `imputeTS` package [31] in R [32]. When comparing the temperature data before and after imputation, we find that the mean, minimum and maximum values are quite close, suggesting that our imputation does not alter the distribution of temperature in any meaningful way; details available upon request.

Table 1 presents descriptive statistics of hourly electricity consumption and temperature for our data. As previously noted, South Africa has mild weather; our data's average temperature is 17 °C, which is slightly lower than the average for the country from 1960 to 2003. DEL covered January to August, or two typical seasons in the country: mild summer and early fall weather (January–April), as well as late fall and winter months (May–August), but did not include additional spring and early summer weather (September–December); thus, one would expect our merged temperature data to be lower than the country average. In terms of electricity consumption, average hourly electricity usage is 0.5 kWh, approximately one-quarter of the usage in Sandton [21], which is explained at least in part by the differences in economic prosperity between Sandton and the regions incorporated by DEL. We also see disparities in electricity usage across locations. For instance, the average is 0.19 kWh in Dipelaneng vs 0.8 kWh in Wattville (summaries not presented, but available upon request).

### 2.3. Household survey data

To extract household characteristics and some variables related to energy consumption, we match meter data and survey data by household identifiers. The 2014 DEL household survey was conducted between and including May and August, winter time in the country. In case of access difficulties, efforts were undertaken to improve access to households. Where possible, the household head was asked to respond, although other residents might have responded. Survey enumerators were instructed to obtain at least an 80% response rate within a particular location (suburb or settlement). Therefore, locations would be revisited until the target was reached; some homes were revisited up to 3 times. The data is not designed to be nationally representative, therefore, weights are not supplied [29]. In DEL, monthly income was inflated by the consumer price index (CPI) [27]; however, exact income values are not relevant for the analysis. As we discuss below, because the survey was completed once, there is no time varying information to include in the analysis; thus, we rely on household fixed effects to address household level heterogeneity, although we do group households into high and low income groups to examine the potential for income heterogeneity in temperature response behaviour.

Table 2 presents descriptive statistics of selected variables. It shows that average monthly household income is ZAR 5,591; when multiplied by 12 we find an annual average of ZAR 67,092. The DEL households are, on average, poorer than the average South African household (ZAR 138,168) in 2014 (ZAR 10.58 = 1 USD, April 1, 2014). The rural households in our sample are also poorer than the average rural South African household (R84,897); both comparisons are based on the Living Conditions Survey (LCS) 2014/2015 [33]. The households live in relatively small dwellings, with a mean floor area of 78.5 $m^2$. As can be seen in Table 2 appliance ownership is not extensive. Most households own a refrigerator, kettle and TV, while roughly half of

**Table 1**
Descriptive statistics of hourly electricity consumption and temperature.

| | Mean | St. dev. | Min | Median | Max |
|---|---|---|---|---|---|
| Temperature (°C) | 16.99 | 7.52 | −9.1 | 17.60 | 41.1 |
| Hourly electricity consumption (kWh) | 0.49 | 0.61 | 0.0 | 0.28 | 4.6 |

*Note:* Number of observations: 3,358,301.

**Table 2**
Descriptive statistics: households characteristics and appliance ownership ($N = 611$).

| Statistic | Mean | St. dev. | Min | Max |
|---|---|---|---|---|
| Monthly household income (ZAR) | 5,590.99 | 7,108.36 | 0.00 | 54,000.00 |
| Floor area ($m^2$) | 78.50 | 52.32 | 9 | 539 |
| Household size | 3.48 | 2.12 | 1 | 12 |
| Number of children (<16 years old) | 1.25 | 1.37 | 0 | 7 |
| Number of adults | 2.23 | 1.20 | 1 | 7 |
| Stove with oven (3-plate/4-plate) | 0.55 | 0.50 | 0 | 1 |
| Fridge/freezer | 0.84 | 0.36 | 0 | 1 |
| Geyser (electric water heater) | 0.16 | 0.36 | 0 | 1 |
| Heater | 0.17 | 0.38 | 0 | 1 |
| Hotplate | 0.42 | 0.49 | 0 | 1 |
| Iron | 0.42 | 0.49 | 0 | 1 |
| Kettle | 0.86 | 0.35 | 0 | 1 |
| Microwave oven | 0.55 | 0.50 | 0 | 1 |
| TV (television) | 0.78 | 0.42 | 0 | 1 |
| Washing machine | 0.39 | 0.49 | 0 | 1 |

*Notes*: With respect to appliance ownership, the participants had been requested to indicate the number of appliances in their home in the survey. In this table we present the percentage of households having one or more of each appliance in their homes.

the households have electric cooking (3-plate or 4-plate stove, or microwave oven).[3] However, only 16% of surveyed households own a geyser (electric water heater), indicating that few heat large quantities of water using electricity, despite the fact that water heating contributes approximately 30% of South African households' energy consumption [34].

All data processing, analysis and reporting are undertaken using R [32], as well as many user-written packages that have helped with the process. These packages include: `tidyverse` [35], `lubridate` [36], `haven` [37] and `readxl` [38] for reading and manipulating the data. We also apply reproducible methods, knitting our code and manuscript via `rmarkdown` [39] and `knitr` [40,41]; furthermore tables are built and presented using `stargazer` [42] and `kableExtra` [43], while figures are prepared and illustrated using `ggplot2` [44]. We impute missing temperature data via `imputeTS` [31] and run our fixed effects regression models with `plm` [45]. All code is available from the authors, upon request, and the data is publicly available.

