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Income elasticity of residential electricity consumption in rural South Africa

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ABSTRACT

Analyses of residential electricity demand primarily rely on expenditure or aggregate data. However, newer sources of data, such as that from meter readings, are becoming available. In most circumstances, these newer sources cannot be matched to detailed information about the household. In this research, we make use of South Africa's Domestic Electrical Load Study, one of the only sources available in a developing country that includes both meter and household level data. Due to some gaps in the meter readings, we focus our attention on average peak electricity consumption, estimating the income elasticity with respect to morning, evening, and the average across both morning and evening peaks. Although we find differences in income responsiveness in the morning, relative to the afternoon, and across quantiles of electricity consumption, these differences tend not to be statistically significant. We do, however, find heterogeneities in those elasticities that can be correlated with, in particular, appliance ownership, suggesting that the ownership of appliances makes electricity more of a necessity, or at least makes the services derived from electricity more necessary for the household.

1. Introduction

Energy consumption in non-OECD countries is expected to contribute two-thirds of global energy consumption by 2040 (Balarama et al., 2020). Rising income is expected to increase appliance ownership (Gertler et al., 2016), while developing county electrification programmes further increase access to the grid (Dinkelman, 2011). For the most part, literature on electricity consumption, especially from developing countries/regions, has either relied on aggregate data (see Masike and Vermeulen, 2022 and Bohlmann and Inglesi-Lotz, 2021 for recent analysis) or expenditure data (Ye et al., 2018, offers one fairly recent analysis). However, research underscored by aggregate data is not able to consider much in the way of heterogeneous responses that might be of interest to the policymaker, while research underscored by expenditure data relies heavily on the ability of the survey respondent to correctly recall their expenditures. Thus, our understanding of residential electricity demand might be improved, if we could better disaggregate or if we had better data from the household.

One appealing source is the electricity meter. Data from meters has been available in developed countries, underpinning estimates of income elasticities over time (Vesterberg, 2016), regional differences in residential demand (Deryugina et al., 2020), as well as general hourly demand characteristics and welfare (Karimu et al., 2022). We are aware of only a few developing country studies using meter data: Jack and Smith (2015), Yu and Guo (2016), Sakah et al. (2019), Berkouwer (2020) and Twerefou and Abeney (2020). Two of these are from China, one from Ghana and two from South Africa. For South Africa, neither Jack and Smith (2015) nor Berkouwer (2020) have information on income and, although Sakah et al. (2019) is limited to 60 households, they, along with Yu and Guo (2016) and Twerefou and Abeney (2020) are able to match some information from the household to the meter readings. However, none of these studies offers insight into rural household electricity demand. Thus, there is a need to consider more households, more types of households – especially rural – and examine additional household characteristics, where possible, which we do.

In this research, we estimate the income elasticity of rural domestic electricity consumption using meter data collected across South Africa in 2014. meter readings are merged with a household survey collected from many of the metered households; we describe the data more fully, below. This data offers the opportunity to examine the variability in electricity responses over time (of day). Although the meter data is quite rich, the survey data is less so, having only been collected just once for each household, while containing limited potential controls. Due to a large number of missing values in terms of hourly meter readings, we focus on average consumption during peak load periods. Using this data, we estimate the income elasticity of average peak load consumption over an approximate eight-month period. We apply ordinary regression, as well as quantile and nonparametric regression;

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the latter two are used to determine the appropriateness of the former. We find that income elasticities of (average) peak load electricity consumption range from 0.125 to 0.353, depending on the included variables. Although we find variability in this across quantiles, that variability is not statistically significant, suggesting, at least in the case of this data, that a simple linear log–log model is appropriate for estimating the income elasticity of residential electricity demand.

Our study contributes to the literature in a number of ways: (1) we estimate an income elasticity for rural residential electricity demand in a developing country setting, that is underpinned by meter data, rather than expenditure or aggregated data; since the analysis relies on data that is more accurate and more localised, it should more appropriately reflect the true income responsiveness of these households; (2) we find results that are rather similar to those previously available for South Africa – inclusive of both urban and rural households – that were underpinned by expenditure data, and, therefore, our research suggests that rural household electricity demand responsiveness is similar to that of a wider cross-section of the population; (3) we are able to explore heterogeneities in that elasticity, finding that the ownership of assets reduces income elasticities, a result that is similar to other research using expenditure data and offers further support to the suggestion that rural household electricity demand responsiveness is similar to that of a wider cross-section of the population; and (4) given the similarity between our results, which should be a truer reflection of behaviour, and the wider literature that is generally underpinned by non-metered data, our results offer an additional source of credibility to that research.

2. Literature review

Our research is certainly not the first to examine the relationship between electricity consumption and income (or other household characteristics). Demand behaviour is often characterised through income and price elasticities and examined at the household level (Zhu et al., 2018; Espey and Espey, 2004). The literature tends to find price elastic (although not always) and income inelastic demand (Pouris, 1987; Holtedahl and Joutz, 2004; Anderson, 2004; Narayan and Smyth, 2005; Filippini and Pachauri, 2004; Halicioglu, 2007; Dergiades and Tsoulfidis, 2008; Louw et al., 2008; Ziramba, 2008; Amusa et al., 2009; Inglesi, 2010; Inglesi-Lotz, 2011; Filippini, 2011; Shi et al., 2012; Ye et al., 2018; Twerefou and Abeney, 2020; Bohlmann and Inglesi-Lotz, 2021; Liddle and Huntington, 2021). However, that literature is underscored by either aggregate or expenditure data, which may not be ideal for such estimates.

Some recent research captures income and price elasticities for specific types of electricity usage, such as that for heating, cooling and cooking. Jia et al. (2023) estimates an income elasticity of annual electricity consumption (in kWh) of 0.104 and 0.064 for electricity used in water heating and lighting, respectively, for urban households. The income elasticity of electricity consumption is 0.088, 0.068 and −0.132 if used for laundry, lighting, and entertainment, respectively, for rural households. Khanna et al. (2016) estimates an income elasticity of electricity usage (in kWh) of 0.15 and a price elasticity of −0.51. In the analysis, cooling captures an important share of the total, with elasticities ranging from 0.21 to −0.32. Although we capture appliance ownership in the analysis, we feel its is a step too far to decompose the elasticities across appliances, since we cannot be sure which appliances are in use at any particular time.

In South Africa, income elasticities of electricity consumption are inelastic and generally below 0.5 (Anderson, 2004; Ziramba, 2008; Louw et al., 2008; Inglesi, 2010; Ye et al., 2018; Masike and Vermeulen, 2022). There are a few studies suggesting elasticities between 0.5 and 1 (Pouris, 1987; Inglesi-Lotz, 2011; Bohlmann and Inglesi-Lotz, 2021), although one result suggests an income elasticity well in excess of 1 (Amusa et al., 2009). In one instance, where income was not available, Jack and Smith (2015) find property value elasticities that lie between 0.221 and 0.530 for prepaid electricity customers. Sakah et al. (2019), using meter and survey data for 60 households in China, finds an income elasticity near 0.5. On the other hand similar research relying, instead, on expenditure data and monthly meter data in Ghana yields income elasticities between 0.04 and 0.07 (Twerefou and Abeney, 2020), while Yu and Guo (2016), which similarly matches meter and household survey data in China, finds an income elasticity of −0.02; both of these are much smaller than we have found in any of the literature. In other words, there are few studies that capture extensive household level data including electricity meter readings – none that consider rural households – while some of the estimates arising from previous analyses are unexpected. Our research relies on data that matches households to meters, offers insight into rural household demand responsiveness (from meter data) and allows us to determine how similar the results are to related research.

In another line of research, and partly because there is limited direct electricity consumption data, researchers have examined the energy ladder. For example, Ma et al. (2022) investigates the effect of income growth on cooking fuel use finding, as expected, that the probability of cleaner cooking fuels increases with the income quantile. In South Africa, Davis (1998) finds that access to electricity affects the nature of the transition to cleaner fuels in rural areas and that access is mainly driven by income. The income ladder hypothesis might also be captured indirectly, through increased appliance use, as appliances are more likely to be owned by households with more income (Auffhammer and Wolfram, 2014; Wolfram et al., 2012; Fowlie and Phadke, 2017), which tends to increase electricity expenditure (Tiwari, 2000; Khanna et al., 2016). Although Diawuo et al. (2020) combines survey data and hourly consumption data, their focus is on peak demand modelling and appliance ownership finding that the latter is influenced by income and urbanisation – it does not provide an income elasticity estimate. More generally, directly measured electricity consumption via meters has the potential to provide better insight than many of the previous studies, or at least confirm the findings arising from those studies. Two separate meta-analyses argue that better information with respect to income and price, especially with respect to peak-hour consumption would improve our ability to implement monetary dis/incentives related to consumption behaviour (Labandeira et al., 2020; Mi et al., 2021). However, Rahman et al. (2017) finds that peak pricing may lead to higher costs for low-income households.

3. Data and background

3.1. South African electricity provision

South Africa, the focus of this research, is a middle-income country (identified by the World Bank) located in the Global South with weather that is generally mild to warm. Domestic energy consumption accounted for 25% of total electricity consumption (DOE, 2016), a proportion that has likely increased as the demand for energy-using assets has increased with rising incomes (Wolfram et al., 2012; Gertler et al., 2016), as well as its national electrification programme. The electrification rate stood at 80% in 2018 in both rural and urban areas. Given this level of access, electricity from the grid has become the major source of energy for lighting (87.2%), water heating (82.5%), cooking (81.3%) and space heating (38%) in the residential sector (Statistics South Africa, 2019). Despite the significant achievement with respect to electricity access, household energy consumption patterns especially for rural households have been influenced by historical developments with respect to electricity provision in the country.

