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

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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 12 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.

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


**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 12 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 (2011) 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 (Auffhammer and Mansur 2014; Alberini et al. 2019; Kang and Reiner 2022; Auffhammer 2022). For the most part, this research supports the supposition that rising temperatures will increase energy demand (Van Ruijven, De Cian, and Sue Wing 2019). 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 (A. C. Kruger and Shongwe 2004; A. Kruger and Sekele 2013) – global warming could lead to a 2°C average temperature increase over the next few decades and considerable climate change challenges for the country (World Bank 2021). South Africa is already facing electricity supply challenges associated with rolling blackouts (load-shedding to South Africans) that have negatively affected economic performance (Walsh, Theron, and Reeders 2021) and could worsen, especially, the rural-urban divide (Inglesi-Lotz 2023). 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 (2023) suggest 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. The data 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 (Statistics South Africa 2023). Admittedly, L. Davis et al. (2021) 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 [Deschênes and Greenstone (2011); auffhammer2011simulating; auffhammer2012erratum; auffhammer2022climate] or increased electricity bills and the potential for disconnections (Barreca, Park, and Stainier 2022). 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 M. Zhang et al. (2020). In other words, the literature from a wide range of countries points to a $U-$shape relationship 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 (Alberini et al. 2019), 4000 homes in Ireland (Kang and Reiner 2022) and nearly 6000 homes in one of the wealthiest regions of South Africa (Berkouwer 2020). Although Alberini et al. (2019) find support for increased electricity consumption, when temperatures rise, they find little evidence that it also rises when temperatures are low. Kang and Reiner (2022) find a negative relationship between consumption and temperature. Berkouwer (2020) uncovers a similar negative relationship, as well as some evidence of an increase at extremely high temperatures. Thus, with less aggregated data, the $U$ 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 (Cui, Xie, and Zheng 2023; Harish, Singh, and Tongia 2020; Li et al. 2023; S. Zhang et al. 2022). With the exception of Cui, Xie, and Zheng (2023) and G. Zhang, Shen, and Su (2023), 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 (Cui, Xie, and Zheng 2023). For households in a northwest province in China, urban households follow the $U$, but electricity consumption increases with temperature for rural households (G. Zhang, Shen, and Su 2023). With billing data, electricity increases at moderate to high temperatures for 7000 households across China (S. Zhang et al. 2022), increases with temperature for households in Anhui province, China (Li et al. 2023), and follows a range of possibilities (including flat, increasing and $U$) depending on the area in Delhi from which the data are collected (Harish, Singh, and Tongia 2020).

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 (Berkouwer 2020), one of the wealthiest areas of the country, while the other uses data aggregated for the entire domestic sector each day (Chikobvu and Sigauke 2013). 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 (-3 to 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 household income differences.

# 2 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. DEL aimed to inform South Africa's electrification strategy, providing inputs towards policy development and technical design guidelines for domestic electricity distribution (Toussaint 2020). 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 (Toussaint 2019a) and household survey data (Toussaint 2019b) for each year. The meter data can be merged with the household survey data by household identifier.

Geographically, DEL included twelve different sites across seven provinces in 2014 inclusive of inland and coastal regions; see Figure 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 350kWh 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 less than 350 kWh and 8%, otherwise (Eskom 2014). According to (Auffhammer 2022), 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 (Berkouwer 2020).

The hourly metering dataset contains the current readings in Amperes (A) aggregated over a 60 minute interval defined to start daily at 00:00:00 - 00:59:59. We convert the current (A) readings to energy usage

