Tariffs, temperature and household electricity consumption in rural South Africa

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Abstract

This paper examines household electricity consumption responses to price changes under increasing block tariffs (IBTs) in rural South Africa. Using hourly meter data from 610 households, matched with household survey information, regulated tariff data, and hourly temperature records, we apply difference-in-differences to estimate the effect of a relative tariff increase across consumption blocks. The tariff adjustment increased prices for both low- and high-usage households, but the marginal price increase was larger for households consuming above the 350 kWh monthly threshold. This setting allows us to provide one of the first estimates of residential electricity price responses at the hourly level in a developing-country rural context. We find that controlling for temperature, time effects, and household fixed effects is essential, as the tariff change coincided with seasonal changes in temperature. Once these observed and unobserved confounding factors are accounted for, electricity consumption declines modestly following the tariff increase. High-usage households are less responsive to the relative price change than low-usage households, suggesting limited scope for short-run adjustment among more electricity-dependent households. The findings suggest that IBTs may induce some demand response among rural households, but their effectiveness is limited where electricity use is constrained by basic needs, infrastructure, and weather-related demand pressures.

Keywords: Residential electricity consumption, rural households, Price response, Increasing block tariffs (IBT), Difference-in-differences

1. Introduction

Residential responses to price changes under nonlinear pricing, such as increasing block tariffs (IBT, also known as incline block tariffs), has long been a feature of electricity, gas and water demand estimation (Borenstein, 2009; Nataraj and Hanemann, 2011; Ito, 2014; Auffhammer and Rubin, 2018; Alberini et al., 2022). A two-block IBT, which underpins this research, has one threshold and two prices. In that setting, the marginal price is constant, except at the threshold, while the average price is not; see Figure 1 for an illustration of the IBT structure underpinning this research. Nonlinear tariffs allow monopolies to expropriate additional shares of consumer surplus in the form of profit or as a subsidy for lower income households. Such schemes also promote energy conservation, assuming consumers are able to observe the relevant prices and

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respond timeously to them. Furthermore, the underlying pricing decisions, due to the monopoly status enjoyed by these utilities, are subject to regulatory approval. Profitability, cross-subsidization and, thus, regulator decisions, are underscored by consumer responsiveness to price changes, as well as heterogeneity in those responses that might influence overall demand.

Early literature suggests that electricity consumers respond to average price instead of marginal price (Ito, 2014), while water demand is responsive to changes in the marginal price (Nataraj and Hanemann, 2011). Because many appliances use electricity at various rates throughout the day, while water tends to be used intermittently, households might find it easier to respond to changes in water prices. More recent research suggests increased electricity responsiveness at the margin. In the Republic of Georgia, households respond to the average, which is equal to the marginal price, given the country's "wild" tariff scheme (Alberini et al., 2022). In China, consumers respond to relatively large changes in the marginal price (Zhang et al., 2017) and increasing block pricing promotes electricity conservation (Zou et al., 2020); the latter implies some response to prices, although not necessarily which price. In Ghana, where price changes are not large, Ayertey et al. (2024) find relatively small electricity responses. Thus, IBT responses depend on context, an important component of which is the size of the price change. Furthermore, limited research on IBT and related nonlinear responses is available from Africa.

Electricity demand estimation from developing countries/regions, including South Africa, is often from aggregate data (Inglesi-Lotz, 2011; Masike and Vermeulen, 2022), possibly disaggregated by sector (Inglesi-Lotz and Blignaut, 2011; Inglesi-Lotz, 2014) or expenditure data (Ye et al., 2018; Bohlmann and Inglesi-Lotz, 2021). Aggregate data does not offer researchers an opportunity to address or consider much in the way of heterogeneity, while expenditure data rarely incorporates useful price information. Ye et al. (2018) match regulator approved tariffs by location, while Bohlmann and Inglesi-Lotz (2021) use average retail prices. Although both are able to examine heterogeneity in average price responses, neither are able to examine hourly behaviour, marginal price responses or other differences related to tariff blocks. Furthermore, measurement error in reported electricity expenditure and average prices, which determine consumption levels, could lead to incorrect estimates of the response to prices.

Thus, accurate consumption data, such as that from meters, offers an avenue for improved price response estimates. Meter data has been used to estimate income elasticities (Vesterberg, 2016; Koch et al., 2024), the consumption relationship to property valuations (Jack and Smith, 2015), temperature responses (Berkouwer, 2020; Ye et al., 2025) and the effect of switching from post-paid to pre-paid meters (Jack and Smith, 2020). However, meter data matched to the household, allowing researchers to capture numerous measures of heterogeneity remains rare. Similarly, we are not aware of any research using such data to examine the response to changes in the price in a primarily rural setting. In other words, whether rural households manage their consumption in the face of block tariffs, has not received much attention in the literature, primarily due to limited data.

In this research, we estimate the percentage hourly household electricity consumption response to an increase in relative electricity prices that arise from a regulator approved tariff change in South Africa. We do so in a context that is different from much of what has been previously considered. Specifically, we use hourly meter data, matching that to weather data and astronomical data separating night from day. Our data comes from more than 600 households across South Africa, who were also surveyed; the meter data is available both before and after a regulatory approved price rise, and that price change differed by usage block.

Under strong fixed-effects and treatment selection assumptions, our estimates represent causal evidence on differential responses to prices by different types of households. The block price changes underpin a difference-in-differences (DD) method, which we combine with numerous fixed effects and other controls. Because our data is collected on the hour for 600 households over approximately seven months, we are able to control for a variety of time-invariant unobserved factors related to hourly and daily load patterns, local infrastructure conditions, household income and appliance ownership that are likely correlated with electricity consumption. Controlling for these addresses possible treatment endogeneity concerns. We further examine sensitivity to our treatment definitions, as well as household behaviour around the block threshold to mitigate concerns related to non-random treatment assignment.

Our analysis offers a few useful contributions to the literature. We are neither aware of any previous research examining household responses to IBTs in rural areas of a developing country, nor are we are aware of any research examining responses to IBT changes. Within this rural setting, we find that, although consumption increases following the price increase, that increase is also associated with the changing of seasons, as South Africa moves into winter during that same time. Accounting for winter (conditioning on temperature and night-time effects), yields the expected negative relationship between price and electricity consumption. Furthermore, relatively energy dependent households are less responsive at the margin than those with less dependency. We do not find any evidence that households respond to the block pricing structure, even though they can plausibly observe their consumption through their prepaid meter. Our results suggest that temperature is a more important determinant of electricity consumption than price, especially among high-usage households – they tend to have more appliances and income than low-usage households.

2. Data

We triangulate data from a variety of sources, including: survey data, meter data, weather data and regulatory data. The primary data source is South Africa's Domestic Electrical Load (DEL) study; we limit our attention to 2014, the most recent – unfortunately, similar (but newer) data is not available. DEL contains both hourly meter readings (Toussaint, 2019a) and a household survey (Toussaint, 2019b); these can be merged via a household identifier. This data has been used to estimate income elasticity (Koch et al., 2024) and the impact of temperature on household electricity consumption (Ye et al., 2025).

2.1. Tariff data

Electricity tariffs in South Africa are regulated by the National Energy Regulator of South Africa (NERSA). For residential consumption, the electricity tariff was constant, adjusted every year up until 2010. From 2010, pricing was changed to an IBT structure, and rate adjustments follow Eskom's financial year; thus, electricity prices increase on April 1 every year. Eskom is the state electricity utility and all of the households in our data are served directly by Eskom. For historical reasons, Eskom primarily serves residential customers who are poorer, rural and reside outside of the centralised network, where basic services (water, sanitation and electricity) are not available (Essex and de Groot, 2019).

A variety of tariff schemes exist. There are Homelight 20 Amperes (A) and 60A tariffs for low-income residential customers, where 20A and 60A refer to the size of the circuit board. The former yields limited consumption capacity at 20A on a single-phase 230 Volts (V) alternating current (AC) supply; these meters are prepaid. The latter, 60A on a single-phase 230V AC supply, can be either prepaid or post-paid. For middle- and higher-income residential customers, Eskom provides Homepower and Homeflex tariffs, but these do not apply to our data. We focus our attention on households in DEL with 20A circuit boards - nearly all of them - matching them to the Homelight 20A tariff: consumers pay per kWh following the IBT structure and are not subject to any fixed fees.