During the colonial and apartheid periods (before 1994), energy was mainly supplied either in cities and towns with mining operations and industry or white areas only, resulting in few connections from the centralised network for non-whites (Essex and de Groot, 2019). In the post-apartheid era (after 1994), the government put more emphasis on improving poor households' access to basic services, such as water, sanitation and electricity. In terms of electricity access, Eskom, as the only national producer in South Africa, continued to distribute about 60% of the electricity, mainly to rural areas.[1] These newly electrified rural households, i.e. Eskom direct residential customers, are most likely poor households, not able to afford home appliances that consume large amounts of electricity and therefore have limited electricity demand. We see this in our data, where the sample average for the years of electrification stood at 16 years (surveyed in 2014), suggesting the average household was electrified well after apartheid ended. Further, the size of the "mains" switch (i.e. circuit board) for our surveyed households is 20 Amperes (A), which is much smaller than in urban households. In urban areas, the "mains" switch is generally 60 A or higher, indicating that electricity demand for our sample households is relatively lower than it is for urban households.[2] Although the infrastructure has been improving in rural areas, path dependence related to historical energy provision underscores energy access and shapes the energy consumption patterns of rural households in the country.

Along with improvements in electricity access, affordability has become another compelling issue in South Africa (Ye and Koch, 2021, 2023). In order to alleviate household energy burdens, a free basic electricity policy has been available for many, since 2003 (DME, 2003). It is meant to provide 50 kWh of free electricity to poor households, as long as the household is registered in the national indigent programme and the household uses prepaid meters. Unfortunately, our data offers no information on indigence, whether households use prepaid devices or any indication of access to free basic electricity (FBE). Despite that, FBE limits are well below average consumption in our households.[3] In addition, it has been argued that the allocated amount of free electricity is too low to satisfy the basic needs of poor households. For this reason, households have to economise on their electricity usage, which may complicate their daily life (Essex and de Groot, 2019). The inability to afford electricity consumption could result in sustained use of dirty/traditional fuels.

In the last decade, South Africa has experienced (and continues to experience) an electricity crisis underpinned by insufficient generation capacity. Electricity generation at Eskom failed to keep pace with demand, causing rolling blackouts (i.e. load shedding) across the country. The first energy crisis, in 2008, forced consumers and businesses to learn to deal with rolling blackouts, which were used to forcibly reduce demand on the system. From near the end of 2014 to early 2015, the country was again severely affected, and by 2017, load shedding had become a relatively common occurrence, so common that an app has been developed to allow users to follow the schedule and plan their days around expected load shedding times. Since September 2022, the country has implemented load shedding almost everyday. As implied by Inglesi-Lotz (2023), load shedding could deepen the rural–urban divide, because rural households tend to be poorer and less able to afford back-up or alternative energy supplies. On the other hand, newly electrified households represent an important driver of future demand (through their increased reliance on the services provided by electricity). Thus, our sample – rural households whose electricity is directly supplied by Eskom, which cannot produce enough electricity to satisfy demand – is relatively important from a policy and load management perspective.

3.2. Data

The data used for our empirical analysis are sourced from the South Africa Domestic Electrical Load (DEL) study, which contains domestic electricity metering hourly data (Toussaint, 2019a) and household survey data (Toussaint, 2019b). The DEL study is a component of the national load research programme, which aims to collect electricity consumption data to inform South Africa's electrification strategy and to provide inputs towards policy development and technical design guidelines for the domestic electricity distribution business in the country (Toussaint, 2020). The programme was started in 1994, and continued until 2014. During that time, it collected electricity meter readings and conducted an annual socio-demographic survey of metered households throughout South Africa. The metering data can be easily merged with the DEL household survey data via a household identifier. Initially, the study covered electrified households receiving their electricity via their local municipality. However, from 2000, Eskom – the state-owned power production monopoly and supplier to a large share of households (primarily rural households) – joined the DEL study. For the 2014 survey, data is available from customers directly supplied by Eskom; thus, there is some concern that the results here might not be generalisable to the rest of the population or to more recent times. We explore generalisability, below, by comparing this 2014 data to a nationally representative survey collected in 2014 and 2015, the South African Living Conditions Survey (Statistics South Africa, 2017). We also discuss the relevance of working with the 2014 meter data we have at our disposal, which is the most recent available.

Unfortunately, the DEL data did not capture information on electricity price. In South Africa, electricity prices are determined via the National Energy Regulator of South Africa (NERSA), following requests for tariff increases made by Eskom – those tariff increases are usually approved. However, local prices can be managed by the local municipality, also subject to NERSA approval, and such prices often follow an incline block (Ye et al., 2018). Since all households for this study are supplied directly by Eskom, they faced a standard two-block tariff structure with a threshold at 350kWh per month – price increases typically happen once per year, but also have to be approved by NERSA. More specifically, the price increased by roughly 6% for households whose monthly consumption was less than 350 kWh and 8%, otherwise, from April 1, 2014. Keeping in mind the block structure and its 350 kWh threshold (±11.7 kWh per day), our data suggests that few households were likely to meet that threshold in any given month. In other words, prices should not vary substantially for households in the study (Eskom, 2014).[4] Although we are not able to uncover price elasticities, it is also unlikely that any bias arises from the omission of price data.

For our analysis, we extract peak hourly electricity consumption (in kWh) and household characteristics that are likely to be correlated with hourly consumption surveyed that year. The scope of the hourly data includes current in Amperes (A) aggregated over a 60 min interval, starting daily at midnight (thus, the first hour is 00:00:00 - 00:59:59). We convert Amperes to energy usage (kWh) using the following conversion equation: $x_t \times \frac{230}{1000} \times 1 \text{ h} = y_t$ kWh, where x_t (A) refers to the aggregate hourly Ampere readings in the data and y_t is the real electricity usage (kWh) for hour t, with $t = 0, \ldots, 23$. We use a default

[1] Eskom also supplies parts or all of some cities, while municipalities distributed the remaining 40% of electricity. In South Africa, Eskom generates 96% of the country's electricity and few municipalities have capacity to do so; therefore, municipalities have to purchase electricity from Eskom and re-sell it for municipal revenue generation.

[2] Within 608 households for our analysis, only one household has a 22 A main switch, one has 60 A and one has 80 A; for the rest, their "mains" switch is 20 A. Although the infrastructure capacity is limited, the electricity consumption that we outline below – average hourly consumption – is well below that limit, suggesting that our results are not driven by the size of the switch.

[3] We show in Table A.1, average peak hour consumption is approximately 0.5 kWh in the morning and 0.75 kWh in the evening. With peak defined to cover four hours morning and evening, that represents 2 kWh in the morning and 3 kWh in the evening, or about 5 kWh per day. Over 30 days, that is at least 150 kWh per household per month, well beyond the free basic limit.

[4] See Table A.1 for the details. The average total peak is 0.66 kWh, and that average is for 8 h. Thus, peak average usage is approximately 5.28 kWh, which is about half of the 11.7 kWh required to get to the next block.

230 voltage (V) instead of real voltage readings because the volume of the original DEL datasets is too large to be available through internet access (Toussaint, 2019a). Unfortunately, there are additional issues, when it comes to tidying the electricity usage data. The time period covers early January to the end of August, at an hourly interval for nearly 650 households.[5] Thus, there are a few million observations, although we limit our analysis to the household level, rather than the electricity consumption unit level.

Specifically, we focus our attention on peak-hour electricity consumption, where peak period covers eight hours for each day: 05:00-09:00 in the morning and 17:00-21:00 in the evening. Eskom defines the national peak period as 06:00-09:00 and 17:00-19:00 for morning and evening, respectively. In our analysis, we extend both the morning and evening peak hours according to the load patterns based on our data. For each household, we separately calculate the average hourly electricity usage during morning and evening peak periods. For example, a household's average morning peak usage is the sum of all its usage during the morning peak period over the entire eight months period, divided by total number of hours for which we observe data; there are missing values in the data that are not included in the sum. In the consumption data, 17.44% of peak-hour data consist of zeros (10.10%) and missing values (7.34%). On the other hand, 19.47% of the off-peak hours consist of zeros (12.19%) and missing values (7.30%). Moreover, 80.95% of the households have at least 6 of the 8 peak hours captured as actual usage, while only 77.98% of all the households have at least 11 of the 16 off-peak hours captured as actual. The data collection time span covers summer, fall and winter; it is expected that electricity usage varies by temperature and daylight hours, which are correlated with season, but not in the same way every day.[6] Given these issues, our dependent variable is (log) average peak hour consumption over the entire time period, which should balance out the weather, sunlight, zeros and missing values, unless, for example, missing values are disproportionately higher at one time of year or a particular temperature, which is not easily ascertained.

In addition to metering data, we capture proxies of electricity usage, such as appliance ownership (three- and four-plate electric stove, refrigerator and/or freezer, geyser, space heater, hotplate, iron, kettle, microwave oven, and washing machine) and the size of the dwelling (in square meters).[7] In terms of appliance ownership, we generate a dummy variable for each appliance, if at least one of those appliances is owned; in some cases, households own more than one. We also consider a five category measure of ownership underscored by principle components analysis (PCA) to reduce the dimensions of ownership data.[8] The household survey also contains household monthly income, some measures of employment (we include the head's employment status as employed (full/part-time), unemployed or retired (the data does not capture other forms of non-participation in the labour force), and household composition in terms of the number of children (aged less than 16) and adults (anyone older), the number of males and females (it is possible to separate adults by gender, but we do not do so in this analysis).