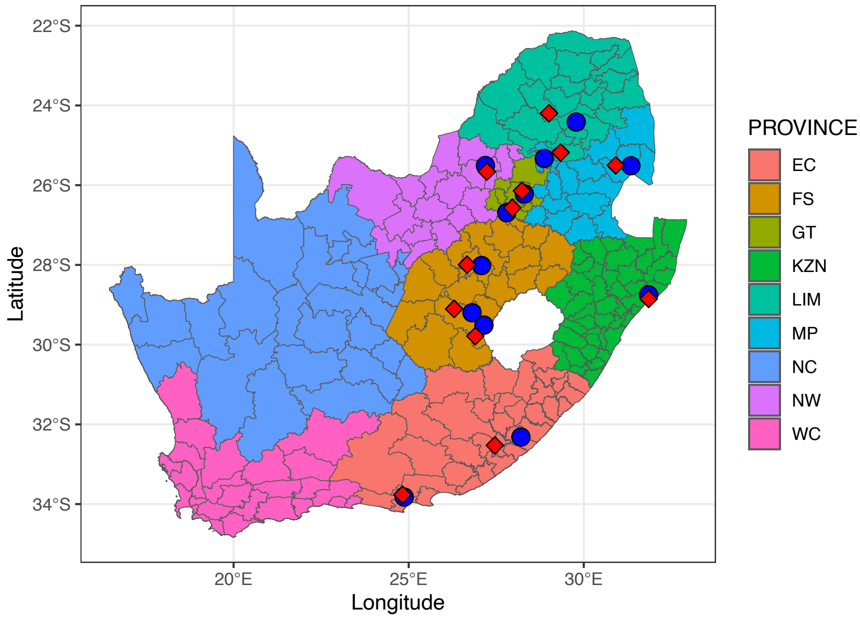


Figure 1: Locations of the data collection sites (circle in blue) and matched weather stations (diamond in red)

(kWh)[1]: $x_t$ A $\times \frac{230}{1000}$ V $\times$ 1 hour $= y_t$ 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 $t = 0, ..., 23$. When extracting the hourly consumption, observations with missing/invalid meter readings were removed (5.6%, 183057 out of 3294228 hourly readings). The data also includes valid meter readings of 0 kWh. This is true of 11.4% of the hourly readings. Since these are valid readings, we keep them for the empirical analysis. Eventually, we are left with 3375173 hourly observations from 613 households.

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 all 36 South African weather stations, assigning the temperature of the closest weather station for that survey site. However, SAWS data is not complete. For our study period, there are 5832 total hours ($= 24 \times (31 \times 5 + 30 \times 2 + 28)$), therefore, there should be 69984 ($= 5832 \times 12$) hourly temperature records; however, 0.9% of these temperature values (576 out of 69984) are missing. We linearly interpolated the missing hourly values using the `imputeTS` package (Moritz and Bartz-Beielstein 2017) in R (R Core Team 2024). 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.

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

[1]This calculation is an approximation of energy consumption, not the actual measured value. Power quality varied across households and the measured voltage was not always stable. For an accurate energy calculation the voltage readings from the original DEL dataset should be used @DELmeteringHourlyData. In this study we use a default value 230 voltage (V) instead of real readings.

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 (Toussaint 2019b). In DEL, monthly income was inflated by the consumer price index (CPI) (Toussaint 2020); 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.

All data processing, analysis and reporting are undertaken using R (R Core Team 2024), as well as many user-written packages that have helped with the process. These packages include: `tidyverse` (Wickham et al. 2019), `lubridate` (Grolemund and Wickham 2011), `haven` (Wickham, Miller, and Smith 2022) and `readxl` (Wickham and Bryan 2023) for reading and manipulating the data. We also apply reproducible methods, knitting our code and manuscript via `rmarkdown` (Xie, Dervieux, and Riederer 2020) and `knitr` (Xie 2014, 2015); furthermore tables are built and presented using `stargazer` (Hlavac 2022) and `kableExtra` (Zhu 2021), while figures are prepared and illustrated using `ggplot2` (Wickham 2016). We impute missing temperature data via `imputeTS` (Moritz and Bartz-Beielstein 2017) and run our fixed effects regression models with `plm` (Millo 2017). 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. Due to the fact that we have hourly data each day for approximately 8 months and 600 households, spread across 12 sites, we include fixed effects to capture: household heterogeneity; hourly heterogeneity; site location heterogeneity; monthly differences and day of the week differences. Standard errors are clustered at the household level and $\epsilon_{itdms}$ is the error term. The core relationship between temperature and hourly load is in equation (1):

$$y_{itdms} = \sum_{j=1}^{39} \delta_j T_{tsj} + \alpha_i + \beta_t + \gamma_d + \lambda_m + \xi_s + \tau \cdot night.time_t + \epsilon_{itdms}, \tag{1}$$

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 $s$. In this model, hourly temperatures are assigned to one of 39 temperature bins. Thus, we do not specify a functional form for the temperature effect. Nearly every temperature bin has a width of 1°C; each temperature dummy $T_{tsj} = 1$, 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 -4°C, temperatures between -2°C and -4°C, and temperatures above 34°C, but used every single degree in between, $\{-2, -1, \ldots, 34\}$. Each coefficient $\delta_j$ can be interpreted as the causal effect on household electricity consumption of one hour at each temperature bin relative to the 29-30°C bin, which is excluded from the regression.