Table 1 presents the electricity tariff for the relevant financial years: 2013/2014 and 2014/2015. The tariff structure is consistent; there are two blocks and a constant threshold (350 kWh per month) across the financial years. However, the marginal price increase differs. For Block 1, it is 5.6%, but 7.6% for Block 2. The regulated tariff revision is a natural experiment, with differentiation across the blocks, which is appropriate for DD methods.

Table 1: Electricity tariffs in 2013/2014 and 2014/2015 (cent/kWh)

	April 2013 to March 2014	April 2014 to March 2015	Price increase
Block 1 ($\leq$350 kWh)	83.47	88.14	**5.6%**
Block 2 ($>$350 kWh)	89.60	96.41	**7.6%**

Notes: Eskom Homelight 20 Amps tariffs (cent/kWh). Financial year 2013/2014: from 1^{st} of April of 2013 to 31^{st} March of 2014; Financial year 2014/2015: from 1^{st} April of 2014 to 31^{st} March of 2015. All amounts in nominal South Africa Rand (ZAR) and inclusive of 14% VAT; the average exchange rate in 2014: ZAR 10.83 $\approx$ 1 USD. The electricity price data have been collected from Eskom's yearly tariff booklets (Eskom, 2013, 2014).

We illustrate the block tariffs before and after the change, as well as the average prices faced by households before and after the change. See, Figure 1 for details. The key takeaway from the figure is that average and marginal prices are the same (at least before and after) in the first block of the IBT. However, the average price does not match the marginal price after, because the higher tariff is charged on each additional unit consumed; all units before the threshold represent a fixed cost that is spread over the remaining additional units.

2.2. Hourly electricity consumption data

The hourly metering data includes the current readings in Amperes aggregated over a 60 minute interval that begins daily at 00:00:00 - 00:59:59. The current readings are converted to energy (kWh) using a default 230V value for residential customers in South Africa: 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 $t = 0, ..., 23$. We extract hourly meter data from January to July 2014, due to the large number of missing values in August (the meter data were captured only to mid-August in the year). Most DEL households were equipped with a 20A circuit box; there were nine exceptions with either 60A or 80A circuits. Given the tariff structure, we limit our attention to only the 20A circuits; therefore, we remove the nine non-20A households.

Because our analysis is based on DD methods and our treatment is determined by electricity consumption per month (the IBT threshold of 350 kWh), consumption accuracy is paramount. The data contains a few outliers, where recorded hourly consumption exceeds the maximum load for the circuit box (230V $\times$ 20A = 4.6 kWh). In total, 0.15% (4758 out of 3103680) of the hourly observations are outliers, i.e. the value is greater than 4.6 kWh. We replaced these outliers with predicted values from an initial fixed effect panel

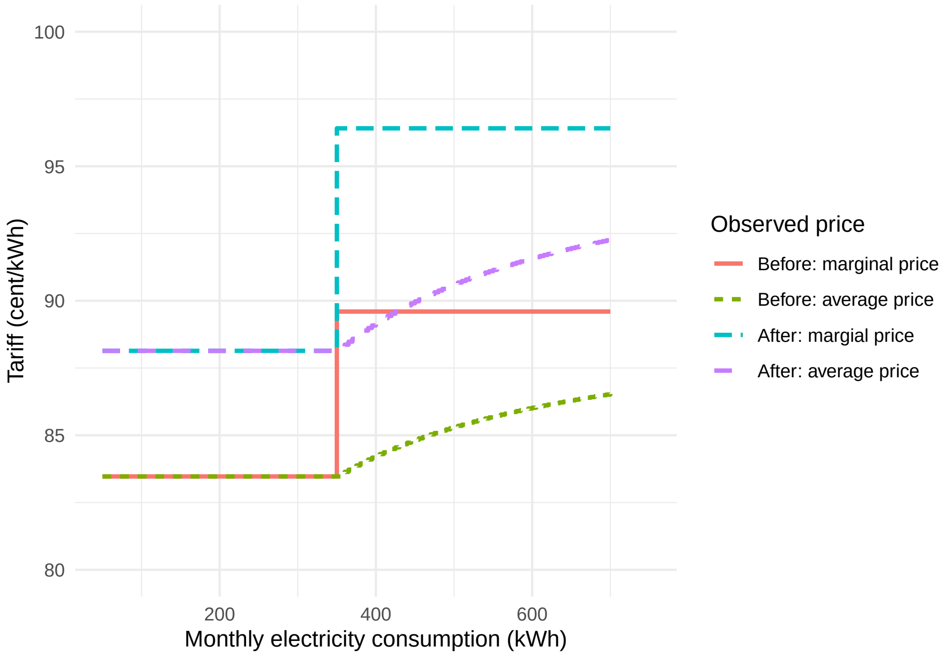


Figure 1: Block tariff stucture before and after April 1, 2014

regression controlling for temperature, as well as household, hour, day of week, month and location fixed effects as in Ye et al. (2025). The fixed effects regression is described in Appendix A, while the estimated temperature effects are shown in Table A.1. There were also some missing values, approximately 2.8% (87914 out of 3103680). We imputed those missing values from the same regression. Finally, there are valid meter readings of 0 kWh, 11% (344170 out of 3103680) of the hourly readings. Since these are valid readings, they are left as is. After imputation and prediction, we are left with 3103680 hourly observations from 610 households across the first seven months of 2014. To be sure that the imputation did not alter the data, we examined the distributional features of the hourly electricity data before and after imputation; no meaningful differences across the the mean, minimum and maximum values were observed. Thus, we are comfortable with the imputation; details available upon request.

Treatment and control groups are defined by consumption levels, given the differential price change across the IBT cutoff of 350 kWh. Given the hourly nature of the data, we sum consumption across those hours for each of the months, inclusive of imputation and predictions for outliers. The difficulty arising is that there are multiple months, and household consumption could be on either side of the threshold in any month. For this reason, we define treatment and control in two ways. In our initial analysis, the control group definition is average monthly household consumption to be no more than 350 kWh; this average is taken over the first three months of the data, which is the time preceding the price change. The treatment households average more than 350 kWh over the data period before April 1, 2014. For robustness checks, the control group definition is altered. Rather than using an average, we require household consumption to be equal to or less than 350 kWh for all three of the months before the price change; treatment households are, instead, always above 350 kWh. The main difference between these two definitions is that the latter reduces the sample from 610 to 518 households, because it drops households that cross the 350 kWh threshold in the first three months.

2.3. Household and temperature data

The 2014 DEL household survey was conducted during the winter months: between and including May and August of the year. The survey aimed to capture socio-demographic characteristics of the metered households. As indicated by Toussaint (2019b), the data was not designed to be nationally representative, therefore weights are not supplied. In addition, monthly income was inflated by the consumer price index (CPI) in DEL (Toussaint, 2020). Since the survey was completed only once within the year, there is no time varying information to include in the analysis; thus, we rely on household fixed effects to address household level heterogeneity.

Since the price increase happened at the beginning of April, and much of the second half of the data covers winter months, we incorporate temperature data within the analysis. As shown by Berkouwer (2020) and Ye et al. (2025), South African household electricity consumption responds to temperature, especially cold temperatures. If temperature was ignored in the analysis, the price change effect might be conflated with the temperature response. We discuss the relationship between temperature and electricity consumption in more detail in the Results section.

We sourced hourly temperature data for the 12 survey sites from the South African Weather Service (SAWS). We calculated the centroid distance between each survey site and all weather stations, assigning the temperature from the closest weather station to that survey site. For missing temperature data (0.9%= 576/61056 in our study period), we linearly interpolated the missing hourly values. We compared the temperature data before and after imputation, finding similar distributional values: the mean, minimum and maximum values are quite close, suggesting that imputation does not meaningfully alter the distribution of temperature; details available upon request.

