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Abstract

Wholesale electricity prices can rapidly change in real-time, yet households usually face fixed-price electricity tariffs. Therefore, households that predominantly use energy when wholesale prices are low implicitly cross-subsidize households whose energy use is more weighted to high-price periods. We develop a decomposition method that maps substation data on electricity use to demographic data, identifying the household characteristics associated with this cross-subsidization in Victoria, Australia. We find that households in areas with low house prices and high levels of renters and elderly residents are the net funders of this implicit subsidy. These households currently have the lowest average energy cost for retailers to service, and may be the greatest immediate beneficiaries if real-time retail tariffs are made available to them. Finally, we present evidence that cross-subsidy magnitudes have been growing in recent years, coincident with rapid solar generator penetration.

JEL classification: D12, D18, H23, L94, Q41
Keywords: Real-time pricing, Energy demand, Cross-subsidies, Tariff design

1 Introduction

Since the restructuring of electricity sectors in many countries there has been a disconnect between very volatile wholesale prices and almost completely rigid retail tariffs. Volatility in the wholesale market reflects the time-varying supply and demand conditions; for example in peak demand periods it is necessary to elicit more expensive sources of energy, temporarily increasing spot prices. In other words, these volatile prices reflect the marginal wholesale procurement cost of electricity throughout the day. It is well established that fixed-rate tariffs are not economically efficient; under any fixed-rate tariff, the private marginal cost of energy faced by end-users is constant over time, while the social marginal cost of supplying that energy is not.[1] Moreover, households are (obviously) heterogeneous in their electricity consumption, both in quantity and in timing. Some tend to use energy when the fixed price is relatively low when compared to spot prices,

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[1] See, for example, Borenstein (2005b,a); Borenstein and Holland (2005).

and others use energy when the fixed price is relatively high when compared to spot prices. It follows that fixed-price tariffs entail cross-subsidies between consumers, in addition to an inefficient allocation of resources.

In this paper we tease out these cross-subsidies. We estimate the average wholesale procurement cost of energy for segments of the population to identify the demographic and locational characteristics associated with funding and receiving these implicit subsidies. Identifying these groups can provide distributional guidance as to who may be more likely to benefit or be harmed if electricity tariff norms were to transition toward being more cost-reflective in real-time. For example, could the efficiency benefits from real-time pricing also have pro-social equity consequences? While real-time pricing is known to be efficient (Borenstein, 2005b,a), it is often feared to be distributionally unacceptable because it is said to be too costly to vulnerable households.[2] We can inform this question.

The novelty of our study relates to the method that maps local dwelling, demographic, and area characteristics to real-time electricity use. Many settings for prior studies of electricity usage that utilize high frequency data are unable to examine the issue of cross-subsidization because it is aggregated over large geographical regions (Cicala, 2020), or if disaggregated, usually only for an experimental or an otherwise selected sample of households (for example, Jessoe and Rapson, 2014; Wolak, 2015; Lynham et al., 2016; ACIL Allen Consulting, 2019). Prior studies that link demographic characteristics to energy use are usually confined to point-in-time surveys that are unable to disentangle the timing of consumption and implicit cross subsidies (Brounen et al., 2012; Lyubich, 2020). Our analysis first matches electrical substations to neighborhood characteristics, with our statistical model disaggregating half-hourly substation electricity flows into electricity use by connecting businesses and households, and allowing average household usage to vary with key demographic aggregates. Our method produces state-wide estimates of cross-subsidies across key demographic features and is applicable to settings anywhere in the world given the availability of (a) census or equivalent data on dwelling stocks and household demographics at a neighborhood level, (b) a high frequency substation panel for electricity use, and (c) high frequency wholesale electricity price data – the method does not require the rollout of interval ("smart") meters throughout the State or Country of study.

We find that in our setting of Victoria, Australia (population 6+ million), households in areas with low

[2]For example, media coverage of policy considerations for time-varying retail electricity prices in Western Australia highlight that the "Opposition [party] says 'bad policy' will disadvantage poorer households" (Mercer, 2020).

house prices, high levels of renters, and more elderly residents are the net *funders* of this implicit subsidy. For example, in 2018, we estimate that the average wholesale procurement cost for a household in a high rental neighborhood is 9.91 c/kWh, 11% less than the equivalent household in a low rental neighborhood (11.15 c/kWh).[3]

The analysis raises some important features of electricity use profiles and cross-subsidization. First, we find electricity consumption is not monotonically increasing or decreasing in many demographic characteristics – for example, we identify households in middle income neighborhoods as the highest users of energy. Second, households with higher weights of energy use at the evening demand peak tend to be more expensive to service, and these weights are also not monotonically increasing or decreasing in many demographic characteristics. However, we do observe monotonicity with respect to rental shares, house prices and the elderly population in a manner that suggests that tariff reforms that entail lower levels of cross-subsidies may benefit segments of the population that are usually considered more vulnerable.