In terms of fixed effects, $\alpha_i$ controls for time-invariant household characteristics, such as demographics, housing conditions and ownership of electric appliances that are assumed unchanged during the 8-month study period.[2] With hour of day fixed effects ($\beta_t$), we assume that a component of household electricity usage patterns are constant at each hour, but likely different across hours; for example, we are likely to observe fairly similar load patterns from day-to-day, but peak and off-peak usage is different Koch, Nkuna, and Ye (2024)]. We include day of week fixed effects ($\gamma_d$) to account for the likelihood that household consumption differs each day, or at least differs between week and weekend days. We include month of year fixed effects ($\lambda_m$) to address seasonal changes in terms of energy use, or at least household behaviour. In summer, households may spend more time outdoors, and, therefore, use less electricity; similarly, during the school term, households may need to use more electricity to support student study efforts. Our final fixed effect, $\xi_s$, captures differences in electricity usage patterns by region that might arise from differences in access to alternative fuels, overall climate, or culture, for example.

In addition to temperature and a series of fixed effects, we also include a night-time dummy variable, $night.time_t = 1$ if a larger share of hour $t$ happens at night as opposed to during the day. We include these night-time fixed effects to capture differences in usage between night and day that are distinguishable from the hour fixed effects. According to our data, the average night-time temperature is 13.8°C, which is much lower than average day-time temperature (20.1°C) – it also is darker and people are more likely to sleep at night – suggesting that there could very well be differences in usage related to night-time that are distinct from temperature effects. 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, there are 42 minutes of the hour, before sunrise occurs, yielding an hour ratio of 0.7 ($42/60 = 0.7$); therefore, hour ($t = 6$) occurs at night, according to our definition.

# 4 Results and discussion

We begin by describing the data, which includes standard descriptive statistics, as well as two simple bivariate analyses, separately examining the relationship of temperature to average daily electricity consumption and the relationship between temperature and average hourly electricity load. After the bivariate analyses, we discuss the full empirical model.

## 4.1 Descriptive statistics

The starting point for the analysis is the average hourly electricity consumption and temperature for our data, which is presented in Table 1. 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). In terms of electricity consumption, average hourly electricity

[2] The data is only collected once from each household. Thus, it is not possible to examine this assumption further.

usage is 0.5 kWh, approximately one-quarter of the usage in Sandton (Berkouwer 2020), 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, not presented.

Table 1: Descriptive statistics of hourly electricity consumption and temperature

| | Mean | St. Dev. | Min | Median | Max |
|---|---|---|---|---|---|
| Temperature (°C) | 16.99 | 7.51 | -9.1 | 17.60 | 41.10 |
| Hourly electricity consumption (kWh) | 0.50 | 0.64 | 0.0 | 0.28 | 10.71 |

*Note:*
Number of observations: 3375173

Table 2 presents descriptive statistics of selected variables. It shows that average monthly household income is ZAR 5588, and when multiplied by 12 yields an annual average of ZAR 67056. The DEL households are, on average, poorer than the average South African household (ZAR 138168) 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 (R84897); both comparisons are based on the Living Conditions Survey (LCS) 2014/2015 (Statistics South Africa 2017). The households live in relatively small dwellings, with a mean floor area of 78 $m^2$. As can be seen in Table 2 appliance ownership is not extensive. Most households own a refrigerator, kettle and TV, while roughly half of 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 electric water heating is approximately half of South African households' electricity consumption expenditure (Meyer 2000).

## 4.2 Temperature and electricity load

We extend the data discussion to 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. Please, see Figure 2. The histogram in the figure shows us that the temperature data is unimodal and negatively skewed, which matches expectations, given that South Africa's weather is mild and cold weather is not observed often. On the other hand, the dots in the figure 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 fixed effects that are included.

Second, we illustrate the average temperature over the course of the day, along with average electricity use, i.e., the electric load. See Figure 3 for details. Given that morning is amongst the coldest times of the day, it is not surprising that morning peak coincides with the coldest temperatures. However, the same inverse relationship is not observed in evening peak usage, which occurs at temperatures well above the minimum for the day. Following morning peak, electricity consumption tapers slightly, presumably, because fewer people are in the house during those times of the day. The small reduction in electricity usage during the day also coincides with relatively higher temperatures; thus, again, there is an indication of a strong negative

[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.