The household surveys were conducted every winter between and including May and August. When access was difficult, briefings with a body corporate, estate managers or the traditional leaders in the area were facilitated to improve access to households. Where possible, the household head was asked to respond, although other residents might have answered the survey. Survey enumerators were instructed to obtain at least an 80% response rate within a particular location (suburb or settlement). Revisits would be done until this target was reached and individual homes were revisited up to 3 times. The data is not designed to be nationally representative – we discuss this more below – and, therefore, weights are not supplied. Unfortunately, the survey requests more information than is provided in the publicly accessible data. Of potential interest, for example, are questions related to energy consumption behaviours beyond electricity (Toussaint, 2019b).

All data processing, analysis and reporting are undertaken using R (R Core Team, 2023). A variety of packages are available that have made this easier. These packages include `tidyverse` (Wickham et al., 2019), `lubridate` (Grolemund and Wickham, 2011), `haven` (Wickham et al., 2023) 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 et al., 2020) and `knitr` (Xie, 2014, 2015); furthermore tables are built and presented using `qwraps2` (DeWitt, 2021), `stargazer` (Hlavac, 2022) and `kableExtra` (Zhu, 2021), while figures are prepared and illustrated using `ggplot2` (Wickham, 2016), as well as the plotting features contained in `np` (Hayfield and Racine, 2008). All code is available from the authors, and the data is publicly available.

4. Methodology

Our focus is on estimating the income elasticity of average peak electricity consumption (as measured in kWh). We focus our attention on log–log specifications, which simplifies tests of the constancy of that elasticity across the distribution of electricity consumption. To undertake our analysis, we apply numerous methods, including descriptive, ordinary regression, quantile regression and nonparametric regression (loess and multivariate nonparametric regression) analysis. We present those results through both figures and tables, estimating the various models in R (R Core Team, 2023) – nonparametric regressions are estimated via the `np` package (Hayfield and Racine, 2008), while quantile models are estimated via the `quantreg` package (Koenker, 2023), as well as the associated `Qtools` package (Geraci, 2016, 2022). Thus, defining e as electricity consumption, y as monthly income, x as a vector of additional controls and u as an additive error term, the general model follows (1).

$$\ln e = f(\ln y, x) + u \tag{1}$$

Our descriptive analysis conditions only on the employment status of the head of the household – since there are four employment categories, conditioning in this way also provides some insight into potential correlations between the controls in the model. In the ordinary and quantile regression approach, we rewrite f as a linear index function, as in (2).

$$\ln e = \gamma \ln y + x\beta + u \tag{2}$$

The primary difference between ordinary least squares and quantile regression is that ordinary regression minimises the sum of squared deviations between the data and the fitted linear index, and, since each observation is weighted equally, the fit can be affected by leverage points. Quantile regression, on the other hand, minimises the sum of the absolute value of the deviations between the data and the fitted linear index, given a quantile of the outcome variable of interest. Importantly, the approach down-weights observations relatively far from that quantile, reducing the potential impact of leverage points on

[5] Initially, there are 815 metered households and 2064 surveyed households in 2014; however, only 648 households have both. Furthermore, we lose an additional 40 households due to missing information from the household survey related to the control variables in our model.

[6] In related analysis, we are tidying and merging temperature data, as well as imputing the missing electricity data, to examine further features of electricity demand than are possible in this analysis.

[7] In separate analysis, available from the authors, we also examined measures of housing quality related to the walls and the roofing. We found little to suggest these variables mattered, and, therefore, we do not continue with them here.

[8] Specifically, we use the appliance ownership dummies to construct the principle components, and we further generate the categorical measures by dividing the scores of the first principal component into five pieces with equal length (the fifth category represents relatively extensive ownership and is the reference in our regressions; see Tables A.1, B.4, C.4, D.4, and E.4).

the estimated fit; more details are available in Koenker and Hallock (2001), Angrist and Pischke (2009), and numerous other locations.

In the fully nonparametric model, on the other hand, we treat f as an unknown function of the data. Given that regression focuses on the conditional expectation, we express the nonparametric model as a conditional expectation; see (3).

$$E\left[\ln e \middle| \ln y, x\right] = \frac{f_{e,x,y}\left(\ln e, \ln y, x\right)}{g_{x,y}\left(\ln y, x\right)} \tag{3}$$

The structure in (3) requires estimates of $f_{e,x,y}$ and $g_{x,y}$, which are estimated via product kernels that admit both continuous and categorical variables; for details, see Li and Racine (2004), Racine and Li (2004) and Hayfield and Racine (2008). We apply local linear regression, where bandwidth selection is data-driven through leave-one-out least-squares cross-validation. As the name implies, the approach minimises the squared distance between the fitted function and the unobserved 'true' function, where the true function is meant to be locally linear (and smooth). The approach followed has been shown to yield linear fits, when the optimal bandwidth for a continuous variable becomes large enough (Li and Racine, 2004; Racine and Li, 2004).[9]

5. Results and discussion

5.1. Descriptive statistics

Table A.1, Figs. 1 and 2 offer descriptive insight into the data used for this analysis. The descriptive statistics are separated by the head of household's employment status; however, we do not test for statistically significant differences across status. This breakdown does show us that employment rates (full and part-time) are less than 1/2, unemployment rates are approximately 22%; national unemployment rates were 22.6% at the time of the survey. In terms of peak electricity consumption, recall that morning and evening peak represent four hours each, there is limited electricity consumption amongst these households. On average, households use between 0.45 and 0.58 kWh per hour during the morning peak hours of 05:00-09:00 and between 0.69 and 0.83 kWh per hour during the evening peak of 17:00-21:00. Averaging across both peak periods, yields usage in between the morning and evening. On the other hand, households exceed four individuals, on average, and there tends to be more adults in a household than children. These households live in relatively small dwellings, somewhere between 60–85 m^2. Households with an unemployed head have monthly income of ZAR 1480 (= $e^{7.3}$, 1 USD = 10.3 ZAR), while monthly income in households with an employed head exceeded ZAR 7480, which highlights the disparate conditions of rural South African households.

Finally, surveyed households do not own an extensive array of appliances, although an iron and a refrigerator and/or freezer were the most commonly owned. Less than half of any households own a washing machine, while only about a quarter of households with an employed head own a geyser (water heater). Considering the different types of stoves, the data suggests that households have at least one of these (the 3 and 4 plate stoves and hotplates are only owned together in two households). Microwaves are also owned by about half of the households. When these different appliances are used to create an asset index, we find that households with either a retired head or an employed head are more likely to be in the top two ownership tiers, than other types of households, while households with a part-time employed head are more likely to be in the bottom two/three tiers. In the analysis below, we see that this ownership pattern, which is correlated to both income and household head employment status, offers some insight into heterogeneous income elasticities.

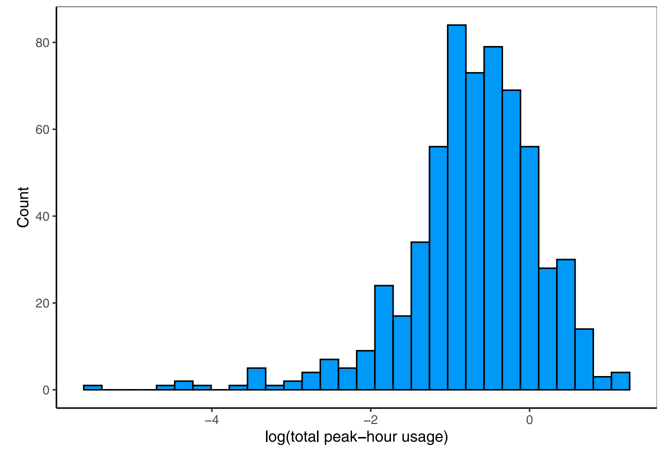


Fig. 1. Histogram of total peak-hour usage.

Before turning to regression, we present a brief descriptive analysis of the outcome variable(s). Fig. 1 illustrates a histogram of log(total peak-hour electricity consumption) from the meter data; the distribution is skewed, and, therefore, the application of quantile methods might be appropriate. Although not illustrated, the histograms for both (log) average morning and evening peak-hour usage are similarly skewed.

Given the possible support for non-standard regression arising from Fig. 1, we undertake and illustrate a simple smooth estimate – using the Loess smoother – of log average peak electricity usage against the log of monthly income. That illustration is presented in Fig. 2 for both morning and evening peak consumption. Although the smoothed fit does not incorporate additional controls (no other controls can be considered using the loess smoother), it suggests a constant income elasticity. We explore that further in the remaining analysis.