3. Method

The block tariff structure in Figure 1 appears to support a regression discontinuity design (RD). However, the typical RD uses a discontinuity in the running variable to estimate a treatment effect on some other outcome. For example, it is common to use an age discontinuity (as in a minimum schooling law) to estimate the effect of education on labour outcomes; in the first-stage of that analysis, the age discontinuity is assumed to create exogenous variation in schooling outcomes, which is then related to labour market outcomes in the second stage (Harmon, 2017; Strawiński and Broniatowska, 2021). Although, by design, block tariffs are discontinuities in price at different monthly electricity consumption values, it is the electricity consumption values that determine the price, which means there is no exogenous variation in price with respect to electricity consumption. Thus, it is not possible to use the tariff block (price) discontinuity to examine the effect of price on electricity consumption. However, it is possible to examine, whether there appears to be manipulation of that running variable at the block threshold. Thus, we apply running variable density tests, to see if there is any evidence of manipulation in monthly electricity consumption. See, for example, McCrary (2008) and Cattaneo et al. (2020). We discuss why and our interpretation of those tests, below.

3.1. Difference-in-Differences

Instead of an RD approach, note that the block tariff structure and tariff adjustment process described above yield two potential household consumption groups: households that consume only within Block 1, as shown in Table 1, which can be classified as low-usage households; and households that consume only within Block 2, which can be classified as high-usage households.[1] Furthermore, there was a relative change in prices across Blocks 1 and 2 following the tariff adjustment on April 1. Assuming households are randomly assigned to the two blocks, households in each block behave similarly over time, unobserved factors are stable over time and independent of the tariff adjustment, it is possible to estimate the effect of the relative tariff change on the relative consumption difference across blocks via difference-in-differences.

Under those assumptions, which we discuss more fully below, our formulation is described by equation (1). A standard DD model includes three terms. The $post = \mathbb{1}(\text{on or after April 1})$ term defines the timing associated with the tariff change, and its coefficient is an estimate of the average change in control group consumption following the tariff increase. The $treatment = \mathbb{1}(\text{monthly consumption} > 350\text{kWh})$ term defines high-usage households to be the treatment group – they are subject to a relatively larger price increase – and its coefficient is the *average difference* in electricity consumption across low- and high-usage households. The final interaction term, $post \times treatment$, defines the treatment group, when it is treated, and its coefficient captures the relative difference in average consumption between the high-usage and low-usage households, following the relative increase in prices. It is the treatment effect that we can estimate. However, for most of the models, we use the panel nature of the data with household fixed effects. In that scenario, treatment status is constant across households, given our definitions. Therefore, *treatment* nets out of the main analysis, leaving only the *post* and $post \times treatment$ terms.

Although both groups are *treated* with an increased tariff, our DD application, under the above assumptions, identifies the average treatment effect as the relative difference in consumption arising from the relative increase in price. Our model follows,

$$\begin{aligned} E_{idst} &= \alpha_i + \beta_1 post + \beta_2 treatment + \tau \cdot (post \times treatment) \\ &\quad + \sum_{j=1}^{38} \delta_j T_{jst} + \beta_3 night.time_{idst} + \mu_t + \gamma_d + \lambda_s + \upsilon_{idst}. \end{aligned} \tag{1}$$

In (1), dependent variable is the inverse hyperbolic sine (IHS) of hourly electricity consumption, defined as $E_{idst} = \ln\left(y_{idst} + \sqrt{y_{idst}^2 + 1}\right)$, where y_{idst} is household i's electricity consumption in kWh for hour t, day of the week d, at survey site s. We use the IHS transformation in all the regressions, due to the relatively large share of real zeroes in the data. The IHS transformation allows for interpretation of the DD terms of interest similar to those arising from a log transformation: the parameter estimates represent percentage changes, as long as the estimates are not too large (Bellemare and Wichman, 2020).

Given the modelling structure, β_1 measures the percent difference in average hourly consumption for the control group after tariffs increased, while β_2 represents the percent difference in average hourly consumption between the low- and high-usage groups before tariffs increased. The DD estimator is τ; it is the percent difference in hourly consumption for the high-usage households after the tariff increase relative to the low-

[1] Technically, there is another block up to 50 kWh representing a free basic electricity subsidy. It is outside the scope of this research.

usage households (whose tariff increase was smaller) after the increase. This is the average effect of treatment on the treated. Economically, it captures the effect of a relative price change.

Additional controls include the temperature categories and various fixed effects. T_{jst} represents temperature as a series of dummies; $T_{jst} = 1$, when the temperature falls in bin j at hour t at site s.[2] As implied by its name, $night.time_{ist}$ is a dummy for hours that are mostly after sunset and precede sunrise.[3] We also include numerous fixed effects. These include α_i for time invariant household features, μ_t for constant hourly load patterns, γ_d capturing fixed daily patterns, and λ_s to control time invariant location fixed effects. Finally, υ_{idst} is the error term.

3.2. Identification considerations

As noted above, identification of the effect of interest requires that households be randomly assigned to blocks (treatment status is random), amongst other things. Since we have panel data, we incorporate household fixed effects in the analysis. Thus, treatment status is exogenous to all time invariant unobserved household factors that might be correlated with electricity consumption. We further include day-of-week, time-of-day and location-based fixed effects. Thus, treatment status is also exogenous to unobserved factors that are correlated with daily, weekly and location-specific load patterns.

Furthermore, identification requires unobserved components to remain stable over time. For that reason our model incorporates temperature, which is known to affect electricity consumption in South Africa (Berkouwer, 2020; Ye et al., 2025); we illustrate the electricity consumption – temperature relationship for this data in Figure A.1. As the blue triangles in Figure 2 show, temperature is not stable during the analysis period; instead, we see a decreasing temperature trend. Similarly, we control for variation in night-time, which correlates with electricity consumption (Ye et al., 2025) and changes with the season.

Despite the preceding assumptions, whether treatment is conditionally randomly assigned remains a question mark. Specifically, treatment status is determined by total monthly electricity consumption, which might be correlated with unobserved factors not netted out across the fixed effects in the model. For instance, since all surveyed households have access to their meter and can observe their consumption, households might observe their consumption getting close to the block threshold and choose to reduce their consumption for a few days to stay inside the low-usage block. Unfortunately, no instrument is available to test treatment status exogeneity. Instead, we acknowledge the concern that households may choose to manipulate their consumption behaviour, and we test for it, via a running variable density test (McCrary, 2008; Cattaneo et al., 2020). In RD designs, identification is underpinned by an assumption of constant *endogeneity*, where the correlation between the running variable and the unobserved factors can be assumed constant in a window near and on either side of the discontinuity. That constancy is examined via a density test of the running variable: if the running variable is bunched at either boundary, the running variable is hypothesized to be manipulated, and, therefore, the *endogeneity* is not constant, and the RD no longer valid.

Although we have already outlined why RD estimation is not appropriate for the identification of price effects in this analysis, the manipulation test, if rejected, offers additional support for our random treatment

[2] Hourly temperatures are assigned to bins of 1°C, with some exceptions. Due to limited observations in the tails, 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, $\{-1, 0, \ldots, 34\}$; 29-30°C is the reference bin.

[3] We calculate sunrise and sunset times for each day and location, according to the latitude and longitude of the survey site. With sunset/sunrise times, we determine a night-time share of each hour, assigning 'night' when the share exceeds one-half.

assignment assumption.[4] A smooth density at the discontinuity implies that households are not adjusting their electricity consumption decisions to avoid the higher block tariff. It is also evidence that households are not directly responding to the block pricing structure. However, it should be noted that households do *switch* blocks from one month to another, both before and after the tariff change. Specifically, only 163 households are always at or above the threshold before the tariff change, while 355 are always below the threshold. February is particularly noteworthy, given that it has fewer days, and, therefore, fewer households exceed the block one threshold in this month than any other month. On the other hand, 305 are always below the threshold and 167 are always above following the price increase.