Table 2: Descriptive statistics: households characteristics and appliance ownership ($N = 613$).

| Statistic | Mean | St. Dev. | Min | Max |
|---|---|---|---|---|
| Monthly household income (ZAR) | 5,588.15 | 7,099.55 | 0.00 | 54,000.00 |
| Floor area ($m^2$) | 78.38 | 52.27 | 9 | 539 |
| Household size | 3.49 | 2.12 | 1 | 12 |
| Number of children (< 16 years old) | 1.25 | 1.37 | 0 | 7 |
| Number of adults | 2.24 | 1.21 | 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.

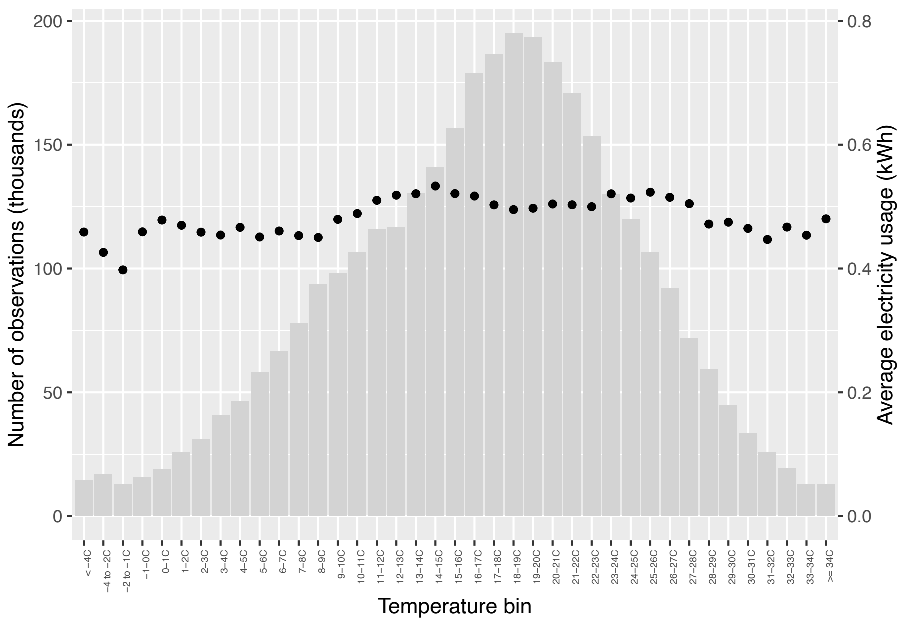


Figure 2: Observations (bars) and electricity consumption (dots) by temperature bin

relationship between electricity consumption and temperature. That negative relationship occurs during times with moderate to higher temperatures, on average. As we see below, that relationship (in moderate temperature regions) holds up in the empirical analysis, even after we control for electric load patterns and night-time, amongst other fixed effects.

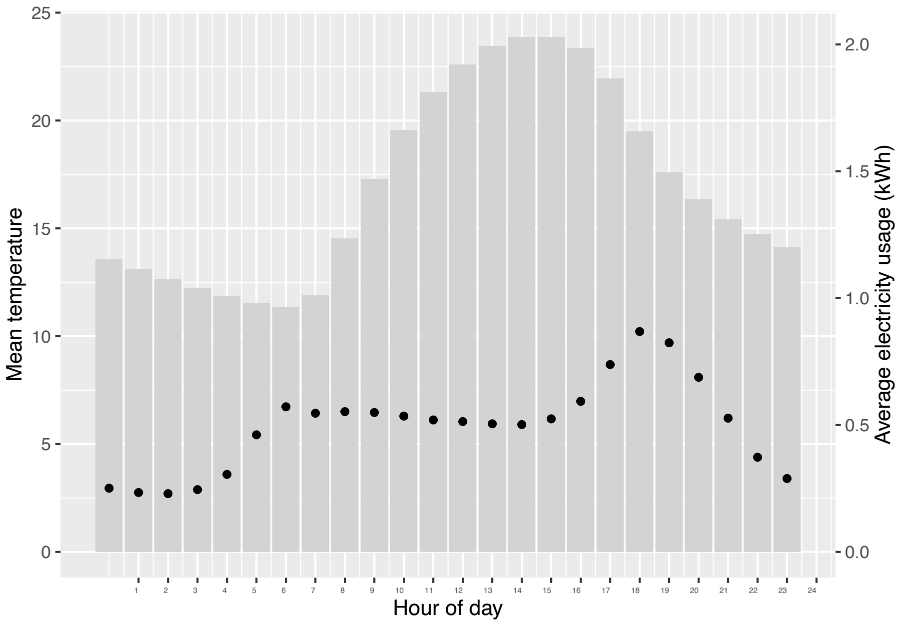


Figure 3: Hourly temperature (bars) and electricity consumption (dots) distributions