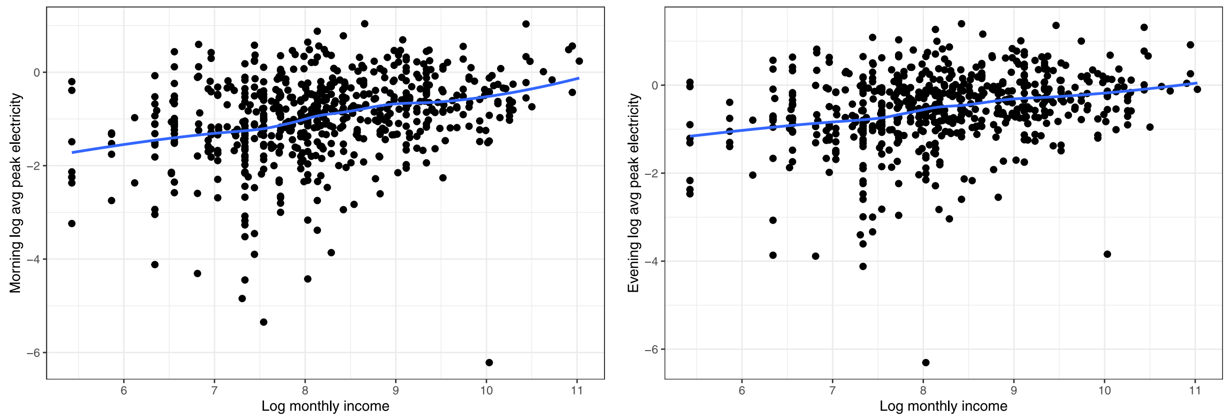
5.2. Regression

5.2.1. Ordinary regression results

Although the descriptive results were suggestive of some differences in household characteristics and electricity usage by the household head's employment status, that discussion did not offer a direct assessment of the underlying income elasticity of electricity, other than to suggest that it was likely independent of log income, i.e., constant. In Table 1, we present estimates of that elasticity underpinned by the constancy assumption. The table contains three columns and five rows. The columns delineate estimates for average morning, evening and total peak electricity usage, respectively, while the rows represent different sets of included controls, starting with a model including only log income. The full results from that series of regressions is presented in Tables B.1–B.5.

Overall, we find that electricity consumption is inelastic, with our estimates ranging from 0.125 to 0.353, depending on the time of day and the included controls. Our results point to larger income elasticities in the morning, followed by the total, and then the evening, regardless of controls, although the differences are not always statistically significant. When including additional variables, such as the employment status of the household head and the size of the household, we find some variation in the estimated elasticity. It increases, when we control for employment status, but nearly returns to its initial level if we control for both employment status and size. Not surprisingly, increased household size is associated with increased electricity consumption. Our estimated household size elasticity is approximately 0.3 across all specifications – see Tables B.2–B.5.; Thus, a 100% increase in the size

[9] Generally, as the bandwidth decreases, variability in the estimate increases, although the fit tends to improve. It is this bias/variance trade-off that determines the optimal bandwidth. The nonparametric estimates are presented primarily for comparison with the main results, and, therefore, we do not present extensive detail regarding either the methods or the estimated bandwidths. All code and results are available from the authors.



(a) Morning (b) Evening

Fig. 2. Relationship between peak electricity usage and log monthly income.

Table 1
Ordinary regression model estimated elasticity for morning, evening and total average peak electricity consumption.

	Morning	Evening	Total
Monthly income only			
Log monthly income	0.266***	0.221***	0.242***
	(0.033)	(0.031)	(0.031)
Monthly income and head employment status			
Log monthly income	0.321***	0.271***	0.294***
	(0.041)	(0.039)	(0.038)
Monthly income, head employment and household structure			
Log monthly income	0.238***	0.197***	0.218***
	(0.042)	(0.040)	(0.039)
Monthly income, head employment, household structure and energy controls			
Log monthly income	0.181***	0.148***	0.167***
	(0.042)	(0.040)	(0.039)
Monthly income, head employment, household structure and appliance controls			
Log monthly income	0.143***	0.118***	0.134***
	(0.044)	(0.042)	(0.041)

Coefficient estimates from ordinary linear regression with a variety of controls included. Each set of models includes a range of additional controls, as described in the table. Appendix B presents full regression results.

of the household implies an approximate 30% increase in electricity consumption.

Furthermore, adding controls for appliance ownership, either through our ownership index or through the ownership of separate appliances, we see decreases in the estimated elasticities, although the relationship between morning, evening and the total remains. In terms of economic theory, inelastic demand implies goods that are necessities. Since additional appliances imply an increased dependence on electricity, or at least an increased dependence on the conveniences associated with the use of electricity, it is not surprising that the inclusion of appliances in the model will lead to reduced elasticities.

5.2.2. Sensitivity analysis

The preceding results were based on models that assumed a constant income elasticity. For that reason, we estimate two less restrictive models. We estimate a fully nonparametric regression, including the same controls as in the regression model reported in Table B.4. We also estimated a series of quantile regression models including the exact same sets of controls, and in the exact same order, as for the linear model. We report results for the 0.2, 0.4, 0.6 and 0.8 quantiles. We further test for the constancy of the income elasticity across the quantiles. The full results are reported in Tables C.1–C.5 for morning peak, Tables D.1–D.5 for evening and Tables E.1–E.5 for the total peak average.

For morning peak, we find elasticities ranging from 0.091 (0.2 quantile, Table C.5) to 0.392 (0.2 quantile, Table C.2). For evening peak, the elasticity range is 0.057 to 0.363, while the totals range is from 0.078 to 0.412. Within any set of morning, peak or total quantile regressions across the four quantiles reported, there is further variation, and, for the most part, that variation suggests a decreasing elasticity for heavier users of electricity, which is intuitive. If we look at the household size elasticity across morning, evening and total, we see similar variation. Estimated household size elasticities tend to be larger at lower quantiles of the log average peak electricity distribution, and vice versa. The household size elasticities range from approximately one-half to about 0.122, depending on the time of day.

Although there is variation in the estimated elasticities across the quantiles, we find no evidence of location-shift in our models, i.e., whether or not the underlying distribution of electricity consumption is shifted by any of the controls. We also tested for location-scale-shift, which also considers whether the spread of the distribution is affected (would be heteroskedastic and related to any of the controls). We employ a series of Khmaladze Tests, described in Koenker and Xiao (2002) that is implemented in Koenker (2023). We find that neither the income elasticity nor the household size elasticity differences that we observe are statistically significant either for location or scale shifts at 10%. These results strongly support both the use of the ordinary linear model, and the results reported, therein.

To be completely certain, we also estimate a fully non-parametric regression of log average peak electricity usage against the log of monthly income, controlling for a number of household level variables (log income, log household size, an index of asset ownership, and the employment status of the household head), which are similar to those used in the preceding models. We illustrate the estimated smooth fit from these fully nonparametric specifications in Fig. F.1, wherein the optimal bandwidths yield a linear relationship between log income and log average peak electricity consumption across all three peaks. Thus, our nonparametric analysis presents further confirmation for the Khmaladze test results: the estimated income elasticities are constant; full results are available upon request.

5.3. Discussion

Our primary conclusion is not entirely different from the literature. Electricity consumption in rural South Africa, as is the case in the rest of South Africa and much of the rest of the world, is a necessity. To some degree, our result is to be expected; we focused on peak hours, after all. A further conclusion is that metered rural household income responsiveness is on the low end of estimates previously presented in the South African and broader international literature, which includes both household-level estimates, primarily underscored by expenditure data, and time series estimates arising from aggregate data. In comparison, household income elasticities from the literature include: (i) Louw et al. (2008), which ranges from 0.243 to 0.532; (ii) Anderson (2004), an estimate of 0.32; and (iii) Ye et al. (2018), which ranges from 0.128 to 0.427. On the other hand, time series estimates include much of the unit interval (Inglesi-Lotz, 2011), as well as estimates from about 0.3 (Ziramba, 2008) to 0.42 (Inglesi, 2010), 0.71 (Pouris, 1987), 0.65 to 0.73 (Bohlmann and Inglesi-Lotz, 2021) and even 1.67 (Amusa et al., 2009), which is the only one of which we are aware suggesting electricity consumption might be a luxury.

Although our results are on the low end, they are certainly in-line with what has been previously estimated. Thus, our sample of Eskom-supplied rural households is nearly as responsive in their electricity demand, given income differences, as the rest of South Africa. Given that these households have not been electrified all that long, are somewhat poorer, and have access to a relatively small "mains" switch, and often intermix traditional sources of energy with grid electricity (Davis, 1998; Nkosi et al., 2021; Chidembo et al., 2022), one might have expected greater responsiveness. Furthermore, even though our sample of households does not own an extensive array of appliances, that ownership is also associated with a further reduction in the income elasticity of electricity consumption for rural households. Thus, even rural households with relatively few appliances appreciate the convenience associated with appliances enough to strengthen the necessity component of electricity consumption.

One limitation with this research is that it is not able to reflect on price responsiveness. Although we are able to control for many factors likely to influence electricity consumption, our data does not incorporate price; thus, our income elasticity could be incorporating some pricing aspects, and, therefore, be biased. However, there is little in the way of price variation that could be captured, given that our respondents all receive their electricity directly from the national monopoly producer, while price changes during this time period happened once during the meter reading time period. Further, the price increase was only 6%. Thus, we do not think pricing issues are a serious concern in this analysis.

One concern that might arise in our context is that our analytic dataset is rather small. Specifically, it includes only 608 households with both metered electricity readings and a household survey module.[10] Thus, we offer a brief comparison to the 2014–15 South African Living Conditions Survey (LCS) (Statistics South Africa, 2017), which is nationally representative and collected at approximately the same time. The DEL data is inflated to December 2016, while the LCS data was initially in/deflated to April 2015. Thus, for comparison, we multiply the LCS income data by the CPI ratio for December 2016, relative to April 2015, using the appropriate Statistics South Africa data (Statistics South Africa, 2023). We then estimate and illustrate the densities of both household size, separated by number of children and adults, and reported log monthly incomes; see Figs. F.2 and F.3. Although they look similar, applying Kolmogorov–Smirnov tests to the different distributions yields statistically significant differences across all of them, primarily due to the number of observations.[11] Although the number of households in our survey is relatively small, the broad distribution of at least some of the controls looks fairly similar to the LCS. However, as we know, one should take care, when extending results to the general population, even though there appear to be many similarities in the underlying samples.