These results provide an early empirical platform to consider the distributional consequences from a large-scale adoption of real-time pricing. While there may be good reasons for some households to elect a fixed-price tariff – it delivers perfect insurance against price volatility – our results emphasize that jurisdictions with uniform fixed-price tariffs are a vehicle for cross-subsidies.[4] Without behavior change, our estimates show that households in more vulnerable neighborhoods would on average pay less under real-time pricing. The reason is that the *timing* of consumption matters a great deal. On the flip side, the households that would face higher prices because their energy use is concentrated in peak periods tend to be owner-occupiers in wealthier areas, and one might speculate they are best equipped to be price-responsive and deliver economic efficiency gains. Optimistically, it may be that jurisdictions with fixed, socialized electricity prices may be able to both improve economic efficiency *and* redistribute payment shares away from more vulnerable segments of the population with the adoption of real-time pricing.

Finally, we observe that cross-subsidization magnitudes have substantially increased in recent years in Victoria, coincident with rapid rooftop and utility-scale solar penetration. This penetration is linked to lower

[3]These estimates only consider the wholesale energy procurement costs for households. Average prices paid per kWh for Victorian households in 2018 were approximately 30.3 c/kWh which includes network charges, environmental scheme charges and retailer costs and margins (in addition to wholesale payments). See Australian Competition and Consumer Commission (2018), Figure 1.5.

[4]Removing cross-subsidies would require either wholesale cost passthrough (real-time pricing) or a fixed-price tariff that is tailored to each household (that may have zero cross-subsidies in expectation).

daytime and higher evening peak wholesale prices, exacerbating the average absolute difference between spot prices and a fixed-rate socialized price. Historically, replacing flat-rate tariffs with real-time tariffs might have been undesirable with respect to social equity, where prices were higher during the daytime and evening, coinciding with most of the energy use by less-wealthy households. However, the penetration of solar might be reinforcing both the social equity and economic efficiency consequences from real-time pricing, as wealthier households may be the ones more likely to be at work and out of the home during the now cheaper daytime periods, concentrating much of their home electricity use to the expensive evening peaks.

The paper proceeds by reviewing the relevant literature on retail electricity tariffs before outlining a simple model to outline the cross-subsidies inherent to fixed-rate tariffs that motivates our statistical exercise. We then outline the statistical model, data and results. The paper concludes with a discussion that considers the relevance of the findings to tariff reform debates.

2 Literature

This paper contributes to the vast literature on welfare economics. Under a (unique) fixed-rate tariff, the social marginal cost of electricity can never be equal to the private marginal cost of users; that marginal cost is constant, while the social marginal cost of supplying energy varies over time. Borenstein and co-authors (Borenstein, 2005b; Borenstein and Holland, 2005, among others) repeatedly make the point that real-time pricing better serves consumers and society, precisely because these marginal benefits and cost can align under real-time pricing (now RTP). Borenstein (2005b) provides a comprehensive review of the benefits of RTP, including that it promotes efficient investment in the long run and curbs market power in the short run. Our results focus more on the distributional impact of a unique fixed-price tariff; in particular, we identify broad population groups that fund and benefit from these cross-subsidies. Any reform should be cognizant of both effects; that is, unwinding the cross-subsidies inherent to a unique fixed-price tariff produces new winners and new losers, and in addition it promotes efficiency to the benefit of all. Borenstein (2005a) further disentangle the wealth transfers from producers to consumers, which typically stem from a simple price reduction, from the efficiency gains. These gains arise from lower overall consumption and from a better allocation: the high-cost producers supply less frequently. Moreover, Borenstein and Holland (2005) show that any fraction of consumers on a (unique) fixed-price tariff is deleterious to efficiency because marginal utility can never equal marginal cost (except on a set of measure 0) for consumers on a fixed-price tariff. They also establish that corrective actions in the form of taxes and subsidies tailored to adjust the investment level do not lead to the first-best because they introduce new inefficiencies. Holland and Mansur (2006) simulate the PJM market and find results that are consistent with the efficiency results put forth by theory. Our paper stops short of efficiency claims.

In a closely related paper to this one, Cahana et al. (2020) studies the distributional impacts of real-time pricing on households. They rely on a large-scale, natural experiment in Spain, in which RTP became the default option for households, and have access to meter-level data for a large sample. Thus they can study the actual distributional effects of RTP. Our work approaches almost the same problem from the opposite direction: most households still operate under a fixed-price regime, and under that regime we ask who benefits, and who are disadvantaged, by the implicit subsidies of a fixed-price regime. These two papers are complementary in the quest for the answer to this question. Along the same vein, Lyubich (2020) shows statistically significant disparities in the cost of energy of African American and Caucasian households. Most the differences in costs stem from poorer housing stock and less energy-efficient appliances. Lyubich (2020) is able to distinguish consumption by income brackets and housing status, as we do. We add more demographic variables, and are able to study the dynamics of consumption and cross-subsidies over the course of a day.