### 4.3 Main results

We plot the main results in Figure 4 and present the main coefficients in Table A1; all estimates are based on versions of equation (1) with different sets of fixed effects. Model (1) is our initial model – see Table A1 – 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 day of week and month of year fixed effects. Finally, Model (4), not illustrated, includes location fixed effects as well as the rest; it is not illustrated, because 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 inverted $U$ or $J$ across all models estimated.

Recalling that the reference temperature is 29-30°C, the appropriate interpretation of the illustrated (and presented) coefficients is that they represent the average increase in electricity consumption (in kWh) due to an increase/decrease in temperature relative to the reference temperature. Assuming that temperature is conditionally randomly assigned – i.e., not correlated with other unobserved information that also affects electricity consumption, conditional on the controls included – allows us to interpret these changes as being caused by temperature differences. The flattening of the temperature response curve at low to moderate temperatures suggests that the included fixed effects capture a number of temperature related unobserved factors. As suggested by the illustrations in Figure 4, the various fixed effects reduce the coefficients at, especially, lower temperatures.

Certainly, different households will have different needs, and temperature will affect those needs differently.

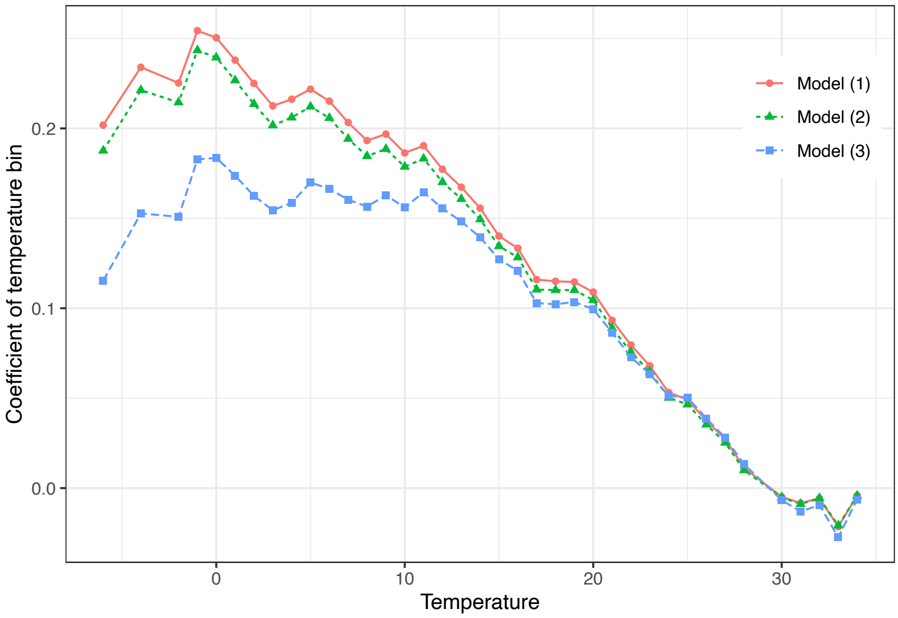


Figure 4: Temperature effect comparison across models. Model (1) controls for temperature, household and hour fixed effects; Model (2) adds in night-time fixed effects, while Model (3) adds day of week and month of year fixed effects. Model (4) adds location fixed effects; however, it is not shown, as the estimates lie on top of those for Model (3).

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. Yet, 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. During summer, the cooler temperatures along with extended periods of light allow individuals to spend more time outside and use less electricity. As expected, the fixed effects are addressing unobserved variation that is correlated with temperature and electricity consumption, and, therefore, our Model (3) results, because they include more fixed effects, are the preferred results.[4]

The temperature estimates for Model (3) suggest that at very low temperatures, an increase in the temperature leads to an increase in electricity consumption. At cool temperatures (0°- 10°C), however, 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, although 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, relative to the reference temperature (29-30°C), the estimated coefficient is still negative.