Another concern that might arise in our context is the use of data from 2014; things may have changed since then. For example, given the positive income elasticity estimated here, and the potential for increased income since 2014, one might expect rural households to purchase additional appliances, which we have also shown to drive elasticities even lower or otherwise more deeply influence electricity demand responsiveness. Given how the economic situation has evolved in South Africa over the last 15 years, as well as the similarity in our results compared to the rest of the literature, we believe that our results remain relevant. Firstly, as highlighted above, South Africa (has since 2008 and) continues to experience load-shedding – only a few days since September 2022 have been spared from its tentacles. In other words, electricity supply has not kept up with demand, overall, which limits the convenience benefits associated with appliances, and reduces appliance demand. Secondly, unemployment in the country remains stubbornly high. In 1994, "narrow" unemployment, which does not count those who might be discouraged from seeking work, was 20%. By 2000, it was 26.7% (Francis and Webster, 2019), and in 2019 it stood at 27.3% (Milasi, 2019). Thus, the economy is also not creating jobs in a way that would further spark electricity or appliance demand. Finally, despite the remarkable achievement in electricity access, the intermix usage of traditional fuel and grid electricity is prevalent in rural South Africa (Ye and Koch, 2023; Bohlmann and Inglesi-Lotz, 2018). Although adoption of rooftop solar photovoltaic (PV) has been increased significantly in recent years due to the rolling blackout, rural households perceive solar energy as a relatively cheap but unreliable energy, and its adoption highly depends on household's financial situation (Chidembo et al., 2022). Rural households have relatively limited access to finance to obtain backup power sources (Inglesi-Lotz, 2023) which make them more vulnerable in terms of mitigating the impact of load shedding and could further restraint their demand of appliances.

6. Conclusion

We have estimated the income elasticity of rural domestic electricity consumption using meter data collected from approximately 600 households across South Africa in 2014. Due to a large number of missing values in terms of hourly meter readings, we focused our attention on (log) average consumption during peak load periods. Our results are underpinned by linear regression, which we show is appropriate in this setting, after testing the appropriateness of constant income elasticities via quantile and nonparametric methods. We find that income elasticities of (average) peak load electricity consumption range from between 0.125 and 0.353, depending on the included variables. Thus, income elasticities for rural households in South Africa imply that electricity is inelastic. Given the broad literature, it is not unexpected to find that electricity is a necessity, even for relatively poor rural households in South Africa. However, the similarity between these rural households

[10] As described above, we do lose a few observations for households with completely missing meter readings, and no reported income.

[11] In order, we present p-values for monthly income, household size, adults and kids: 0.0000001750439, 0, 0.000181 and 0.

Table A.1
Summary statistics by household head employment status.

	full-time (N = 220)	part-time (N = 52)	retired (N = 203)	unemp (N = 135)
Peak electricity usage				
Morning peak: mean (sd)	0.58 (0.41)	0.45 (0.37)	0.50 (0.41)	0.51 (0.42)
Evening peak: mean (sd)	0.83 (0.59)	0.69 (0.53)	0.75 (0.57)	0.74 (0.59)
Total peak: mean (sd)	0.70 (0.48)	0.57 (0.46)	0.63 (0.48)	0.63 (0.49)
Household composition				
Children: mean (sd)	2.00 (1.21)	2.21 (1.43)	2.34 (1.38)	2.59 (1.50)
Adults: mean (sd)	2.10 (1.02)	2.37 (1.51)	2.40 (1.34)	2.15 (1.14)
Child Share: mean (sd)	1.06 (0.69)	1.07 (0.73)	1.21 (0.88)	1.41 (0.95)
Income and wealth				
Floor area: mean (sd)	78.22 (49.14)	65.23 (35.68)	85.56 (55.95)	71.91 (54.42)
Log income: mean (sd)	8.92 (0.93)	7.52 (0.88)	8.18 (0.70)	7.30 (0.94)
Appliances				
Stove: 3 plate	2.73%	3.85%	1.97%	3.70%
Stove: 4 plate	55.91%	25.00%	59.61%	43.70%
Hot Plate	39.09%	67.31%	35.47%	48.89%
Microwave	66.82%	19.23%	54.19%	48.89%
Washing Maching	49.09%	17.31%	38.42%	31.11%
Fridge/Freezer	89.55%	67.31%	83.74%	80.00%
Geyser	26.82%	1.92%	10.34%	11.11%
Heater	27.27%	1.92%	12.81%	12.59%
iron	94.09%	78.85%	87.19%	83.70%
Appliance ownership index				
Lowest	28.64%	46.15%	21.18%	34.07%
Second lowest	7.73%	23.08%	14.29%	14.81%
Middle	9.55%	21.15%	14.78%	10.37%
Second highest	26.82%	7.69%	37.93%	29.63%
Highest	27.27%	1.92%	11.82%	11.11%
Location				
Butterworth	15.00%	7.69%	2.46%	3.70%
Dipelaneng	2.27%	7.69%	9.85%	16.30%
Ga-Nkoane	1.82%	9.62%	15.27%	9.63%
Hankey	8.18%	3.85%	8.87%	8.15%
Ga-Luka	13.64%	9.62%	6.90%	5.93%
Matsulu	8.64%	13.46%	2.96%	10.37%
Matshana	5.91%	15.38%	4.93%	5.19%
Bophelong	5.00%	7.69%	9.36%	10.37%
Phomolong	6.82%	7.69%	13.79%	11.11%
Seloshesa	23.18%	0.00%	1.97%	5.93%
Vlaklaagte	5.45%	7.69%	14.78%	4.44%
Wattville	4.09%	9.62%	8.87%	8.89%

Note: Categorical variables are presented as the percent of observations in each category within each column. For continuous variables, the mean is presented with its standard deviation, separated by ±.

and the rest of the country and wider literature was unexpected, even though our elasticity estimates are on the lower end previous literature, which has relied upon either expenditure data or aggregate time series data.

Given that similarity, at least in the case of South Africa, our results offer some solace to researchers not able to access such accurate electricity consumption data, as we have been able to access here. However, additional research across a wide range of countries is needed to determine if South Africa is an anomaly or the norm, in that regard. Furthermore, we find lower elasticities, when we include appliance ownership measures, suggesting that individuals view electricity as more of a necessity, after they have become accustomed to the benefits of the household services that can be provided by such appliances.

There are additional years of data, and, therefore, it might be possible to capture price differences using a longer span of data. We have also not been able to use all, or at least most of the hourly data, which would allow us to control for temperature and sunlight effects, opening up the potential to impute a large share of the missing data, and undertake a more nuanced analysis than considered here.

Inclusion and diversity

One or more of the authors of this paper self-identifies as an underrepresented ethnic minority in science. One or more of the authors of this paper received support from a programme designed to increase minority representation in science.

CRediT authorship contribution statement

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

Declaration of competing interest

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

Appendix A. Descriptive statistics

See Table A.1.

Appendix B. Ordinary regression results

See Tables B.1–B.5.

Appendix C. Quantile regression results for morning peak

See Tables C.1–C.5.

Table B.1
Average peak ordinary regression results with only monthly income.

	Dependent variable:		
	Morning	Evening	Total
Log monthly income	0.266***	0.221***	0.242***
	(0.033)	(0.031)	(0.031)
Constant	−3.142***	−2.357***	−2.696***
	(0.273)	(0.256)	(0.252)
Observations	610	610	610
R^2	0.096	0.077	0.093
Adjusted R^2	0.095	0.076	0.092
Residual Std. Error (df = 608)	0.870	0.817	0.805
F Statistic (df = 1; 608)	64.819***	51.030***	62.580***

Note: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table B.2
Average peak ordinary regression results with monthly income and head employment status.

	Dependent variable:		
	Morning	Evening	Total
Log monthly income	0.321***	0.271***	0.294***
	(0.041)	(0.039)	(0.038)
Head part-time	0.072	0.132	0.092
	(0.145)	(0.137)	(0.135)
Head retired	0.0002	0.003	0.012
	(0.089)	(0.084)	(0.083)
Head unemployed	0.296**	0.244**	0.273**
	(0.116)	(0.109)	(0.107)
Constant	−3.669***	−2.829***	−3.198***
	(0.370)	(0.348)	(0.343)
Observations	610	610	610
R^2	0.110	0.088	0.106
Adjusted R^2	0.104	0.082	0.100
Residual Std. Error (df = 605)	0.865	0.814	0.801
F Statistic (df = 4; 605)	18.648***	14.568***	17.891***

Note: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table B.3
Average peak ordinary regression results with monthly income, head employment and household structure.

	Dependent variable:		
	Morning	Evening	Total
Log monthly income	0.238***	0.197***	0.218***
	(0.042)	(0.040)	(0.039)
Head part-time	−0.066	0.010	−0.032
	(0.143)	(0.135)	(0.132)
Head retired	−0.130	−0.111	−0.106
	(0.089)	(0.084)	(0.083)
Head unemployed	0.095	0.067	0.090
	(0.117)	(0.110)	(0.108)
Log household size	0.345***	0.305***	0.314***
	(0.055)	(0.052)	(0.051)
Constant	−3.250***	−2.459***	−2.817***
	(0.365)	(0.345)	(0.339)
Observations	610	610	610
R^2	0.164	0.137	0.158
Adjusted R^2	0.157	0.129	0.151
Residual Std. Error (df = 604)	0.839	0.793	0.778
F Statistic (df = 5; 604)	23.653***	19.114***	22.669***

Table B.3 (*continued*).