## 3. Method

To estimate the effect of outdoor temperature on household hourly electricity consumption, we specify a panel regression model that is satiated in the temperature dimension, via dummy variables representing (nearly) every 1 °C observed in the SAWS data. The baseline empirical modelling assumption is that the effects of temperature on electricity consumption can be identified from the random variation in temperature over time. Our approach is consistent with previous studies, for example, Auffhammer [5], Berkouwer [21], and Alberini et al. [3]. Each of these studies assumes that the temperature variable is exogenous, conditional on a variety of fixed effects.

One concern that arises when modelling household or individual behaviour is the potential for endogeneity. For this analysis, endogeneity bias in our energy-temperature gradient would arise when unobserved information is correlated with both temperature and electricity consumption. Although temperature is exogenously given – households are not able to control the weather – endogeneity may still arise, since family behaviour may be related to weather. For example, if temperatures are generally lower at night compared to daytime, families might use blankets rather than heaters. On the other hand, families with greater resources might own appliances that offer them respite from cold or hot temperatures. As implied above, we address these concerns primarily through fixed effects, although we also consider the sensitivity of our results to the underlying fixed effects assumptions.

The standard approach to addressing unobserved family behaviour in a panel model is through family fixed effects. As shown in numerous textbooks (Wooldridge [46] for example) the inclusion of fixed effects eliminates any endogeneity bias arising from unobserved time-invariant family characteristics. Given that the dataset is captured over an eight-month period, it is reasonable to assume that demographics, housing conditions, income and ownership of electric appliances, amongst others, has not changed much. Thus, we will treat them as constant, or time-invariant. In the model, $\alpha_i$ controls for these factors, and, therefore, we do not include appliance ownership, income or housing conditions in the model. Furthermore, the household data is only available at one point in time; thus, we do not have multiple observations of the household to include. Despite this limitation, we are able to split the analysis by household type – comparing households with different levels of income and different appliance ownership structures, for example – to examine how sensitive our results are to the family fixed effects assumption.

Given that temperatures also vary over time, endogeneity bias could arise if controls for time were not included in the analysis. Thus, our analysis includes further fixed effects for hour of the day, day of the week, month of the year, and night-time. The hour of the day fixed effects assume that within any hour, there is a constant energy consumption component. For example, we are likely to observe fairly similar load patterns from day-to-day at any particular time, but peak and off-peak usage is different [47]. In terms of our model, see below equation, household energy consumption behaviour differs by hour of the day ($\beta_t$), day of the week ($\gamma_d$), month of the year ($\lambda_m$), and even

[3] The survey captured the number of 3-plate or 4-plate stoves for each household, but it is not clear if it is a gas or electric stove.

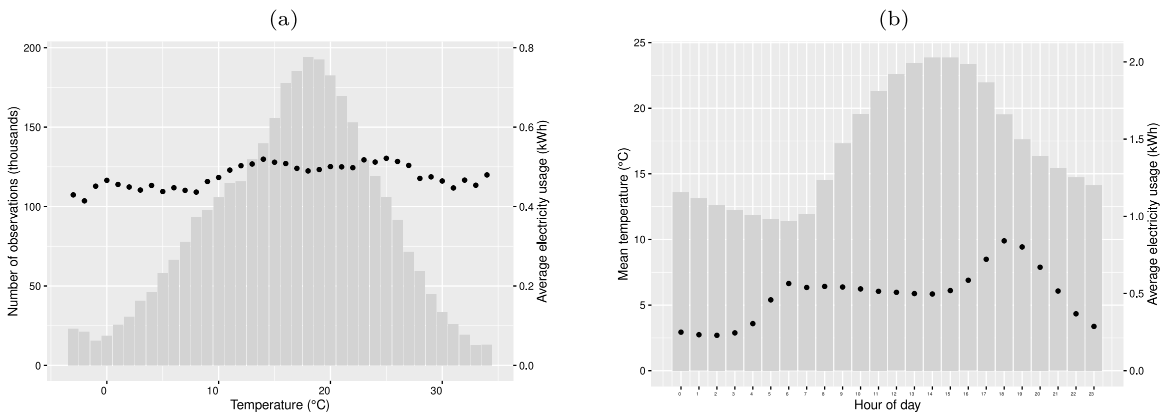


**Fig. 2.** Hourly temperature (bar) and electricity consumption (dots) distributions.

at night relative to the day ($\tau$).[4] Our final fixed effect ($\xi_s$) captures differences in electricity usage patterns by region that might arise from unobservable, but constant, differences in access to alternative fuels, overall climate, or culture, for example.

When all of the above is put together, the core relationship between temperature and hourly electricity load is shown by Eq. (1):

$$y_{itdms} = \sum_{j=1}^{38} \delta_j T_{tsj} + \alpha_i + \beta_t + \gamma_d + \lambda_m + \xi_s + \tau \cdot night.time_t + \epsilon_{itdms}, \quad (1)$$

where $y_{itdms}$ is household $i$'s electricity consumption in kWh for hour $t$, day of the week $d$, month of the year $m$, at site $s$. Standard errors are clustered at the household level and $\epsilon_{itdms}$ is the error term. Error terms could also be spatially correlated, because similar households are likely to live near each other, and serially correlated. To account for both spatial correlation and autocorrelation of the error terms, we also estimate standard errors clustered by household, week and region. Doing so does not change the energy-temperature gradient.