As noted, we observe a flattening of the response curve, due to the inclusion of the additional fixed effects. We also observe that the three curves align rather closely for temperatures above 20°C. Thus, at moderate

[4]As already noted Model (4) does include the most fixed effects, although the temperature response is not affected by the inclusion of the additional location fixed effects.

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.

In further analysis, we split the data according to income, such that the electricity-temperature relationship for those whose income is below the median (referred to as "low income") can be compared to the response for those whose income is above the median. Those results are illustrated in Figure 5. The results mirror what has been presented in Figure 4, i.e., an inverse $U$ or $J$. In addition, the illustration shows that, on average, there is a flatter temperature response for those in the low income group. Again, however, at moderate to high temperatures, we see that income, in addition to time of day, day of week and month of year, is not an important contributor to the response curve. Each of these results is consistent with what we learned initially about the temperature response for these 12 sites. Furthermore, the implied lower income elasticity of electricity is not surprising, although Koch, Nkuna, and Ye (2024) 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.

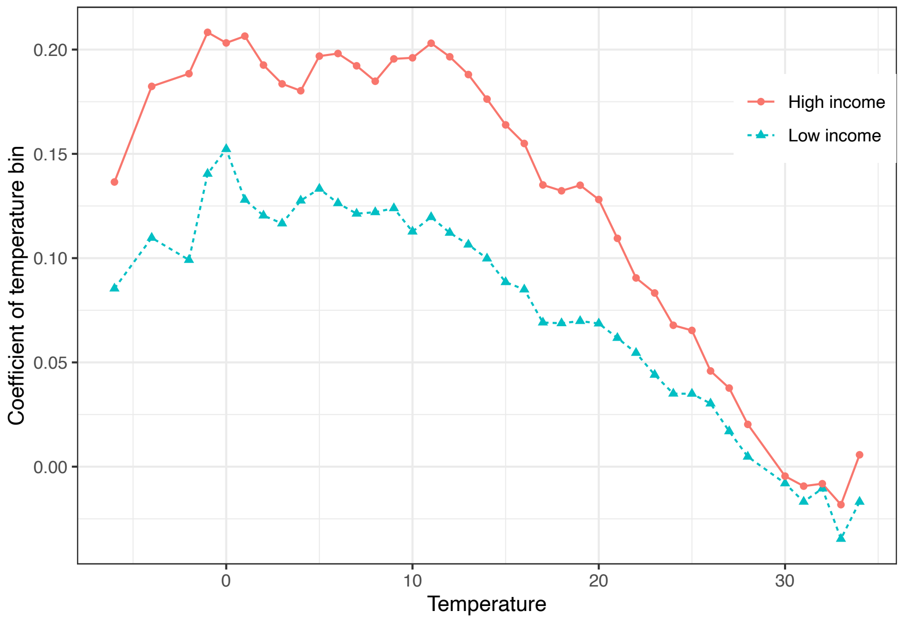


Figure 5: Temperature bin coefficients by income

## 4.4 Discussion

As highlighted above, the temperature response for our relatively poor rural households is fairly flat at low temperatures, and negative from moderate to high temperatures. The limited response at lower temperature 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 (Statistics South Africa 2017). Thus, 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 L. W. Davis and Gertler (2015), who indicate both a limited electricity response on cold days and a limited stock of electric heating appliances in Mexican households.

The low temperature response curve estimated for our rural households is flatter than the response estimated by (Berkouwer 2020). Berkouwer (2020) has hourly meter data for a high-income group from one district in South Africa, while our study included households from seven provinces of the country. Although Berkouwer (2020) 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[5]. Thus, it is clear that Sandton households earn more and own more appliances; thus, it is reasonable to expect a flatter response curve for our households than those included in Berkouwer (2020).

On the other hand, the inverted $U-$ or $J-$shape is opposite much of the literature, including that from the developed world Barreca, Park, and Stainier (2022), which finds a right-side up $U$ or $J$. With the exception of our findings, as well as Berkouwer (2020) and L. W. Davis and Gertler (2015), much of the developed country literature agrees with the developing country literature: electricity consumption is higher at lower and higher temperatures M. Zhang et al. (2020); 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 (Alberini et al. 2019), Ireland (Kang and Reiner 2022), some areas of Dehli (Harish, Singh, and Tongia 2020) and one of the wealthiest suburbs in South Africa (Berkouwer 2020), is more similar: electricity consumption decreases with temperature, especially from relatively moderate temperatures. Alberini et al. (2019) also find limited 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 average 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.