As noted previously, the block structure change represents a change in both marginal prices, which also increases the average price schedule; see Figure 1. Since there are households that 'cross' the IBT threshold after the price change, neither the marginal nor the average price schedules stay the same for all households.[5] Thus, we are not able to speak directly to whether it is average or marginal price changes that are behind any observed change in behaviour.

4. Results

We begin by describing the household data, which are reported in Table 2 for the overall household sample, as well as by treatment status. The table shows that household average electricity consumption is 351.66 kWh per month, which is slightly higher than the IBT threshold. The households live in relatively small dwellings, with a mean floor area of $78m^2$, while appliance ownership is limited. Most households have an electric stove (3-plate or 4-plate stove with oven, or hotplate), and own a refrigerator, kettle and TV. However, only 16% of surveyed households own a geyser (electric water heater), indicating that few households heat large quantities of water using electricity, despite the fact that electric water heating is approximately 30% of South Africa residential electricity consumption expenditure (Ritchie et al., 2024).[6]

Overall averages, however, are a weighted average of treatment and control households, and we see differences across treatment status. Treated households consume more electricity, 607 kWh per month, than do control households, 219 kWh per month. We also see that treatment households have higher income (ZAR7800 compared to ZAR4400), have large houses ($93m^2$ versus $79m^2$), and with the exception of irons, own more appliances, especially when it comes to electric heaters and geysers. In other words, household total well-being, as measured by asset ownership and income, are important determinants of treatment status, and, therefore, treatment status is strongly determined by observed factors. Thus, controlling for selection on observables mitigates some of the concerns related to treatment endogeneity. As noted earlier, this data is collected once; therefore, in our analyses, selection on observables is managed through household fixed effects.

[4]Recall that we do not apply an RD model to examine the effect of discontinuities in electricity consumption on some other outcome; rather the outcome of interest is a disaggregation of the running variable. For that reason, we not believe an RD analysis is appropriate.

[5]Keeping with the treatment group, where average monthly consumption is more than 350 kWh before prices increase, 151 of the initial 208 treatment group continue to consume more than 350 kWh each month after the price increase. With respect to the control group, 296 out of the initial 402 continue to consume no more than 350 kWh each month after the price increase.

[6]One concern that might arise in our analysis is the degree to which our data 'represents' rural South Africa. From Table 2, we see that average monthly household income is ZAR5595 – an annual average of ZAR67140. In comparison, our households are poorer than the average South African household (ZAR138168) in 2014 (ZAR 10.83 ≈ 1 USD, 2014). The 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 (Stats SA, 2017).

Table 2: Descriptive statistics by treatment status

Variable	Overall, N = 610	Control, N = 402	Treatment, N = 208
Monthly Income	5,594.99 (7,113.50)	4,406.86 (5,132.64)	7,891.30 (9,476.22)
Average Monthly Electricity	351.66 (252.33)	219.43 (109.41)	607.21 (254.07)
Floor Area	78.56 (52.34)	70.94 (46.86)	93.30 (58.94)
Household Size	3.49 (2.12)	3.25 (2.09)	3.95 (2.11)
Children	1.26 (1.37)	1.14 (1.39)	1.47 (1.31)
Adults	2.23 (1.20)	2.10 (1.15)	2.48 (1.25)
Electric Stove	591 (97%)	388 (97%)	203 (98%)
Fridge	515 (84%)	327 (81%)	188 (90%)
Geyser	96 (16%)	43 (11%)	53 (25%)
Heater	105 (17%)	51 (13%)	54 (26%)
Iron	257 (42%)	197 (49%)	60 (29%)
Kettle	524 (86%)	335 (83%)	189 (91%)
Microwave	335 (55%)	190 (47%)	145 (70%)
Television	473 (78%)	310 (77%)	163 (78%)
Washing Machine	237 (39%)	123 (31%)	114 (55%)

Descriptive statistics reported by treatment status and for entire household sample. Continuous variables reported as Mean (standard deviation) and categorical variables reported as observation counts (percentage of sample).

4.1. Event analysis

Next, we undertake a descriptive analysis of monthly electricity consumption by treatment status, as well as monthly temperature across the sites, which is illustrated via an event plot in Figure 2. From this figure, we see that electricity consumption increases following the rate increase, and does so for both the control and treatment groups, possibly more for the treatment group. The temperature data follows the opposite trend. Given that South African autumn (March-May) and winter (June-August) occur (mostly) after the price increase, it is not surprising to see temperatures decrease following the price increase. Importantly, that negative temperature relationship over time corresponds with the positive electricity consumption relationship over the same time period. Presumably, the temperature/electricity correspondence relates to the need for increased lighting and/or heating, due to additional night-time hours and generally cooler temperatures. Therefore, as described earlier, our analysis controls for temperature, and also separates night-time from day-time.

The previous figure suggests parallel trends before treatment across treatment status and divergence afterwards. We formally test that in Figure 3, which illustrates the difference in energy consumption across the treatment and control groups before and after the relative price increase on April 1, 2014. The figure supports the pre-treatment parallel trends assumption and suggests there is statistically significant post-treatment divergence. The event plot is based on a simple model incorporating household, group (treatment

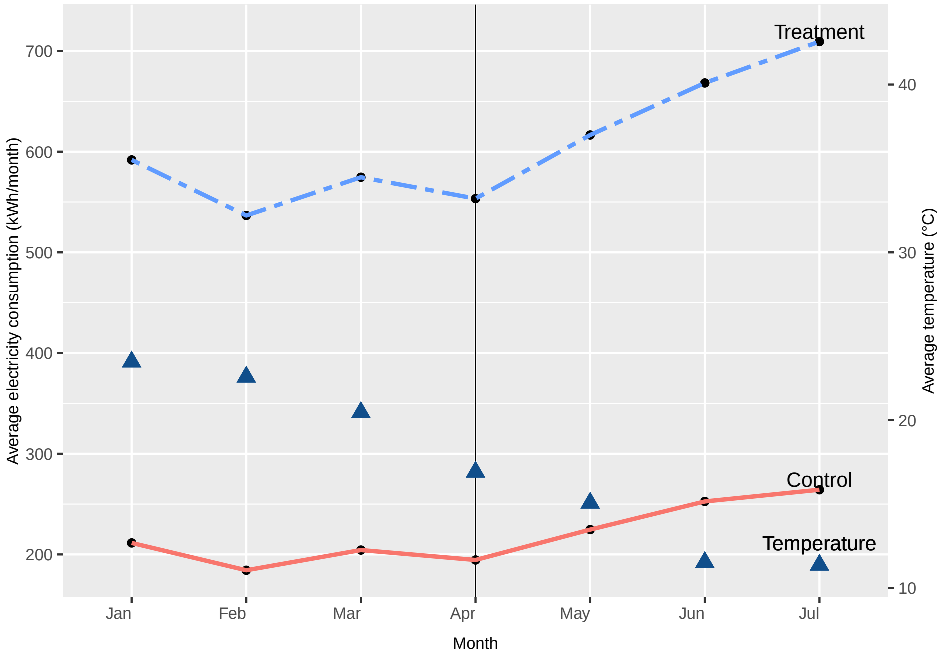


Figure 2: Average monthly electricity consumption in kWh across treatment and control groups, along with average monthly temperature faced by the survey respondents

and control) and month fixed effects to estimate the average difference across groups across the months. The model also includes two monthly temperature measures: heating degree days (the average number of hours per day below 18°C, summed over the entire month) and cooling degree days (the average number of hours per day above 22°C, summed over the entire month).[7]

4.2. Electricity consumption manipulation test

Before turning to the DD results, we consider whether or not households respond directly to the tariff block structure, despite the fact that these households are participating in a consumption monitoring project. Thus, they are able to plausibly observe their consumption (via the meters) and alter their behaviour, if they so choose. With that in mind, we examine the potential for 'running variable manipulation' at the 350 kWh level following McCrary (2008), Cattaneo et al. (2020), Cattaneo et al. (2022) and Cattaneo et al. (2023). The analysis is undertaken with the `rddensity` package (Cattaneo et al., 2024).