Hourly temperatures are assigned to one of 38 temperature bins. Nearly every temperature bin has a width of 1 °C; each temperature dummy is defined as $T_{tsj} = 1$, when the temperature falls in bin $j$ at hour $t$ at site $s$. Due to limited observations in the tails, our bins capture some combined temperature data, as well as single point temperatures. Specifically, we combined temperatures below −3 °C, temperatures between −3 °C and −1 °C, and temperatures above 34 °C, but used every single degree in between, $\{-1, 0, \dots, 34\}$.[5] Given our modelling assumptions, each coefficient $\delta_j$ can be interpreted as the causal effect on household electricity consumption in one hour at each temperature relative to the 29–30 °C bin, which is excluded from the regression.

[4] Initially, we calculate the sunrise and sunset times for each day and location, according to the latitude and longitude of each survey site. We use the hour and minutes associated with sunrise and sunset to compare with the relevant metering hours. Because we only have hour information for the meter data, we calculate an hour ratio — minutes before/after sunrise/sunset over 60, labelling that hour as a night-time hour, if the ratio is no less than one-half. For example, hour $t = 6$ on 21 June 2014 relates to sunrise, which occurs at 06:42am. Thus, it is 42 min before sunrise occurs, yielding an hour ratio of 0.7 ($42/60 = 0.7$); therefore, hour ($t = 6$) occurs at night.

[5] Although extreme temperature data is not common in the data – see Fig. 2(a) – we undertake a sensitivity analysis that includes every single degree temperature bin, rather than combining temperature bins at the top and bottom of the temperature distribution. Results are available upon request.

In further sensitivity analysis, we examine whether there are dynamic temperature effects, as in Eq. (2):

$$y_{itdms} = \sum_{j=1}^{38} \delta_j T_{tsj} + \sum_{\ell=1}^{L} \sum_{j=1}^{38} \phi_{\ell,j} T_{t-\ell,sj} + \alpha_i + \beta_t + \gamma_d + \lambda_m + \xi_s + \tau \cdot night.time_t + \epsilon_{itdms}, \quad (2)$$

where $\phi_{\ell,j}$ captures the bin-specific lagged temperature component, and $\ell$ captures the number of lags. In total, we consider models with $\ell = \{1, 2, 3, 4\}$, to capture up to four hours delay in the energy-temperature gradient; [48] and [49] also consider lag models. If the lagged temperature is only minimally correlated with the current hour's temperature as expected, the dynamic component will not affect the main results. Although there is no doubt of the first correlation – temperature follows a fairly consistent pattern during a 24-h period – the second correlation is not entirely obvious, given that we have already incorporated hour of day fixed effects, which should capture unobserved correlations through time. Our results, below, suggest the dynamic effects are negligible.

## 4. Results and discussion

We begin by examining the basic binary relationship, but then extend this to the multivariate analyses discussed in the methods section.

### 4.1. Temperature and electricity load

At the outset, we highlight a few underlying features of the temperature and electricity consumption data that are relevant for the analysis. First, we illustrate the temperature distribution across the temperature bins, alongside average electricity consumption within each temperature bin; see Fig. 2. Fig. 2(a) includes a temperature histogram, suggesting that temperature is unimodal and negatively skewed. The illustration matches expectations, given that South Africa's weather is mild and cold weather is not observed often. In the same panel, the dots represent average electricity consumption per temperature bin, the gradient to which appears relatively flat, or at least not obviously monotonic. As we show below, the estimated temperature-electricity gradient is not monotonic, regardless of the model estimated.

Second, we illustrate the average hourly temperature, along with average hourly electricity use. See Fig. 2(b) for details. The coldest temperatures occur around 6:00, while the warmest occur at 14:00–15:00, on average. Electricity usage in the morning is also highest, on average, at 6:00. From this point, average electricity consumption

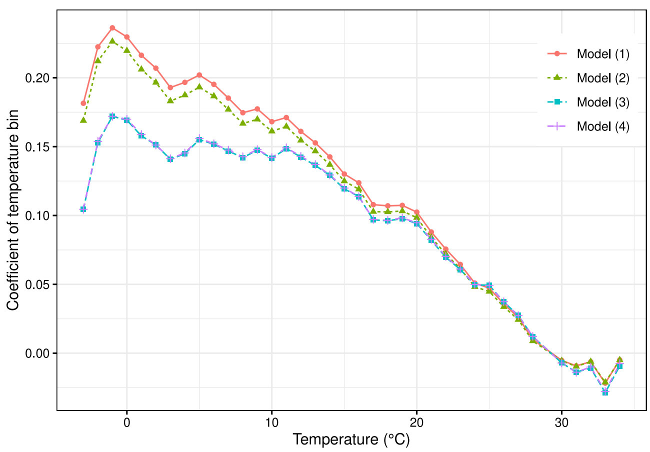


**Fig. 3.** Temperature effect comparison across models. Note: Model (1) controls for temperature, household and hour fixed effects; Model (2) adds in night-time fixed effects, while Model (3) adds month of year fixed effects. Model (4) adds day of week and location fixed effects.

tapers off; as temperatures rise to their peak, electricity consumption is fairly steady. Average hourly consumption peaks around 18:00, well after temperature begins to fall. The relatively low average consumption at night offers some support for the inclusion of night-time fixed effects in our model; the hourly usage pattern, which does not match any obvious functional form supports the inclusion of hourly fixed effects. Both figures are in agreement that, on average, there is no obvious relationship between temperature and energy consumption. The relationship appears to be fairly flat, although there is a suggestion that higher electricity usage occurs at moderate temperatures, as opposed to low or high temperatures. After controlling for a variety of fixed effects, and separating the analysis by household type, this general conclusion holds, although it is somewhat more nuanced.