Note: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table B.4
Average peak ordinary regression results with monthly income, head employment, household structure and energy usage controls.

	Dependent variable:		
	Morning	Evening	Total
Log monthly income	0.181***	0.148***	0.167***
	(0.042)	(0.040)	(0.039)
Head part-time	0.055	0.113	0.074
	(0.141)	(0.134)	(0.131)
Head retired	−0.136	−0.120	−0.113
	(0.088)	(0.084)	(0.082)
Head unemployed	0.078	0.052	0.075
	(0.114)	(0.108)	(0.106)
Log household size	0.338***	0.297***	0.306***
	(0.055)	(0.052)	(0.051)
Log floor area	0.073	0.072	0.079
	(0.059)	(0.056)	(0.055)
Appliance own fourth	−0.041	−0.043	−0.051
	(0.114)	(0.108)	(0.106)
Appliance own third	−0.016	0.020	0.005
	(0.114)	(0.109)	(0.106)
Appliance own second	0.327***	0.286***	0.288***
	(0.091)	(0.086)	(0.084)
Appliance own first	0.462***	0.401***	0.412***
	(0.112)	(0.106)	(0.104)
Constant	−3.255***	−2.495***	−2.867***
	(0.422)	(0.400)	(0.392)
Observations	610	610	610
R^2	0.212	0.178	0.204
Adjusted R^2	0.198	0.165	0.190
Residual Std. Error (df = 599)	0.818	0.776	0.760
F Statistic (df = 10; 599)	16.076***	13.005***	15.329***

Note: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table B.5
Average peak ordinary regression results with monthly income, head employment, household structure and appliance controls.

	Dependent variable:		
	Morning	Evening	Total
Log monthly income	0.143***	0.118***	0.134***
	(0.044)	(0.042)	(0.041)
Head part-time	0.040	0.093	0.057
	(0.141)	(0.134)	(0.131)
Head retired	−0.134	−0.128	−0.117
	(0.088)	(0.084)	(0.082)
Head unemployed	0.059	0.037	0.059
	(0.114)	(0.108)	(0.106)
Log household size	0.333***	0.292***	0.302***
	(0.055)	(0.053)	(0.052)
Log floor area	0.056	0.059	0.064
	(0.060)	(0.057)	(0.056)

(*continued on next page*)

Table B.5 (*continued*).

Stove 3 plate	0.226	0.168	0.165
	(0.176)	(0.168)	(0.164)
Stove 4 plate	0.471***	0.375**	0.384**
	(0.173)	(0.164)	(0.161)
Fridge/freezer	0.025	0.058	0.040
	(0.068)	(0.065)	(0.063)
Washing machine	0.140*	0.155*	0.141*
	(0.084)	(0.080)	(0.078)
Geyser	0.107	0.043	0.079
	(0.107)	(0.102)	(0.100)
Heater	0.136	0.109	0.115
	(0.100)	(0.095)	(0.093)
Hotplate	0.313*	0.193	0.219
	(0.169)	(0.161)	(0.158)
Iron	0.148	0.111	0.124
	(0.120)	(0.114)	(0.112)
Kettle	−0.045	−0.012	−0.018
	(0.112)	(0.107)	(0.104)
Microwave	0.102	0.012	0.046
	(0.081)	(0.077)	(0.076)
Constant	−3.342***	−2.554***	−2.920***
	(0.458)	(0.435)	(0.426)
Observations	610	610	610
R^2	0.223	0.189	0.214
Adjusted R^2	0.202	0.167	0.192
Residual Std. Error (df = 593)	0.816	0.775	0.759
F Statistic (df = 16; 593)	10.653***	8.651***	10.070***

Note: *p < 0.1; **p < 0.05; ***p < 0.01.

Table C.1
Average morning peak quantile regression results with only monthly income.

	Dependent variable:			
	Log average morning peak quantiles			
	0.2	0.4	0.6	0.8
Log monthly income	0.325***	0.251***	0.235***	0.174***
	(0.047)	(0.031)	(0.032)	(0.042)
Constant	−4.201***	−3.127***	−2.671***	−1.718***
	(0.413)	(0.270)	(0.277)	(0.362)
Observations	610	610	610	610

Note: *p < 0.1; **p < 0.05; ***p < 0.01.

Table C.2
Average morning peak quantile regression results with monthly income and head employment status.

	Dependent variable:			
	Log average morning peak quantiles			
	0.2	0.4	0.6	0.8
Log monthly income	0.383***	0.311***	0.316***	0.214***
	(0.048)	(0.041)	(0.040)	(0.050)
Head part-time	0.059	0.168	0.180	0.063
	(0.294)	(0.150)	(0.145)	(0.191)
Head retired	−0.008	0.053	0.086	0.034
	(0.112)	(0.091)	(0.083)	(0.103)
Head unemployed	0.362***	0.231*	0.382***	0.250
	(0.133)	(0.121)	(0.128)	(0.166)
Constant	−4.766***	−3.700***	−3.442***	−2.125***
	(0.458)	(0.378)	(0.368)	(0.461)
Observations	610	610	610	610

Note: *p < 0.1; **p < 0.05; ***p < 0.01.

Table C.3
Average morning peak quantile regression results with monthly income, head employment and household structure.

	Dependent variable:			
	Log average morning peak quantiles			
	0.2	0.4	0.6	0.8
Log monthly income	0.287***	0.242***	0.225***	0.191***
	(0.057)	(0.041)	(0.041)	(0.052)
Head part-time	−0.079	−0.012	0.023	0.020
	(0.353)	(0.136)	(0.156)	(0.134)
Head retired	−0.075	−0.081	−0.039	−0.062
	(0.122)	(0.086)	(0.085)	(0.110)
Head unemployed	0.037	−0.003	0.161	0.242
	(0.150)	(0.122)	(0.125)	(0.156)
Log household size	0.444***	0.357***	0.240***	0.220***
	(0.081)	(0.058)	(0.057)	(0.067)
Constant	−4.281***	−3.466***	−2.868***	−2.135***
	(0.503)	(0.359)	(0.365)	(0.451)
Observations	610	610	610	610

Note: *p < 0.1; **p < 0.05; ***p < 0.01.

Table C.4
Average morning peak quantile regression results with monthly income, head employment, household structure and energy usage controls.

	Dependent variable:			
	Log average morning peak quantiles			
	0.2	0.4	0.6	0.8
Log monthly income	0.183***	0.228***	0.126***	0.157***
	(0.042)	(0.037)	(0.040)	(0.033)
Head part-time	−0.005	0.243	0.274*	0.120
	(0.129)	(0.176)	(0.146)	(0.088)
Head retired	−0.190**	0.040	−0.086	−0.093
	(0.089)	(0.072)	(0.080)	(0.087)
Head unemployed	0.004	0.203**	0.055	0.186
	(0.122)	(0.098)	(0.126)	(0.123)
Log household size	0.434***	0.331***	0.293***	0.236***
	(0.059)	(0.052)	(0.053)	(0.062)
Log floor area	0.173***	0.159***	0.114**	0.017
	(0.064)	(0.054)	(0.052)	(0.057)
Appliance own fourth	0.200	0.004	−0.167	−0.197*
	(0.125)	(0.104)	(0.111)	(0.108)
Appliance own third	0.236	0.028	−0.146	−0.096
	(0.155)	(0.107)	(0.106)	(0.116)
Appliance own second	0.476***	0.333***	0.229**	0.149
	(0.123)	(0.097)	(0.094)	(0.106)
Appliance own first	0.615***	0.487***	0.416***	0.338**
	(0.128)	(0.108)	(0.117)	(0.146)
Constant	−4.413***	−4.256***	−2.705***	−2.049***
	(0.445)	(0.379)	(0.387)	(0.402)
Observations	610	610	610	610

Note: *p < 0.1; **p < 0.05; ***p < 0.01.

Table C.5
Average morning peak quantile regression results with monthly income, head employment, household structure and appliance controls.

	Dependent variable:			
	Log average morning peak quantiles			
	0.2	0.4	0.6	0.8
Log monthly income	0.170***	0.139***	0.073	0.124***
	(0.039)	(0.033)	(0.045)	(0.046)
Head part-time	0.089	0.107	0.183	0.234
	(0.150)	(0.126)	(0.189)	(0.150)
Head retired	−0.062	0.049	−0.063	−0.076
	(0.070)	(0.064)	(0.086)	(0.095)
Head unemployed	0.087	0.123	0.113	0.233*
	(0.105)	(0.083)	(0.125)	(0.126)
Log household size	0.442***	0.350***	0.280***	0.143**
	(0.055)	(0.047)	(0.057)	(0.069)
Log floor area	0.142**	0.141***	0.154***	0.005
	(0.055)	(0.047)	(0.058)	(0.069)
Stove 3 plate	0.310**	0.163	0.125	0.101
	(0.157)	(0.160)	(0.239)	(0.150)
Stove 4 plate	0.474***	0.328**	0.302	0.217
	(0.087)	(0.145)	(0.191)	(0.134)
Fridge/freezer	0.043	0.077	0.067	−0.103
	(0.098)	(0.159)	(0.083)	(0.231)
Washing machine	0.218***	0.139**	0.076	0.085
	(0.068)	(0.064)	(0.078)	(0.084)
Geyser	0.080	0.124*	0.165	0.243**
	(0.071)	(0.069)	(0.118)	(0.102)
Heater	0.098	0.232***	0.237**	0.182*
	(0.082)	(0.064)	(0.095)	(0.102)
Hotplate	0.197*	0.193	0.174	0.095
	(0.101)	(0.147)	(0.189)	(0.142)
Iron	0.368**	0.094	0.068	0.036
	(0.166)	(0.171)	(0.154)	(0.148)
Kettle	−0.207**	−0.006	−0.053	−0.083
	(0.093)	(0.064)	(0.137)	(0.139)
Microwave	0.164**	0.090	0.148*	0.090
	(0.081)	(0.065)	(0.076)	(0.097)
Constant	−4.717***	−3.818***	−2.802***	−1.765***
	(0.418)	(0.411)	(0.488)	(0.522)
Observations	610	610	610	610

Note: *p < 0.1; **p < 0.05; ***p < 0.01.