Figure 4 contains two figures, which examine the potential for electricity consumption manipulation before and after the tariff rate changes in April. In other words, we test whether there is evidence that households alter their energy consumption activities to stay below the higher tariff block, and we test this behaviour before and after the tariff change. The figures suggest no statistically significant difference in the density at the 350 kWh threshold, and, therefore, the incline tariff neither leads to manipulation nor appears to influence household electricity consumption decisions. Formally, the monthly consumption density difference before the rate change in April was -0.0005, while the monthly density difference was 0.0001 following the rates increase; neither was statistically significantly different from 0.

[7]Including (or not) the degree day variables does slightly alter the event estimates, and, thus, the figure. However, the alteration is not large enough to change the conclusions derived here. Results available from the authors upon request.

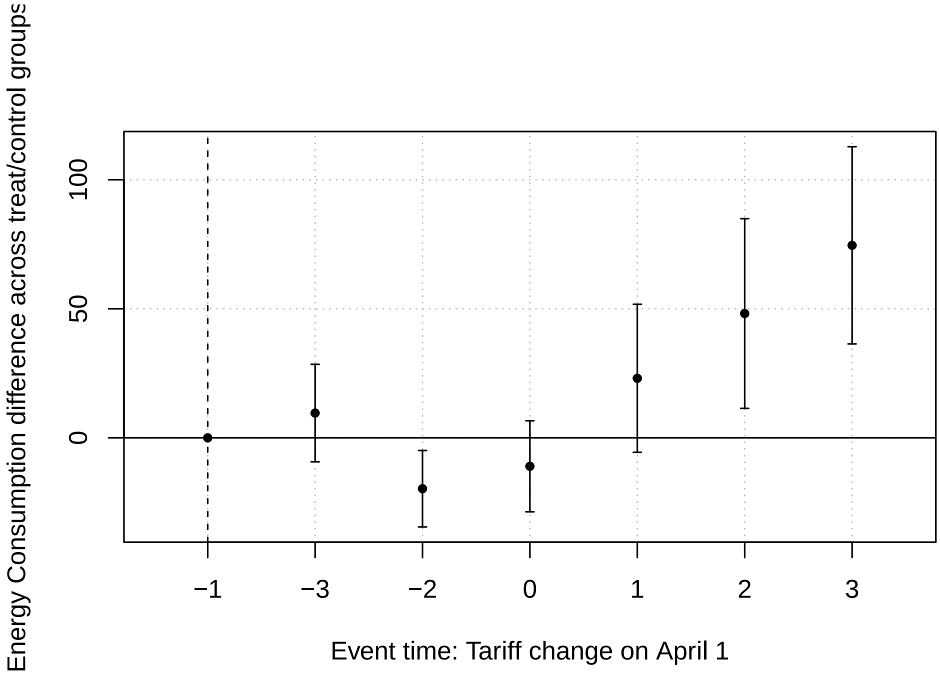
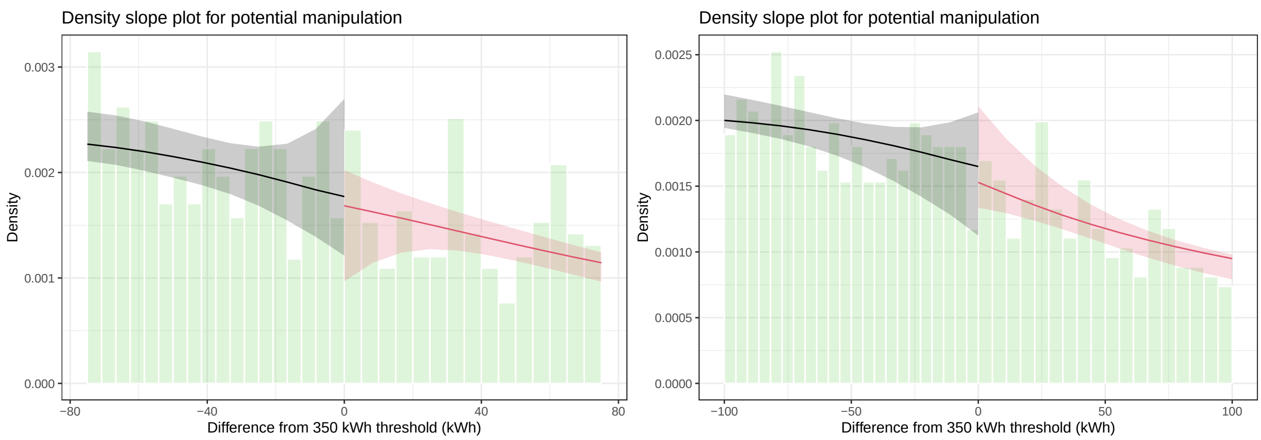


Figure 3: Event study plot: Monthly energy consumption across treatment and control groups before and after relative block price increase for high-usage households.



(a) Before tariff change

(b) After tariff change

Figure 4: Running variable density tests at 350 kWh block threshold

The preceding density results are based on overall consumption data; thus, they do not control for fixed effects, load patterns, or temperature differences, amongst other things.[8] Thus, although the preceding manipulation test results are suggestive of household non-responsiveness, we continue with the DD analysis to incorporate the previously mentioned confounders that might correlate with treatment status.

4.3. Difference-in-differences results

The initial results are shown in Table 3. Column (1) is a baseline regression without controlling for any fixed effects. Columns (2)-(5) differ by fixed effect inclusion (household and hour fixed effects are always included), while column (6) is based on an ordinary least squares (OLS) model. Recall that treatment group is defined to be constant over time; thus, no *treatment* estimate is available in the household fixed effect panel models. However, in the OLS model, we include a range of household controls, including the *post*, *treatment*, *post* $\times$ *treatment* interaction, hour fixed effects, temperature bins, our night-time hour dummy, weekday and location fixed effects. Furthermore, we include a dummy for each household and we drop the intercept; thus, we are able to estimate a *treatment* parameter, which captures the average percentage difference in hourly consumption across the two groups of households.

Table 3: Difference-in-differences estimates: panel fixed-effects and OLS specifications

	Panel linear					OLS
	(1)	(2)	(3)	(4)	(5)	(6)
post	0.025^{***}	0.025^{***}	-0.013^{***}	-0.015^{***}	-0.015^{***}	-0.015^{***}
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.001)
treatment	0.401^{***}					0.213^{***}
	(0.016)					(0.006)
post $\times$ treatment	0.004	0.004	0.005	0.005	0.005	0.005^{***}
	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.001)
HH FE	No	Yes	Yes	Yes	Yes	Yes
Hour FE	No	Yes	Yes	Yes	Yes	Yes
Temperature bins	No	Yes	Yes	Yes	Yes	
Night time dummy	No	No	No	Yes	Yes	Yes
Day of week FE	No	No	No	No	Yes	Yes
Location FE	No	No	No	No	Yes	Yes
Observations	3,103,680	3,103,680	3,103,680	3,103,680	3,103,680	3,103,680

*p<0.1; **p<0.05; ***p<0.01
Dependent variable is inverse hyperbolic sine transformation of hourly usage.
Standard errors have been clustered at household level.

Our initial result - see column (2) in Table 3 - replicates the descriptive result. We only include household and hour fixed effects, but ignore temperature. Thus, the results match the implications in Figures 2 and 3: consumption is higher, on average, after April 1, and is even higher for treated households. In columns (3) - (5), the models include temperature effects while controlling for additional fixed effects. To see the importance of temperature, please, see Figure A.1, which illustrates the (loess) smoothed relationship over the temperature bin coefficients from the regression.

[8]In RD applications, it is necessary to show that such variables are not discontinuous, either. As we are not estimating an RD, and the hourly aggregation period does not lead to an obvious threshold to consider, we do not further consider other possible discontinuities.