### 4.2. Main results

We plot the main results in Fig. 3 and present the main coefficients in Table A.1; all estimates are based on versions of Eq. (1) with different sets of fixed effects. Model (1) is our initial model – see Table A.1 – and it contains temperature, household and hour of day fixed effects. Model (2) extends Model (1), including our night-time dummy. Model (3) extends Model (2) via month of year fixed effects. Finally, Model (4) includes day of week and location fixed effects as well as the rest; although not easily seen, its plot lies directly on top of the plot for Model (3). Rather than a $U-$ or $J-$shape temperature response, as is common in the developed world, we find an (asymmetric) inverted $U$ or $J$ across all models estimated: consumption is increasing at temperatures below 0 °C, relatively flat (maybe decreasing slightly) between 0° and 12 °C, and decreasing from there to about 30 °C.

Recall that the reference temperature is 29–30 °C; by definition, the reference category estimate is normalized to zero. Furthermore, recall our assumption that temperature is conditionally exogenous, given the included fixed effects. Therefore, we interpret the illustrated coefficients as the causal relationship between temperature and energy consumption (relative to the baseline temperature). The energy-temperature gradient is the observed slope. For Models (3) and (4), we see that average electricity consumption at 10 °C is approximately 0.15 kWh, while at 20 °C, it is approximately 0.1 kWh. Thus, over this range, temperature increases by 100% (10 °C to 20 °C), while electricity usage decreases by 33% (0.15 kWh to 0.1 kWh). In other words, the temperature-electricity elasticity over this temperature range is approximately one-third (negative): a 10% increase in temperature leads to a 3% decrease in electricity usage.

Fig. 3 also shows us that the inclusion of additional controls, specifically, the inclusion of the night-time fixed effect and month of year fixed effects, moving from Model (1) to (3) flattens the response curve at low to moderate temperatures (between 0° and 15 °C). However, day of week and location fixed effects, the move from Model (3) to (4), are found to be orthogonal to temperature and electricity consumption and do not change the estimated relationship or gradient. On the other hand, we also observe that the four curves align rather closely for temperatures above 20 °C. Thus, at moderate to high temperatures, we find a consistent response curve, regardless of the specified controls. Although the reason for this is not absolutely clear, it suggests that at these higher temperatures, other unobserved factors are no longer related to both temperature and electricity use. In other words, at these temperatures, electricity use is primarily determined by temperature, at least in our sample.

Estimates of the temperature effect in Fig. 3 suggest that at very low temperatures (<0 °C) an increase in the temperature leads to an increase in electricity consumption. As temperature goes up, at cool temperatures (0–10 °C), the relationship is fairly flat, suggesting that temperature has minimal effects on electricity consumption in that range. As temperatures rise from 10 °C, the relationship is negative. Finally, at very high temperatures (from 34 °C and above), there is a suggestion that increases in temperature are beginning to lead to increased electricity consumption. One should keep in mind, however, that there are fewer observations in our data at those temperatures and that the estimated coefficient is still negative.

### 4.3. Robustness

As assumed in the preceding results, the fixed effects are addressing unobserved variation that is correlated with temperature and electricity consumption; however, it is still possible that our results are not capturing everything that matters. Thus, we consider robustness of and potential heterogeneity in our results. When doing so, we focus only on Model (4), because it includes more fixed effects.

#### 4.3.1. Lagged temperature

We extend our model to allow for up to four temperature lags, as outlined in Eq. (2) and the associated discussion. At that point, we noted that the models included a number of fixed effects for time, while arguing that temperature is exogenously given; thus, we did not expect the inclusion of lagged temperature bins to alter the underlying energy-temperature relationship. As seen in Fig. 4, the results match our expectation. There is negligible evidence that the first lag changes the response curve between approximately 5 °C and 20 °C. However, there is no evidence that additional lags matter. The five curves nearly overlap each other at all points. In summary, lagged temperature is not an important feature of the energy-temperature gradient, at least in our sample of mainly rural households in South Africa.

#### 4.3.2. Heterogeneity

Unfortunately, the data does not offer more than one observation per household; thus, we are not able to include any observed time varying factors. Instead, in order to assess heterogeneity in the temperature-electricity gradient, we split the data by household type and day type. Thus, we compare the relationship for high vs low income (relative to the median reported income), appliance ownership (geyser or refrigerator or neither), as well as weekday vs weekend. Fig. 5 presents these comparisons. Given that lagged temperature does not matter, as shown previously, we do not include it in these models.

Fig. 5(a) contains the relationship and implied gradient for households, whose income is below the median, as well as those with greater than median income. Figs. 5(b) and 5(c) focus, instead, on differences in appliance ownership. The first thing to notice about these three

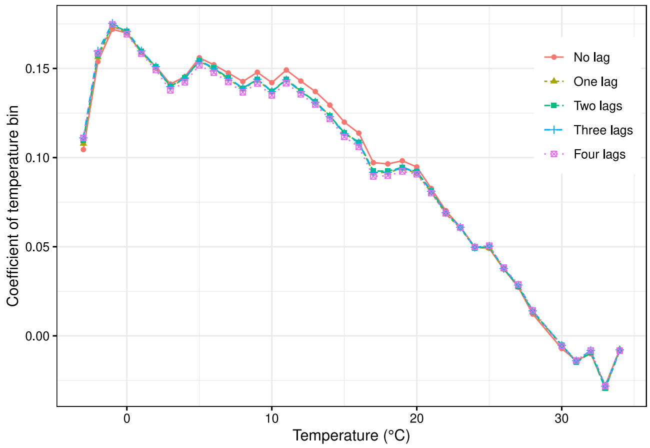


**Fig. 4.** Temperature effect including lagged temperature bins.

figures is that the overall patterns are (mostly) similar to the main estimates. We do find a $J$, although geyser owners are better described as following an inverse $U$. Although not identical, the low income, non-refrigerator and non-geyser increase their energy consumption up to about 0 °C, but have decreasing consumption from there to about 33 °C. The high income and refrigerator owning households are also similar to each other. Their energy consumption increases up to about −1 °C, decreases marginally between −1 °C and 11–12 °C, before decreasing more abruptly until 33 °C. Across these curves, it is also clear that there is an overall flattening of the response curve for those in disadvantaged economic circumstances (less income, no refrigerator and/or geyser) compared to those in advantaged economic circumstances. The implied lower income (socio-economic circumstances) elasticity of electricity consumption is not surprising, although Koch et al. [47] suggests a fairly constant income elasticity for these same households, possibly because they focus on peak hour consumption, considering neither temperature nor off-peak electricity consumption.