Table D.1
Average evening peak quantile regression results with only monthly income.

	Dependent variable:			
	Log average evening peak quantiles			
	0.2	0.4	0.6	0.8
Log monthly income	0.247***	0.205***	0.206***	0.133***
	(0.041)	(0.029)	(0.030)	(0.041)
Constant	−3.043***	−2.331***	−2.009***	−1.056***
	(0.364)	(0.247)	(0.260)	(0.340)
Observations	610	610	610	610

Note: *p < 0.1; **p < 0.05; ***p < 0.01.

Appendix D. Quantile regression results for evening peak

See Tables D.1–D.5.

Appendix E. Quantile regression results for total peak

See Tables E.1–E.5.

Appendix F. Density and nonparametric regression plots

See Figs. F.1–F.3.

Table D.2
Average evening peak quantile regression results with monthly income and head employment status.

	Dependent variable:			
	Log average evening peak quantiles			
	0.2	0.4	0.6	0.8
Log monthly income	0.293***	0.272***	0.230***	0.166***
	(0.048)	(0.032)	(0.029)	(0.052)
Head part-time	0.121	0.237	0.130*	0.018
	(0.126)	(0.195)	(0.068)	(0.176)
Head retired	0.024	0.087	0.078	0.043
	(0.152)	(0.071)	(0.087)	(0.112)
Head unemployed	0.264*	0.244***	0.117	0.174
	(0.147)	(0.086)	(0.108)	(0.161)
Constant	−3.493***	−2.974***	−2.277***	−1.389***
	(0.464)	(0.293)	(0.276)	(0.475)
Observations	610	610	610	610

Note: *p < 0.1; **p < 0.05; ***p < 0.01.

Table D.3
Average evening peak quantile regression results with monthly income, head employment and household structure.

	Dependent variable:			
	Log average evening peak quantiles			
	0.2	0.4	0.6	0.8
Log monthly income	0.202***	0.206***	0.173***	0.173***
	(0.042)	(0.037)	(0.039)	(0.053)
Head part-time	−0.077	0.138	−0.029	0.096
	(0.244)	(0.114)	(0.104)	(0.163)
Head retired	−0.137	−0.028	−0.042	0.116
	(0.114)	(0.076)	(0.079)	(0.116)
Head unemployed	−0.015	0.040	−0.015	0.218
	(0.119)	(0.101)	(0.127)	(0.158)
Log household size	0.422***	0.301***	0.210***	0.142**
	(0.067)	(0.050)	(0.051)	(0.070)
Constant	−3.116***	−2.672***	−1.963***	−1.613***
	(0.390)	(0.314)	(0.340)	(0.468)
Observations	610	610	610	610

Note: *p < 0.1; **p < 0.05; ***p < 0.01.

Table D.4
Average evening peak quantile regression results with monthly income, head employment, household structure and energy usage controls.

	Dependent variable:			
	Log average evening peak quantiles			
	0.2	0.4	0.6	0.8
Log monthly income	0.093*	0.145***	0.153***	0.082*
	(0.049)	(0.032)	(0.039)	(0.045)
Head part-time	0.106	0.380***	0.231**	0.172
	(0.212)	(0.131)	(0.108)	(0.148)
Head retired	−0.174*	0.001	0.014	−0.030
	(0.105)	(0.064)	(0.074)	(0.090)
Head unemployed	−0.036	0.053	0.089	0.125
	(0.127)	(0.088)	(0.117)	(0.126)

(continued on next page)

Table D.4 (*continued*).

	Dependent variable:			
	Log average evening peak quantiles			
	0.2	0.4	0.6	0.8
Log household size	0.409***	0.296***	0.161***	0.190***
	(0.071)	(0.046)	(0.050)	(0.064)
Log floor area	0.132*	0.130***	0.115**	0.024
	(0.074)	(0.049)	(0.053)	(0.066)
Appliance own fourth	0.187	0.024	0.097	−0.083
	(0.173)	(0.099)	(0.116)	(0.140)
Appliance own third	0.252*	0.034	0.022	−0.115
	(0.144)	(0.092)	(0.096)	(0.180)
Appliance own second	0.536***	0.333***	0.309***	0.200*
	(0.116)	(0.083)	(0.085)	(0.107)
Appliance own first	0.625***	0.410***	0.377***	0.470***
	(0.124)	(0.100)	(0.114)	(0.133)
Constant	−3.021***	−2.923***	−2.481***	−1.105**
	(0.485)	(0.346)	(0.391)	(0.467)
Observations	610	610	610	610

Note: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table D.5
Average evening peak quantile regression results with monthly income, head employment, household structure and appliance controls.

	Dependent variable:			
	Log average evening peak quantiles			
	0.2	0.4	0.6	0.8
Log monthly income	0.054	0.101***	0.115***	0.058
	(0.042)	(0.038)	(0.031)	(0.052)
Head part-time	−0.036	0.240*	0.134*	0.139
	(0.104)	(0.124)	(0.074)	(0.166)
Head retired	−0.191**	−0.004	−0.045	−0.054
	(0.096)	(0.071)	(0.068)	(0.101)
Head unemployed	−0.124	0.038	0.009	−0.009
	(0.127)	(0.094)	(0.097)	(0.145)
Log household size	0.467***	0.302***	0.191***	0.168**
	(0.067)	(0.050)	(0.046)	(0.072)
Log floor area	0.092	0.144***	0.118***	0.006
	(0.065)	(0.055)	(0.045)	(0.072)
Stove 3 plate	0.220	0.111**	0.026	0.309
	(0.197)	(0.054)	(0.263)	(0.213)
Stove 4 plate	0.529	0.356***	0.241*	0.259
	(0.575)	(0.106)	(0.145)	(0.169)
Fridge/freezer	0.077	0.055	0.081	−0.059
	(0.103)	(0.085)	(0.139)	(0.234)
Washing machine	0.152**	0.160**	0.130**	0.100
	(0.071)	(0.066)	(0.058)	(0.094)
Geyser	0.049	−0.020	−0.016	0.231**
	(0.058)	(0.079)	(0.105)	(0.111)
Heater	0.020	0.124	0.161*	0.161
	(0.082)	(0.081)	(0.087)	(0.105)
Hotplate	0.208	0.155	0.107	0.133
	(0.579)	(0.110)	(0.143)	(0.175)
Iron	0.128	0.006	0.038	−0.048
	(0.288)	(0.141)	(0.091)	(0.208)
Kettle	0.055	0.0002	−0.059	−0.029
	(0.135)	(0.122)	(0.085)	(0.187)
Microwave	0.057	0.065	0.027	0.042
	(0.078)	(0.070)	(0.061)	(0.107)
Constant	−2.957***	−2.873***	−2.339***	−0.845
	(0.728)	(0.409)	(0.333)	(0.543)
Observations	610	610	610	610

Note: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table E.1
Average total peak quantile regression results with only monthly income.

	Dependent variable:			
	Log average total peak quantiles			
	0.2	0.4	0.6	0.8
Log monthly income	0.294***	0.222***	0.216***	0.157***
	(0.041)	(0.028)	(0.031)	(0.042)
Constant	−3.608***	−2.626***	−2.267***	−1.421***
	(0.368)	(0.236)	(0.268)	(0.356)
Observations	610	610	610	610

Note: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table E.2
Average total peak quantile regression results with monthly income and head employment status.

	Dependent variable:			
	Log average total peak quantiles			
	0.2	0.4	0.6	0.8
Log monthly income	0.354***	0.289***	0.261***	0.186***
	(0.053)	(0.034)	(0.036)	(0.053)
Head part-time	0.065	0.234	0.125	−0.023
	(0.273)	(0.145)	(0.114)	(0.197)
Head retired	0.073	0.118	0.072	0.077
	(0.134)	(0.074)	(0.083)	(0.116)
Head unemployed	0.293*	0.263**	0.262**	0.281*
	(0.151)	(0.103)	(0.105)	(0.159)
Constant	−4.214***	−3.289***	−2.727***	−1.731***
	(0.490)	(0.315)	(0.333)	(0.490)
Observations	610	610	610	610

Note: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table E.3
Average total peak quantile regression results with monthly income, head employment and household structure.