Following the inclusion of temperature, the *post* coefficient becomes negative. In other words, after the IBT increase and holding all other factors constant, the control group consumes about 1.3-1.5% less electricity. Given that prices rose 5.6% for the control group, the estimated coefficient implies a low-usage household own-price elasticity of approximately -0.23 ($= -1.3/5.6$) to -0.27 ($= -1.5/5.6$), which is in the region of estimates from across South Africa and international literature. We also find the average treatment effect to be positive, approximately 0.5%. Although it is statistically insignificant, it is economically reasonable: compared to low-usage households, those who use more electricity, on average, are less responsive to price changes. Combining the post and interaction results, the implied own-price elasticity for high-usage households ranges from approximately -0.11 ($= -(1.3 - 0.5)/7.6$) to -0.13 ($= -(1.5 - 0.5)/7.6$).

The results in column (6) are similar to those in columns (3) - (5), control group consumption decreases following the price increase (and by less in high-usage households); however, the OLS model also captures the average percentage difference in consumption between blocks. As expected, given the definitions applied, households in Block 2 consume more electricity than those in Block 1, approximately 21%, given the *treatment* coefficient.

4.4. Robustness checks

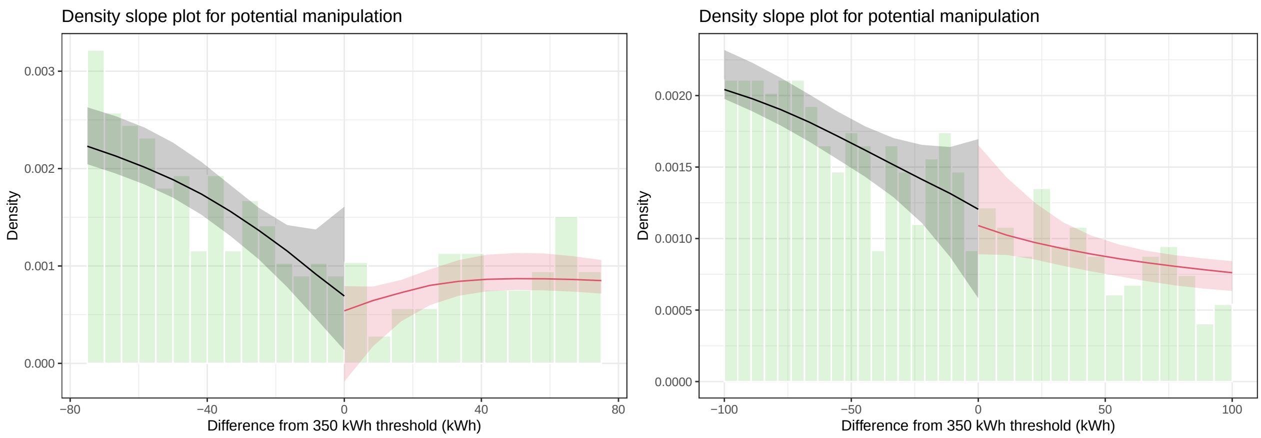
For robustness, we considered several alternatives. Our first robustness check drops the predicted hourly values. The results are presented in Table 4. As can be seen, the estimates are nearly identical; more importantly, they follow the exact same pattern as in all of the previous estimates.

Table 4: Robustness check: excluding predicted hourly values

	Panel linear					OLS
	(1)	(2)	(3)	(4)	(5)	(6)
post	0.027^{***}	0.026^{***}	-0.012^{**}	-0.014^{***}	-0.014^{***}	-0.014^{***}
	(0.006)	(0.006)	(0.005)	(0.005)	(0.005)	(0.005)
treatment	0.399^{***}					0.213^{***}
	(0.016)					(0.008)
post × treatment	-0.002	0.004	0.005	0.005	0.005	0.005
	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)
HH FE	No	Yes	Yes	Yes	Yes	Yes
Hour FE	No	Yes	Yes	Yes	Yes	Yes
Temperature bins	No	No	Yes	Yes	Yes	Yes
Night time dummy	No	No	No	Yes	Yes	Yes
Day of week FE	No	No	No	No	Yes	Yes
Location FE	No	No	No	No	Yes	Yes
Observations	3,011,008	3,011,008	3,011,008	3,011,008	3,011,008	3,011,008

*p<0.1; **p<0.05; ***p<0.01
Dependent variable is inverse hyperbolic sine transformation of hourly usage.
Standard errors have been clustered at household level.

The second focuses on an alternative definition for treatment and control, due to the potential for selection into treatment. Our alternative definition for the control group was to require all of the first three months of reported electricity consumption to fall below the threshold (350 kWh). For treatment households, we, instead, required monthly consumption to exceed 350 kWh in each of the first three months. After applying this definition, 83 households were deleted from the analysis. Under that scenario, the underlying electricity



(a) Before tariff change

(b) After tariff change

Figure 5: Running variable (monthly electricity consumption) manipulation test at 350 kWh block threshold before and after block tariff change

consumption density plots change – households near the boundary, because they are the most likely to cross the boundary, fall out. Only 518 households remain for the analysis. Although the running variable manipulation test continues to reject manipulation, the pre-treatment (Before) density illustration does suggest greater potential for manipulation in this subset; see Figure 5.

In addition to finding no evidence of *treatment* manipulation under the alternative treatment definition, we also find very similar DD coefficient estimates. Table 5 reports the estimates derived from the alternative group definition. The magnitude of the coefficients is similar (to the initial results) across all of the specifications. In terms of comparison, with the alternative definition, control group consumption falls a bit less after the tariff change; thus, the implied control group elasticity is slightly lower. The treatment effect estimate is virtually identical across specifications, remaining statistically insignificant in all.

With the alternative definition for treatment and control, we also present the results by excluding predicted hourly values in Table 6. Again, we find minimal changes in the estimates; these also follow the same pattern as in all of the previous estimates. Given the similarity of our results, across all specifications, including ones that alter the treatment definition, we believe that our model is robust.

5. Conclusion

In this analysis, we apply difference-in-differences to estimate the average hourly household response to a change in IBT pricing in rural South Africa. We use combined hourly meter data and temperature data, together with household level survey and price data. We find that the ability to control for both temperature and time, as well as household features, is important. Once controlling for these features, we find relatively small reductions in electricity consumption, which is not surprising, given the small lapse in time in our analysis, the relatively small changes in price and the relatively small consumption values (which are based on kilowatts per hour).

We also find that high-usage households (i.e., Block 2 households that consume more electricity on average), reduce their consumption less than low-usage households (households in Block 1). In other words, households using more electricity are less responsive to electricity price changes, even when faced with

Table 5: Robustness check: alternative control and treatment groups

	Panel linear					OLS
	(1)	(2)	(3)	(4)	(5)	(6)
post	0.024***	0.024***	−0.011**	−0.013**	−0.013**	−0.013**
	(0.006)	(0.006)	(0.005)	(0.005)	(0.005)	(0.005)
treatment	0.471***					0.219***
	(0.017)					(0.008)
post × treatment	−0.005	−0.005	−0.004	−0.004	−0.004	−0.004
	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)
HH FE	No	Yes	Yes	Yes	Yes	Yes
Hour FE	No	Yes	Yes	Yes	Yes	Yes
Temperature bins	No	No	Yes	Yes	Yes	Yes
Night time dummy	No	No	No	Yes	Yes	Yes
Day of week FE	No	No	No	No	Yes	Yes
Location FE	No	No	No	No	Yes	Yes
Observations	2,635,584	2,635,584	2,635,584	2,635,584	2,635,584	2,635,584

*p<0.1; **p<0.05; ***p<0.01
Dependent variable is inverse hyperbolic sine transformation of hourly usage.
Standard errors have been clustered at household level.