The final figure to consider is Fig. 5(d), which illustrates the response curve and implied gradient for weekend days compared to weekdays. The primary difference between these two is that the weekend day response curve is relatively flatter at moderate temperatures (up to about 20 °C), but steeper at temperatures above. Despite the fact that there are differences between all the curves, suggesting that the initial model did not entirely account for all feature of the energy-temperature gradient, these results remain fairly consistent with what we learned initially.

#### 4.3.3. Zeroes

Fig. 6 depicts our final set of robustness checks, focusing on whether or not the inclusion of zeroes matters, as well as whether the underlying assumed functional form matters. According to the DEL documentation, all zeroes included in the data are actual 0 readings, meaning that no electricity was used. Thus, for all of the preceding analysis, we included those observations. However, doing so, ignored the practical reality that electricity consumption can never be negative — it is bounded. Although one could estimate a Poisson model for bounded data, we chose, instead, to drop the zeroes and see whether doing so affected the main results or whether estimating the model on the natural log of electricity consumption affected the main conclusions.

For Fig. 6(a), the linear panel model, Model (4) with extensive fixed effects, is estimated on a subsample of the data that has excluded all the zero electricity consumption. Comparing Fig. 6(a) to Fig. 3, it is clear that the zeroes are not important enough to alter the relationship. On the other hand, the log-scaled dependent variable model implies a different interpretation. Each bin coefficient in the log model represents the percentage increase/decrease in energy consumption at that temperature bin, relative to the reference bin. Coefficient estimates from the log version are illustrated in Fig. 6(b). Given that the underlying scale of electricity consumption is fairly small and, as we have seen, fairly stable, it is not surprising to find that the (relative to reference) percentage changes are also small. In this figure, we see that the relative percentage changes in electricity consumption between 0 and 20 °C are all rather similar, which reflects the flat temperature response shown in Fig. 6(a).

### 4.4. Discussion

As should be expected, different households will have different needs, and temperature will affect those needs differently. More specifically, work, school and other activities will determine hourly and daily usage patterns that are likely to relate to temperature. For example, many of the dwelling-specific electricity demands related to preparing for work or school, will occur in the morning or evening, which tend to be cooler times of the day. Furthermore, many such activities occur at the same time of the day. On the other hand, in winter, mornings and evenings tend to be both darker and colder; such seasonal factors are expected to be more important in the lower temperature bands. Our analysis included a variety of fixed effects to capture some of these concerns. Incorporating those fixed effects led to robust results for the temperature-electricity gradient.

As highlighted in the analysis, the estimated gradient for our relatively poor rural households is positive at very low temperatures (<0 °C). This positive gradient is not driven entirely by geyser ownership. However, as we have shown, households that do have water heaters are different; their energy-temperature gradient is positive from very low temperatures up to about 11 °C, before decreasing. Thus, such ownership does influence the length of that positive slope. The most likely reason for this gradient amongst non-geyser owning households is that they are increasingly using their kettles to heat water, either for hot beverages or hot water bottles, the latter of which can be used to keep individuals warm.

The estimated gradient is fairly flat at cool temperatures (0–10 °C) and negative from 10 °C to 34 °C. The small response at temperature from 0–10 °C makes sense, given the fact that so few of our households have space heaters (17%) or water heaters (16%). Rural South African households do have access to traditional bio-fuels, especially firewood, for daily needs. For instance, more than 9% of South African households used wood for cooking, space heating and water heating, while the percentages are more than 20% for those households falling into the lowest expenditure decile [33]. Thus, at cool temperatures, rather than using electricity to keep warm, they are using alternative fuels, as well as additional layers, such as blankets. Our results are similar to those reported by [50], who uncovers both a small electricity response on cold days and minimal access to electric heating appliances in Mexican households.

Further, The negative gradient from 10 °C to 34 °C reflect lack of cooling appliances in our sampled households. As noted earlier, air conditioning penetration for the poorest South Africans is expected to remain below 4% out to 2050, despite global warming concerns [13].[6] Thus, our results are also consistent with a lack of behavioural response to high temperatures. Rather than trying to keep cool through cooling appliances; instead, individuals are likely taking advantage of shade, if they have access to it. The positive gradient at very high temperatures (from 34 °C and above) may result from the small number of

[6] Unfortunately, the survey did not capture information related to cooling appliances, such as air conditioners, however, the 20 A circuit box will limit the maximum electric load for each house. Thus, it is unlikely that many could own an air conditioner.