	Dependent variable:			
	Log average total peak quantiles			
	0.2	0.4	0.6	0.8
Log monthly income	0.268***	0.217***	0.229***	0.199***
	(0.037)	(0.038)	(0.036)	(0.056)
Head part-time	0.008	0.133	0.103	0.144
	(0.193)	(0.154)	(0.098)	(0.191)
Head retired	−0.101	−0.015	−0.002	0.031
	(0.086)	(0.077)	(0.078)	(0.119)
Head unemployed	0.043	0.099	0.196*	0.321*
	(0.103)	(0.108)	(0.113)	(0.165)
Log household size	0.439***	0.270***	0.208***	0.165**
	(0.059)	(0.054)	(0.050)	(0.079)
Constant	−3.859***	−2.933***	−2.666***	−2.047***
	(0.341)	(0.334)	(0.319)	(0.497)
Observations	610	610	610	610

Note: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table E.4
Average total peak quantile regression results with monthly income, head employment, household structure and energy usage controls.

	Dependent variable:			
	Log average total peak quantiles			
	0.2	0.4	0.6	0.8
Log monthly income	0.178***	0.156***	0.132***	0.128***
	(0.037)	(0.034)	(0.036)	(0.044)
Head part-time	0.027	0.305*	0.242**	0.130
	(0.212)	(0.161)	(0.101)	(0.155)
Head retired	−0.187**	0.015	−0.014	−0.053
	(0.086)	(0.068)	(0.071)	(0.081)
Head unemployed	−0.034	0.111	0.098	0.165
	(0.100)	(0.087)	(0.105)	(0.150)
Log household size	0.419***	0.308***	0.209***	0.205***
	(0.057)	(0.049)	(0.046)	(0.065)
Log floor area	0.170***	0.158***	0.117**	0.062
	(0.056)	(0.049)	(0.050)	(0.063)
Appliance own fourth	0.221**	0.035	0.030	−0.206
	(0.105)	(0.098)	(0.106)	(0.150)
Appliance own third	0.292**	0.049	−0.015	−0.163
	(0.132)	(0.091)	(0.091)	(0.195)
Appliance own second	0.453***	0.354***	0.301***	0.126
	(0.103)	(0.089)	(0.078)	(0.124)
Appliance own first	0.556***	0.450***	0.428***	0.323**
	(0.110)	(0.098)	(0.115)	(0.143)
Constant	−4.063***	−3.343***	−2.523***	−1.788***
	(0.394)	(0.349)	(0.363)	(0.467)
Observations	610	610	610	610

Note: *p < 0.1; **p < 0.05; ***p < 0.01.

Table E.5
Average total peak quantile regression results with monthly income, head employment, household structure and appliance controls.

	Dependent variable:			
	Log average total peak quantiles			
	0.2	0.4	0.6	0.8
Log monthly income	0.140***	0.131***	0.104***	0.074
	(0.041)	(0.033)	(0.034)	(0.050)
Head part-time	0.019	0.302**	0.183*	0.338*
	(0.155)	(0.133)	(0.108)	(0.177)
Head retired	−0.121*	0.014	−0.016	0.0002
	(0.066)	(0.056)	(0.065)	(0.093)
Head unemployed	0.015	0.088	0.112	0.166
	(0.114)	(0.086)	(0.091)	(0.128)
Log household size	0.421***	0.304***	0.223***	0.175**
	(0.055)	(0.048)	(0.047)	(0.071)
Log floor area	0.080	0.186***	0.124***	0.042
	(0.062)	(0.044)	(0.043)	(0.068)
Stove 3 plate	0.054	0.065	0.063	0.290
	(0.180)	(0.196)	(0.076)	(0.386)

Table E.5 (*continued*).

	Dependent variable:			
	Log average total peak quantiles			
	0.2	0.4	0.6	0.8
Stove 4 plate	0.242	0.179	0.222***	0.319
	(0.258)	(0.163)	(0.075)	(0.195)
Fridge/freezer	0.095	0.089	0.030	−0.092
	(0.134)	(0.157)	(0.140)	(0.267)
Washing machine	0.163**	0.147***	0.137**	0.116
	(0.066)	(0.051)	(0.060)	(0.090)
Geyser	0.037	−0.002	0.114	0.202*
	(0.064)	(0.075)	(0.100)	(0.116)
Heater	0.107	0.172***	0.140*	0.112
	(0.086)	(0.055)	(0.076)	(0.119)
Hotplate	−0.022	0.0001	0.077	0.203
	(0.258)	(0.164)	(0.079)	(0.201)
Iron	0.249	0.126	−0.023	0.038
	(0.177)	(0.120)	(0.085)	(0.186)
Kettle	−0.053	−0.118	−0.033	0.015
	(0.124)	(0.079)	(0.079)	(0.206)
Microwave	0.099	0.109**	0.081	0.138
	(0.079)	(0.055)	(0.066)	(0.101)
Constant	−3.614***	−3.402***	−2.478***	−1.612***
	(0.529)	(0.390)	(0.343)	(0.559)
Observations	610	610	610	610

Note: *p < 0.1; **p < 0.05; ***p < 0.01

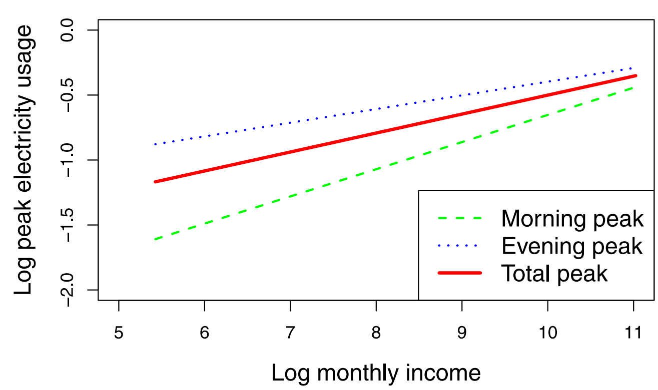
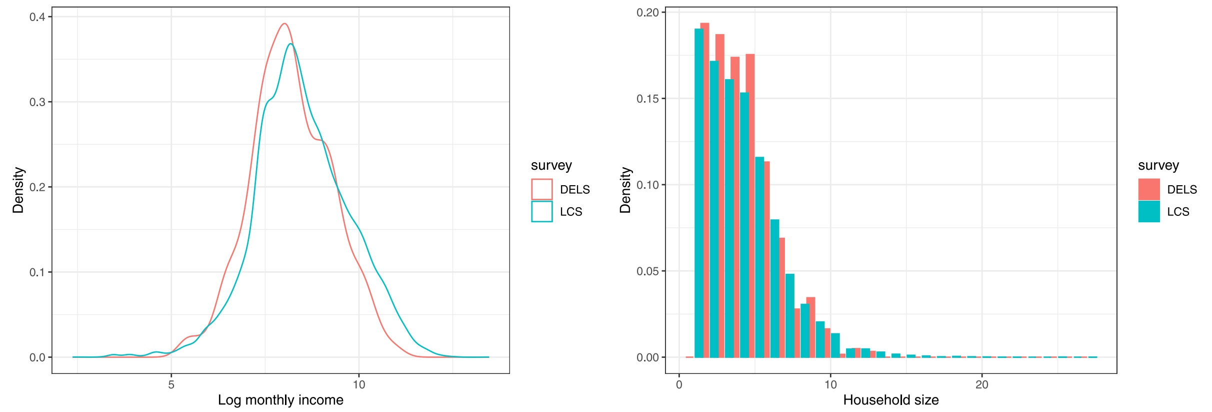


Fig. F.1. Nonparametric regression plots relating monthly income to peak electricity usage, holding all other variables at their median or mode.

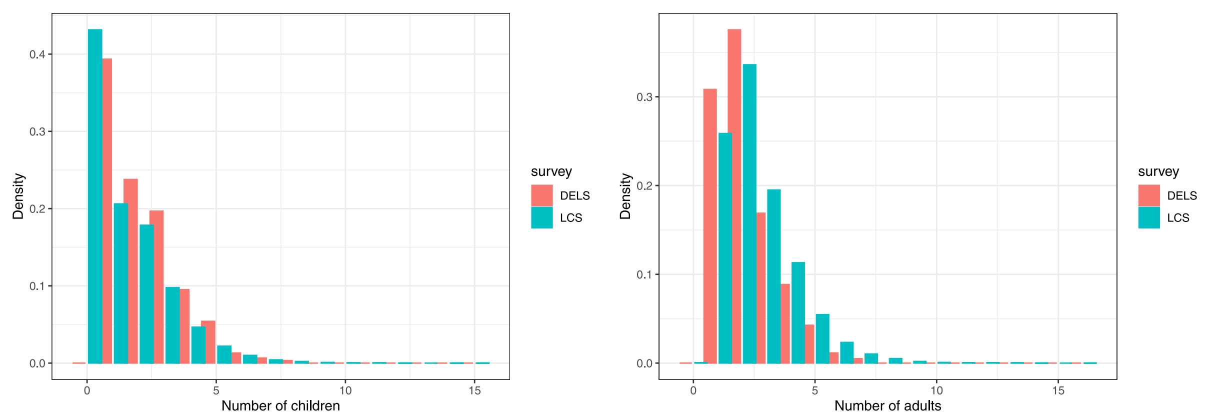
Appendix G. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.eneco.2024.107405.



(a) Density of log income   (b) Density of household size

Fig. F.2. Densities for the 2014–15 Living Conditions Survey (LCS) and the 2014 Domestic Electrical Load Survey (DELS).



(a) Density of children   (b) Density of adults

Fig. F.3. Densities for the 2014–15 Living Conditions Survey (LCS) and the 2014 Domestic Electrical Load Survey (DELS).

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