Table 6: Robustness check: alternative control and treatment exluding predicted hourly values

	Panel linear					OLS
	(1)	(2)	(3)	(4)	(5)	(6)
post	0.026***	0.024***	−0.010*	−0.012**	−0.012**	−0.012**
	(0.006)	(0.006)	(0.005)	(0.005)	(0.005)	(0.005)
treatment	0.469***					0.218***
	(0.017)					(0.008)
post × treatment	−0.012	−0.006	−0.004	−0.004	−0.004	−0.004
	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)
HH FE	No	Yes	Yes	Yes	Yes	Yes
Hour FE	No	Yes	Yes	Yes	Yes	Yes
Temperature bins	No	No	Yes	Yes	Yes	Yes
Night time dummy	No	No	No	Yes	Yes	Yes
Day of week FE	No	No	No	No	Yes	Yes
Location FE	No	No	No	No	Yes	Yes
Observations	2,558,537	2,558,537	2,558,537	2,558,537	2,558,537	2,558,537

*p<0.1; **p<0.05; ***p<0.01
Dependent variable is inverse hyperbolic sine transformation of hourly usage.
Standard errors have been clustered at household level.

relatively larger price changes. These results suggest that consumers do respond to changes in the price, at least when those changes occur within an IBT-type nonlinear pricing structure. Furthermore, temperature is an important feature of consumption decisions that, if ignored, could lead to spurious and implausible conclusions related to consumer price responses.

The results have important implications for IBTs policy in South Africa. First, the findings suggest that relative price changes under IBTs can induce some demand response among rural households, but the magnitude of this response is very limited. One possible explanation is that electricity consumption among these households may already be close to essential levels, leaving limited scope for further reductions. This is further reflected by the weaker response among high-usage households.

Second, higher block prices under IBTs may not be sufficient to substantially reduce consumption among rural households, particularly where electricity use is already constrained by limited infrastructure and basic household needs. In this context, the additional complexity associated with an IBT may impose an administrative burden that is large relative to its demand-management benefits. In that case, policy design, and, thus, pricing should remain quite simple; the removal of IBTs would fit that suggestion. In addition to limiting the administrative burden, it would allow users to more easily equate their payments to their usage. Improving that link might induce better conservation behaviour.

Finally, the importance of temperature in explaining electricity consumption highlights the need to consider the incorporation of weather conditions into both tariff and policy design. For example, if continuing with an IBT, it would be logical to increase the block threshold in winter months, to allow households to use more electricity during winter months, when temperatures are lower and lighting is increasingly needed. In terms of our analysis, ignoring temperature may lead to misleading conclusions about the (in)effectiveness of IBT policy. Overall, while IBT may still be a useful tool for promoting conservation and protecting low-usage households, their effectiveness appears to be quite limited, at least in this setting, wherein price changes are small, households are likely constrained in terms of their needs, and household payments may be undluly influenced by weather-related demand pressure.

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Appendix A. Predicting missing hourly electricity consumption

In order to estimate the effect we need a household level panel across the seven months. However, some of the hourly usage readings are missing in the original data. To have a balanced panel at household level, we construct a fixed-effects model in order to predict hourly usage for each household. The key variable to affect electricity consumption is temperature, which has been intensively examined in previous literature

(Auffhammer, 2022; Alberini et al., 2019; Kang and Reiner, 2022; Berkouwer, 2020; Chikobvu and Sigauke, 2013). In the literature, linear (log linear) model, piecewise linear or polynomial functions have been used in modelling the relationship between temperature and household electricity consumption.

In this study, we adopt a fixed-effects estimator which does not specify any functional form on the relationship between temperature and electricity load. It is also less sensitive to the presence of outliers than a polynomial of order three or higher is likely to be. Its only assumption is that the relationship is linear within the very small temperature range within each bin j (Alberini et al., 2019). These same variables were also included in the main DD model(s). The core relationship between temperature and hourly load is in Equation (A.1) and more details can be referred to Ye et al. (2025).

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

where y_{itdms} is the IHS of household i's electricity consumption in kWh for hour t, day of the week d, month of the year m, at site s.

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, $\{-1, 0, \ldots, 34\}$. Given our modelling assumptions, each coefficient δ_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.

Although the inclusion of temperature dummies may not yield a smooth temperature response pattern – something we are exploring – the advantage of this inclusion is that we do not specify any particular pattern, assuming only that the relationship is reasonably constant over each temperature bin.

We use the square root of hourly usage for our the model, the results are shown in Table A.1 and plotted in Figure A.1.

References

Alberini, A., Bezhanishvili, L., Ščasnỳ, M., 2022. "Wild" tariff schemes: evidence from the Republic of Georgia. Energy Economics 110, 106030. doi:10.1016/j.eneco.2022.106030.

Alberini, A., Prettico, G., Shen, C., Torriti, J., 2019. Hot weather and residential hourly electricity demand in Italy. Energy 177, 44–56. doi:10.1016/j.energy.2019.04.051.

Auffhammer, M., 2022. Climate adaptive response estimation: Short and long run impacts of climate change on residential electricity and natural gas consumption. Journal of Environmental Economics and Management 114, 102669.

Auffhammer, M., Rubin, E., 2018. Natural gas price elasticities and optimal cost recovery under consumer heterogeneity: Evidence from 300 million natural gas bills.

Table A.1: Coefficient estimates across temperature bins

< -3°C	0.014 (0.012)
-3 to -1°C	0.046*** (0.011)
-1-0°C	0.056*** (0.010)
0-1°C	0.057*** (0.009)
1-2°C	0.056*** (0.009)
2-3°C	0.052*** (0.008)
3-4°C	0.047*** (0.008)
4-5°C	0.053*** (0.008)
5-6°C	0.057*** (0.008)
6-7°C	0.059*** (0.007)
7-8°C	0.060*** (0.007)
8-9°C	0.059*** (0.007)
9-10°C	0.065*** (0.007)
10-11°C	0.065*** (0.006)
11-12°C	0.070*** (0.006)
12-13°C	0.072*** (0.006)
13-14°C	0.070*** (0.006)
14-15°C	0.068*** (0.005)
15-16°C	0.063*** (0.005)
16-17°C	0.061*** (0.005)
17-18°C	0.051*** (0.005)
18-19°C	0.053*** (0.005)
19-20°C	0.058*** (0.005)
20-21°C	0.058*** (0.004)
21-22°C	0.052*** (0.004)
22-23°C	0.044*** (0.004)
23-24°C	0.040*** (0.004)
24-25°C	0.035*** (0.003)
25-26°C	0.034*** (0.003)
26-27°C	0.026*** (0.003)
27-28°C	0.021*** (0.002)
28-29°C	0.010*** (0.002)
30-31°C	−0.004** (0.002)
31-32°C	−0.008*** (0.003)
32-33°C	−0.006* (0.004)
33-34°C	−0.015*** (0.005)
>= 34°C	−0.010 (0.006)
Night time	0.024*** (0.003)
Observations	3,011,008

*p<0.1; **p<0.05; ***p<0.01
Dependent variable is square root of hourly electricity usage in kWh.
29-30°C as reference. The model includes household, hour, day of
week and month fixed effects. Standard errors are clustered at household level.

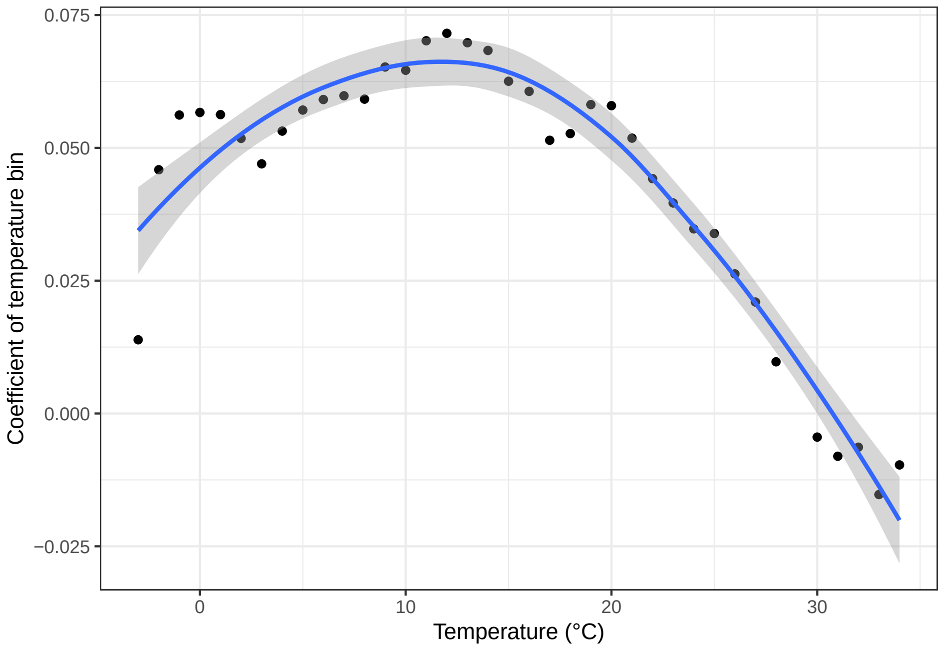

Figure A.1: Smooth plot of the coefficients across temperature bins

Ayertey, W., Sharifi, A., Yoshida, Y., 2024. The impact of increase in block pricing on electricity demand responsiveness: Evidence from Ghana. Energy 288, 129858.