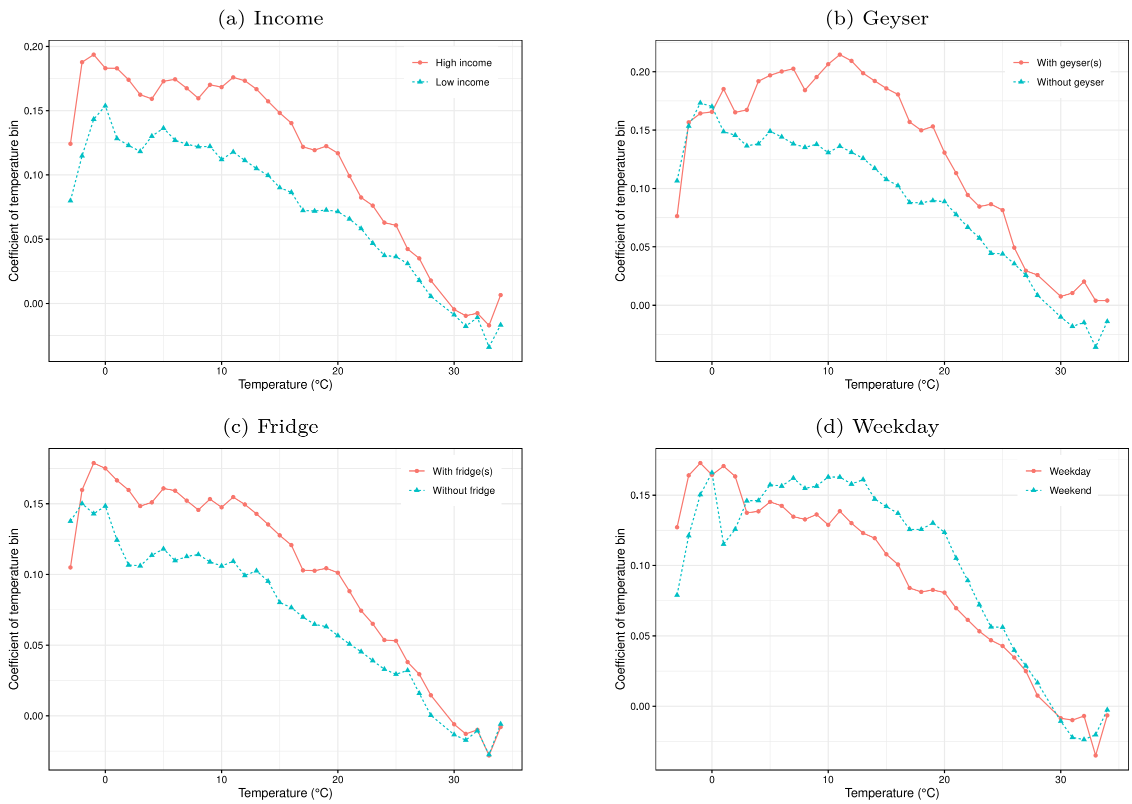


**Fig. 5.** Heterogeneity analysis.

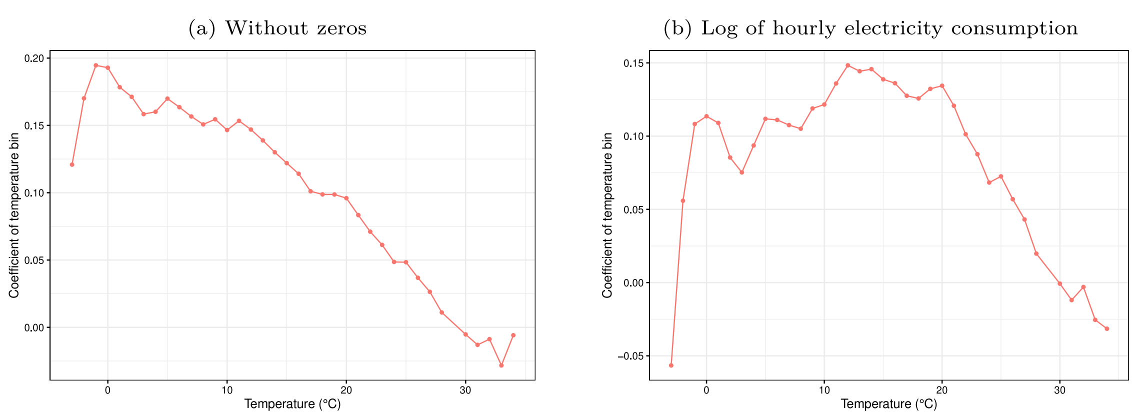


**Fig. 6.** Robustness checks.

observations within this temperature range. On the other hand, cooling appliances like fans (and air conditioning) for the few that might have are more likely to be used and for longer hours. Furthermore, refrigerators and/or freezers, of which a majority of households own at least one, become less efficient at higher temperatures, requiring more electricity consumption.

Overall, the energy-temperature response curve estimated for our rural households is flatter than the that estimated by Berkouwer [21], whose analysis is based on hourly meter data from a high-income group located in one district in South Africa, while our study included households from seven provinces of the country. Although [21] does not have income information from those households, according to the 2011 Census, at least 72% of the households in Sandton earned more than the average household in our sample. Furthermore, nearly 91% had a refrigerator and nearly 94% had a stove.[7] Given that Sandton households earn more and own more appliances, it is reasonable to

[7] https://www.statssa.gov.za/?page_id=4286&id=11304, accessed November 24, 2024.

expect a flatter response curve for our poorer households than those included in [21]; they simply do not have the resources to respond to the cold and heat through appliance usage.