One concern that might arise from this analysis, is that the data is not representative of the entire population. 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 generalised to the entire country. Although the number of households considered is small, just over 600, and they are mainly rural, there is little previous research into the electricity consumption behaviour of relatively poor rural households. Thus, despite concerns over representativity, the research does offer a perspective into households that have not received much attention in the temperature response literature.

In addition to representation concerns, there are potential limitations, as well. For example, data was not collected on space cooling appliances, such as air conditioners. Thus, it was not possible to consider differences in the temperature responses across households that owned space cooling assets as well as space heating appliances, with those owning only space heaters and/or those owning no such appliances. However, given how few own space heaters, it is likely that even fewer households own air conditioners. As the previous discussion implies, there are additional ways to cut the data and undertake the analysis, including location-specific analysis, as well as asset-based analysis. Although those are limitations, we also view those as possibilities for future research.

[5] https://www.statssa.gov.za/?page_id=4286&id=11304

# 5 Conclusion

In this research, we provide estimates of the temperature gradient of household electricity consumption. The data for the analysis is taken from the South African Domestic Electric Load (DEL) study of 2014 (Toussaint 2020), the most recent data available. DEL also contains a household survey module, which we used to offer some comparison information with a previous South African analysis based in one of the wealthiest districts of the country (Berkouwer 2020). We also used that information to consider heterogeneity in the temperature response curve according to income level. We matched hourly temperature to each of the DEL sites, and, thus, to all households. In the end, our analysis included 613 households, covering January through August; thus, there are well over 3 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 the domestic electric load. Finally, we included both month of year and night-time fixed effects to address month specific electricity consumption, as well as relevant nightly patterns, 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 include an inverse $U$ or $J$ pattern. 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 income heterogeneity.

Our focus on mainly rural households is generally different than much of the developing country research to consider temperature effects of electricity consumption, although a negligible response at lower temperatures is observed in Mexico, where there is a limited stock of heating and appliances (L. W. Davis and Gertler 2015). When comparing to a similar previous South African study, which considered only Sandton, one of the wealthiest areas of the country, the main difference is the slope at low temperatures: Berkouwer (2020) finds a negative relationship between temperature and electricity consumption up to about 30°C, while we find a negative slope only for temperatures above 10°C. Finally, our estimated pattern is approximately the opposite of what is observed in most developed countries, as well as in the case of aggregated data, even for South Africa (Chikobvu and Sigauke 2013), 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.


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# Appendix

Table A1 contains the main estimates. Additional details are available from the authors upon request.