Bellemare, M.F., Wichman, C.J., 2020. Elasticities and the inverse hyperbolic sine transformation. Oxford Bulletin of Economics and Statistics 82, 50–61. doi:10.1111/obes.12325.

Berkouwer, S.B., 2020. Electric heating and the effects of temperature on household electricity consumption in South Africa. The Energy Journal 41. doi:10.5547/01956574.41.4.sber.

Bohlmann, J., Inglesi-Lotz, R., 2021. Examining the determinants of electricity demand by South African households per income level. Energy Policy 148, 111901.

Borenstein, S., 2009. To what electricity price do consumers respond? Residential demand elasticity under increasing-block pricing. University of California, Berkeley. URL: https://haas.berkeley.edu/wp-content/uploads/csemwp195.pdf.

Cattaneo, M.D., Jansson, M., Ma, X., 2020. Simple local polynomial density estimators. Journal of the American Statistical Association 115, 1449–1455. doi:10.1080/01621459.2019.1635480.

Cattaneo, M.D., Jansson, M., Ma, X., 2022. lpdensity: Local polynomial density estimation and inference. Journal of Statistical Software 101, 1–25. doi:10.18637/jss.v101.i02.

Cattaneo, M.D., Jansson, M., Ma, X., 2023. Local regression distribution estimators. Journal of Econometrics 240, 105074. doi:10.1016/j.jeconom.2021.01.006.

Cattaneo, M.D., Jansson, M., Ma, X., 2024. rddensity: Manipulation Testing Based on Density Discontinuity. URL: https://CRAN.R-project.org/package=rddensity, doi:10.32614/CRAN.package.rddensity. r package version 2.6.

Chikobvu, D., Sigauke, C., 2013. Modelling influence of temperature on daily peak electricity demand in South Africa. Journal of Energy in Southern Africa 24, 63–70. URL: https://scielo.org.za/pdf/jesa/v24n4/08.pdf.

Eskom, 2013. Eskom Tariff Book 2013/14: Tariffs and Charges Booklet. Eskom. URL: https://www.eskom.co.za/distribution/wp-content/uploads/2021/07/2013-14.pdf.

Eskom, 2014. Eskom Tariff Book 2014/15: Tariffs and Charges Booklet. Eskom. URL: https://www.eskom.co.za/distribution/wp-content/uploads/2021/07/2014-15.pdf.

Essex, S., de Groot, J., 2019. Understanding energy transitions: The changing versions of the modern infrastructure ideal and the 'energy underclass' in South Africa, 1860–2019. Energy Policy 133, 110937. doi:10.1016/j.enpol.2019.110937.

Harmon, C.P., 2017. How effective is compulsory schooling as a policy instrument? IZA World of Labor .

Inglesi-Lotz, R., 2011. The evolution of price elasticity of electricity demand in South Africa: a Kalman filter application. Energy Policy 39, 3690–3696.

Inglesi-Lotz, R., 2014. The sensitivity of the South African industrial sector's electricity consumption to electricity price fluctuations. Journal of Energy in Southern Africa 25, 2–10.

Inglesi-Lotz, R., Blignaut, J.N., 2011. South Africa electricity consumption: a sectoral decomposition analysis. Applied Energy 88, 4779–4784.

Ito, K., 2014. Do consumers respond to marginal or average price? Evidence from nonlinear electricity pricing. American Economic Review 104, 537–563. doi:10.1257/aer.104.2.537.

Jack, K., Smith, G., 2015. Pay as you go: Prepaid metering and electricity expenditures in South Africa. American Economic Review: Papers & Proceedings 105, 237–241.

Jack, K., Smith, G., 2020. Charging ahead: Prepaid metering, electricity use, and utility revenue. American Economic Journal: Applied Economics 12, 134–168.

Kang, J., Reiner, D.M., 2022. What is the effect of weather on household electricity consumption? Empirical evidence from Ireland. Energy Economics 111, 106023. doi:10.1016/j.eneco.2022.106023.

Koch, S.F., Nkuna, B., Ye, Y., 2024. Income elasticity of residential electricity consumption in rural South Africa. Energy Economics 131, 107405. doi:10.1016/j.eneco.2024.107405.

Masike, K., Vermeulen, C., 2022. The time-varying elasticity of South African electricity demand. Energy 238, 121984.

McCrary, J., 2008. Manipulation of the running variable in the regression discontinuity design: A density test. Journal of Econometrics 142, 698–714. doi:10.1016/j.jeconom.2007.05.005.

Nataraj, S., Hanemann, W.M., 2011. Does marginal price matter? A regression discontinuity approach to estimating water demand. Journal of Environmental Economics and Management 61, 198–212.

Ritchie, M., Engelbrecht, J., Booysen, M., 2024. Loadshedding-induced transients due to battery backup systems and electric water heaters. Applied Energy 367, 123421. doi:https://doi.org/10.1016/j.apenergy.2024.123421.

Stats SA, 2017. Living Conditions Survey 2014/2015 statistical release P0310. Statistics South Africa (Stats SA). Pretoria, South Africa.

Strawiński, P., Broniatowska, P., 2021. The impact of prolonging compulsory general education on the labour market. Educational Studies , 1–21.

Toussaint, W., 2019a. Domestic Electrical Load Metering, Hourly Data 1994-2014 [dataset]. Version 1. Johannesburg: SANEDI [funders]. Cape Town: Energy Research Centre, UCT [producers], 2014. Cape Town: DataFirst [distributor], 2019. DOI: https://doi.org/10.25828/56nh-fw77.

Toussaint, W., 2019b. Domestic Electrical Load Survey - Key Variables 1994-2014 [dataset]. Version 1. Johannesburg: SANEDI [funders]. Cape Town: Energy Research Centre, UCT [producers], 2014. Cape Town: DataFirst [distributor], 2019. DOI: https://doi.org/10.25828/mf8s-hh79.

Toussaint, W., 2020. The Domestic Electrical Load (DEL) Study Datasets for South Africa. Energy Research Centre, University of Cape Town. URL: https://zivahub.uct.ac.za/articles/preprint/Domestic_Electrical_Load_Data_Descriptor/11774691/1.

Vesterberg, M., 2016. The hourly income elasticity of electricity. Energy Economics 59, 188–197.

Ye, Y., Koch, S.F., Ye, X., 2025. The effect of temperature on household hourly electricity consumption: Evidence from South Africa. Energy , 134925doi:10.1016/j.energy.2025.134925.

Ye, Y., Koch, S.F., Zhang, J., 2018. Determinants of household electricity consumption in South Africa. Energy Economics 75, 120–133. doi:10.1016/j.eneco.2018.08.005.

Zhang, Z., Cai, W., Feng, X., 2017. How do urban households in China respond to increasing block pricing in electricity? Evidence from a fuzzy regression discontinuity approach. Energy Policy 105, 161–172.

Zou, H., Luan, B., Zheng, X., Huang, J., 2020. The effect of increasing block pricing on urban households' electricity consumption: Evidence from difference-in-differences models. Journal of Cleaner Production 257, 120498.