On the other hand, the inverted $J$–shape that we find in most of our results is opposite that of much of the literature, including literature from the developed world [1,5,14–16], which finds a right-side up $U$ or $J$. With the exception of our findings, as well as [21] and [50], much of the developed country literature agrees with the developing country literature: electricity consumption is greater at lower and higher temperatures [17–20]; however, much of that literature is based on data aggregated to the day or even month. When the data is less aggregated, research in Italy [3], Ireland [4], some areas of Delhi [23] and one of the wealthiest suburbs in South Africa [21], is more similar: electricity consumption decreases with temperature, especially from relatively moderate temperatures. Alberini et al. [3] also find a small electricity response, when temperatures are low. Thus, our research offers further support to the notion that short-term (hourly) temperature responses are rather different from aggregated temperature responses. However, when it comes to managing electric loads and distribution more generally, understanding the short-term response is likely to be more important.

How should we think about the different response pattern that we see in our data, relative to what is observed in more developed countries? We examine this through a simple simulation. Specifically, we predict total electricity consumption for our sampled households, allowing for temperature to be 1 °C higher for each hour, compared to the actual recorded temperatures in the data. Our simulated response is based on the estimated coefficients at each hour. The results show that electricity consumption per household would have decreased from 2,693 kWh to 2,244 kWh, a decrease of approximately 17% of total electricity consumption per household. Although these results may not be expected, it should be recalled that very few individuals have access to cooling appliances; thus, such an increase in temperature will also relate to more difficulty keeping cool.

As noted earlier, although the survey included households from seven provinces (out of the nine provinces in the country), it was not designed to have national coverage, therefore, the data is not representative of the country. For this reason, the results should not be generalized to the entire country. Despite the fact that the number of households considered is small, just over 600, and they are mainly rural, there is very little previous research into the electricity consumption behaviour of relatively poor rural households in Africa or other places. Thus, despite concerns over representativity, the research does offer a perspective into households that has not received much attention in the energy-temperature response literature.

## 5. Conclusion

In this research, we provide estimates of the energy-temperature gradient for hourly household electricity consumption. The data for the analysis is taken from the South African Domestic Electric Load (DEL) study of 2014 [27], the most recent data available. DEL also contains a household survey module, which we used to examine heterogeneity in this gradient across different types of households. The DEL households are rather different from households examined in previous South African analysis, which was undertaken in one of the wealthiest districts of the country and did not have household information allowing for comparisons across household types [21]. In the end, our analysis included 611 households, covering January through August; thus, there are well over three million observations.

Our analysis was underpinned by a series of panel data models applying fixed effects to control for time invariant household behaviours, as well as time invariant location features. In addition, we included fixed effects for the hour of the day and day of the week to capture common features of domestic electric consumption. Finally, we included both month of year and night-time fixed effects to address month specific electricity consumption and relevant nightly patterns that are likely to be associated with the season, with winter being both colder and darker, on average, than other times of the year.

The main features of our results suggest, primarily, an inverse $J$ pattern, although some analysis was more suggestive of an inverse $U$. Thus, at very cold temperatures (below 0 °C), there is evidence of a positive gradient, such that electricity consumption rises as temperature rises. At cold temperatures (0–10 °C), the relationship is fairly constant. While from temperatures above 10 °C, increased temperature leads to decreased electricity consumption. These results are robust to different combinations of fixed effects, as well as potential heterogeneous responses by different types of households. Using our estimates, we evaluated the possible impact of future temperature changes on consumption patterns, assuming that the estimated gradient stays constant over time — plausibly because cooling appliance penetration rates are expected to stay low in Africa for the next few decades. According to our model, a 1 °C increase in temperature would lead to a reduction in total electricity consumption.

Our focus on mainly rural households is generally different than much of the developing country research that considers the temperature-electricity consumption gradient, although a negligible response at lower temperatures is observed in Mexico, where there is also a minimal stock of heating and cooling appliances [50]. When comparing to previous South African research, which considered one of the wealthiest areas of the country, the main difference is the slope at low temperatures: Berkouwer [21] finds a negative relationship between temperature and electricity consumption up to about 30 °C, while we find a negative slope mostly for temperatures above 10 °C. Finally, our estimated pattern is approximately the opposite (upside down) of what is observed in most developed countries. It is also the opposite of what is observed for analysis on data aggregated to the day or month, even for South Africa [17], where the gradient is generally estimated to be negative at low temperatures, somewhat flat at moderate temperatures, and positive at high temperatures. These differences highlight the importance of regional studies in order to develop an understanding of the potential global impact of climate change on energy consumption.

## CRediT authorship contribution statement

**Yuxiang Ye:** Writing – review & editing, Writing – original draft, Methodology, Data curation, Conceptualization. **Steven F. Koch:** Writing – review & editing, Writing – original draft, Methodology, Data curation, Conceptualization. **Xianming Ye:** Writing – review & editing, Writing – original draft, Methodology, Conceptualization.

## Declaration of competing interest

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

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## Appendix

Table A.1 contains the main estimates. Additional details are available from the authors upon request.