Table A1: Temperature bin coefficients

| | Model (1) | Model (2) | Model (3) | Model (4) |
|---|---|---|---|---|
| < -4C | 0.202*** (0.028) | 0.188*** (0.027) | 0.115*** (0.025) | 0.115*** (0.025) |
| -4 to -2C | 0.234*** (0.025) | 0.221*** (0.024) | 0.153*** (0.021) | 0.153*** (0.021) |
| -2 to -1C | 0.225*** (0.023) | 0.214*** (0.022) | 0.151*** (0.019) | 0.151*** (0.019) |
| -1-0C | 0.254*** (0.023) | 0.243*** (0.022) | 0.183*** (0.019) | 0.183*** (0.019) |
| 0-1C | 0.250*** (0.024) | 0.239*** (0.023) | 0.184*** (0.019) | 0.184*** (0.019) |
| 1-2C | 0.238*** (0.022) | 0.227*** (0.022) | 0.174*** (0.018) | 0.174*** (0.018) |
| 2-3C | 0.225*** (0.022) | 0.214*** (0.021) | 0.162*** (0.017) | 0.162*** (0.017) |
| 3-4C | 0.213*** (0.021) | 0.202*** (0.020) | 0.154*** (0.016) | 0.154*** (0.016) |
| 4-5C | 0.216*** (0.021) | 0.206*** (0.020) | 0.159*** (0.016) | 0.159*** (0.016) |
| 5-6C | 0.222*** (0.021) | 0.212*** (0.020) | 0.170*** (0.016) | 0.170*** (0.016) |
| 6-7C | 0.215*** (0.020) | 0.206*** (0.019) | 0.166*** (0.015) | 0.166*** (0.015) |
| 7-8C | 0.203*** (0.019) | 0.194*** (0.019) | 0.160*** (0.015) | 0.160*** (0.015) |
| 8-9C | 0.193*** (0.019) | 0.185*** (0.019) | 0.157*** (0.015) | 0.157*** (0.015) |
| 9-10C | 0.197*** (0.019) | 0.189*** (0.019) | 0.163*** (0.015) | 0.163*** (0.015) |
| 10-11C | 0.186*** (0.018) | 0.179*** (0.018) | 0.156*** (0.014) | 0.156*** (0.014) |
| 11-12C | 0.190*** (0.018) | 0.183*** (0.018) | 0.165*** (0.014) | 0.165*** (0.014) |
| 12-13C | 0.177*** (0.017) | 0.170*** (0.016) | 0.156*** (0.013) | 0.156*** (0.013) |
| 13-14C | 0.167*** (0.016) | 0.161*** (0.015) | 0.148*** (0.012) | 0.148*** (0.012) |
| 14-15C | 0.156*** (0.015) | 0.149*** (0.015) | 0.139*** (0.011) | 0.139*** (0.011) |
| 15-16C | 0.140*** (0.014) | 0.135*** (0.013) | 0.127*** (0.010) | 0.127*** (0.010) |
| 16-17C | 0.133*** (0.013) | 0.128*** (0.013) | 0.121*** (0.010) | 0.121*** (0.010) |
| 17-18C | 0.116*** (0.012) | 0.110*** (0.012) | 0.103*** (0.010) | 0.103*** (0.010) |
| 18-19C | 0.115*** (0.012) | 0.110*** (0.011) | 0.102*** (0.009) | 0.102*** (0.009) |
| 19-20C | 0.115*** (0.011) | 0.110*** (0.010) | 0.103*** (0.009) | 0.103*** (0.009) |
| 20-21C | 0.109*** (0.010) | 0.105*** (0.010) | 0.099*** (0.008) | 0.099*** (0.008) |
| 21-22C | 0.093*** (0.009) | 0.089*** (0.008) | 0.086*** (0.007) | 0.086*** (0.007) |
| 22-23C | 0.080*** (0.008) | 0.076*** (0.007) | 0.073*** (0.007) | 0.073*** (0.007) |
| 23-24C | 0.068*** (0.007) | 0.065*** (0.007) | 0.063*** (0.006) | 0.063*** (0.006) |
| 24-25C | 0.053*** (0.006) | 0.050*** (0.006) | 0.051*** (0.005) | 0.051*** (0.005) |
| 25-26C | 0.049*** (0.005) | 0.047*** (0.005) | 0.050*** (0.005) | 0.050*** (0.005) |
| 26-27C | 0.038*** (0.005) | 0.035*** (0.005) | 0.039*** (0.004) | 0.039*** (0.004) |
| 27-28C | 0.027*** (0.004) | 0.025*** (0.004) | 0.028*** (0.004) | 0.028*** (0.004) |
| 28-29C | 0.011*** (0.003) | 0.010*** (0.003) | 0.013*** (0.003) | 0.013*** (0.003) |
| 30-31C | −0.005 (0.003) | −0.005 (0.003) | −0.007** (0.003) | −0.007** (0.003) |
| 31-32C | −0.008* (0.004) | −0.009** (0.004) | −0.013*** (0.004) | −0.013*** (0.004) |
| 32-33C | −0.006 (0.006) | −0.006 (0.006) | −0.009* (0.006) | −0.009* (0.006) |
| 33-34C | −0.021*** (0.008) | −0.021** (0.008) | −0.027*** (0.008) | −0.027*** (0.008) |
| >= 34C | −0.004 (0.010) | −0.004 (0.010) | −0.006 (0.009) | −0.006 (0.009) |
| Night time | | 0.054*** (0.006) | 0.061*** (0.005) | 0.061*** (0.005) |
| HH FE | Yes | Yes | Yes | Yes |
| Hour FE | Yes | Yes | Yes | Yes |
| Day of week FE | No | No | Yes | Yes |
| Month FE | No | No | Yes | Yes |
| Location FE | No | No | No | Yes |
| Observations | 3,375,173 | 3,375,173 | 3,375,173 | 3,375,173 |

*p<0.1; **p<0.05; ***p<0.01

Estimation based on various versions of equation (1). Dependent variable is hourly electricity usage in kWh. The temperature bin 29 to 30°C is the reference bin. Model (1) contains temperature, household and hour of day fixed effects. Model (2) also includes the night-time dummy. Model (3) adds day of week and month of year fixed effects. Model (4) includes location fixed effects as well as the rest.

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