**Table A.1**
Coefficient estimates across temperature bins.

| | Model (1) | Model (2) | Model (3) | Model (4) |
|---|---|---|---|---|
| < −3 °C | 0.181*** (0.024) | 0.169*** (0.023) | 0.104*** (0.021) | 0.104*** (0.021) |
| −3 to −1 °C | 0.222*** (0.022) | 0.212*** (0.021) | 0.153*** (0.018) | 0.154*** (0.018) |
| −1–0 °C | 0.236*** (0.021) | 0.226*** (0.021) | 0.172*** (0.017) | 0.172*** (0.017) |
| 0–1 °C | 0.230*** (0.022) | 0.220*** (0.021) | 0.169*** (0.017) | 0.170*** (0.017) |
| 1–2 °C | 0.216*** (0.020) | 0.206*** (0.019) | 0.158*** (0.016) | 0.159*** (0.016) |
| 2–3 °C | 0.207*** (0.020) | 0.197*** (0.019) | 0.151*** (0.015) | 0.151*** (0.015) |
| 3–4 °C | 0.193*** (0.019) | 0.183*** (0.018) | 0.141*** (0.014) | 0.141*** (0.014) |
| 4–5 °C | 0.197*** (0.019) | 0.187*** (0.018) | 0.145*** (0.014) | 0.145*** (0.014) |
| 5–6 °C | 0.202*** (0.018) | 0.193*** (0.018) | 0.155*** (0.014) | 0.156*** (0.014) |
| 6–7 °C | 0.195*** (0.017) | 0.187*** (0.017) | 0.152*** (0.013) | 0.152*** (0.013) |
| 7–8 °C | 0.185*** (0.017) | 0.177*** (0.017) | 0.147*** (0.012) | 0.147*** (0.012) |
| 8–9 °C | 0.175*** (0.017) | 0.167*** (0.017) | 0.142*** (0.012) | 0.143*** (0.012) |
| 9–10 °C | 0.177*** (0.017) | 0.170*** (0.016) | 0.148*** (0.012) | 0.148*** (0.012) |
| 10–11 °C | 0.168*** (0.016) | 0.161*** (0.016) | 0.142*** (0.011) | 0.142*** (0.011) |
| 11–12 °C | 0.171*** (0.016) | 0.165*** (0.015) | 0.149*** (0.011) | 0.149*** (0.011) |
| 12–13 °C | 0.161*** (0.015) | 0.155*** (0.015) | 0.142*** (0.011) | 0.143*** (0.011) |
| 13–14 °C | 0.153*** (0.014) | 0.147*** (0.014) | 0.136*** (0.010) | 0.137*** (0.010) |
| 14–15 °C | 0.143*** (0.014) | 0.137*** (0.013) | 0.129*** (0.010) | 0.129*** (0.010) |
| 15–16 °C | 0.130*** (0.013) | 0.125*** (0.012) | 0.119*** (0.009) | 0.120*** (0.009) |
| 16–17 °C | 0.124*** (0.012) | 0.119*** (0.012) | 0.114*** (0.009) | 0.114*** (0.009) |
| 17–18 °C | 0.108*** (0.011) | 0.103*** (0.011) | 0.097*** (0.009) | 0.097*** (0.009) |
| 18–19 °C | 0.107*** (0.011) | 0.103*** (0.011) | 0.096*** (0.009) | 0.096*** (0.009) |
| 19–20 °C | 0.107*** (0.010) | 0.103*** (0.010) | 0.098*** (0.008) | 0.098*** (0.008) |
| 20–21 °C | 0.102*** (0.009) | 0.098*** (0.009) | 0.094*** (0.008) | 0.095*** (0.008) |
| 21–22 °C | 0.088*** (0.008) | 0.084*** (0.008) | 0.082*** (0.007) | 0.083*** (0.007) |
| 22–23 °C | 0.076*** (0.007) | 0.072*** (0.007) | 0.070*** (0.006) | 0.070*** (0.006) |
| 23–24 °C | 0.064*** (0.006) | 0.061*** (0.006) | 0.061*** (0.006) | 0.061*** (0.006) |
| 24–25 °C | 0.051*** (0.006) | 0.048*** (0.005) | 0.050*** (0.005) | 0.050*** (0.005) |
| 25–26 °C | 0.047*** (0.005) | 0.045*** (0.005) | 0.049*** (0.005) | 0.049*** (0.005) |
| 26–27 °C | 0.036*** (0.004) | 0.034*** (0.004) | 0.037*** (0.004) | 0.037*** (0.004) |
| 27–28 °C | 0.026*** (0.004) | 0.024*** (0.004) | 0.027*** (0.003) | 0.027*** (0.003) |
| 28–29 °C | 0.010*** (0.003) | 0.009*** (0.003) | 0.012*** (0.003) | 0.012*** (0.003) |
| 30–31 °C | −0.005 (0.003) | −0.006 (0.003) | −0.007** (0.003) | −0.007** (0.003) |
| 31–32 °C | −0.009** (0.004) | −0.010** (0.004) | −0.014*** (0.004) | −0.014*** (0.004) |
| 32–33 °C | −0.006 (0.006) | −0.006 (0.006) | −0.011* (0.006) | −0.010* (0.006) |
| 33–34 °C | −0.022*** (0.008) | −0.021*** (0.008) | −0.029*** (0.008) | −0.028*** (0.008) |
| >= 34 °C | −0.005 (0.010) | −0.005 (0.010) | −0.009 (0.009) | −0.008 (0.009) |
| Night time | | 0.049*** (0.006) | 0.056*** (0.005) | 0.056*** (0.005) |
| HH FE | Yes | Yes | Yes | Yes |
| Hour FE | Yes | Yes | Yes | Yes |
| Month FE | No | No | Yes | Yes |
| Day of week FE | No | No | No | Yes |
| Location FE | No | No | No | Yes |
| Observations | 3,358,301 | 3,358,301 | 3,358,301 | 3,358,301 |

Estimation based on various versions of Eq. (1). Dependent variable is hourly electricity usage in kWh. The temperature bin 29–30 °C is the reference bin. Model (1) contains temperature, household and hour of day fixed effects. Model (2) adds the night-time dummy. Model (3) adds month of year fixed effects. Model (4) includes day of week and location fixed effects as well as the rest. Standard errors have been clustered at household level.
* $p < 0.1$.
** $p < 0.05$.
*** $p < 0.01$.

## Data availability

Data will be made available on request.

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