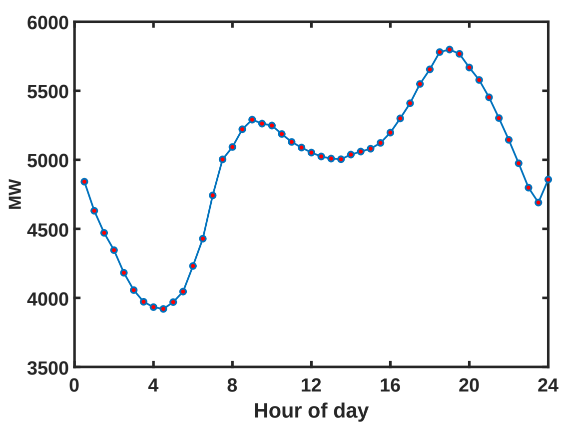
Simshauser and Downer (2016) study a large sample of consumers in Victoria (Australia) and find that the least well-off households are the worst affected by fixed-price tariffs. Simshauser and Downer (2016) have access to a meter-level sample and reconstitute the consumption of what they consider representative households – for example, retirees, low income with family, high dual income and so on. Rather than simulate household consumption profiles, we have substation-level consumption data that we combine with census information to study the distribution of consumption across households. We find more nuanced results; for example, consumption is not monotone in income, so the extent of cross-subsidization need not be monotone in income either. Simshauser (2014) studies network tariffs (not energy), and finds that uniform network tariffs have a similar effect on households: they induce wealth transfers across households. The main reason Simshauser (2014) suggests is that the two-part tariff applied by networks is not discriminating enough: the fixed fee is too low and the linear volumetric component dominates. The result is that too large a fraction of network costs are confounded with energy cost. This paper focuses on energy consumption, not network tariffs, but we note that the same effect is present in our consumption data. In other words, the extent of the cross-subsidies is in fact understated in this paper.

Finally we contribute the policy debate on the energy transition. Our results show that solar penetration induces a different profile of wholesale procurement costs, due to solar accentuating price dynamics over the course of a day. Distributional concerns manifest not only due to the well-documented redistribution tied to net-metering (for example, Borenstein, 2012), but also because the extent that those with higher consumption weights in the middle-of-day cross-subsidise those that consume mostly at the sunset peak is also increasing. Our results emphasize the importance of the timing of electricity use and are a first pass to identify households that may benefit from more cost-reflective pricing.[5]

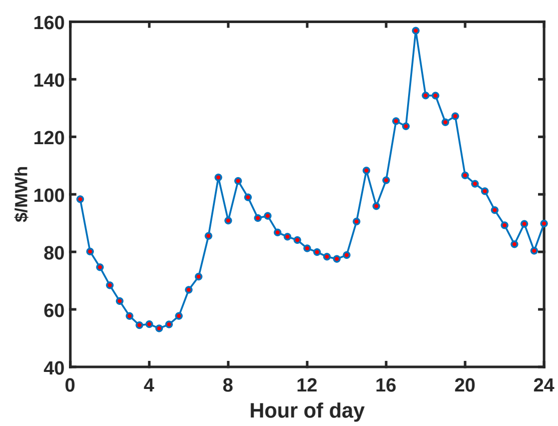
3 Conceptual framework: Fixed-rate tariffs versus real-time pricing

Fixed-rate tariffs are easy to understand: the price of energy, expressed in c/kWh is constant over time. That fixed-rate tariff is also essentially the same across all households; even in settings with retail competition, there are usually large segments of the population concentrated into a few plans. However Figures 1a and 1b clearly show that both demand and (wholesale) price – the retailer's marginal cost – are not constant over time.

Figure 1: Average Victorian wholesale electricity prices and usage by half-hour, 2018.



(a) Usage



(b) Price

[5]We are not able to readily identify *who* can actually offer this flexibility, just who consumes more and less when power is cheap.

That costs vary over time has distributional consequences for households that are subject to a unique fixed-rate tariff. Consider two households, 1 and 2, and to align with our later statistical exercise, suppose we only know characteristics about the area they live (for example household 1 is located in a neighbourhood where most dwellings are rented, while household 2 is located where the least dwellings are rented). Under the fixed-rate tariff they pay the same rate to their retailer. However, the cost per kWh of supplying energy is *not* the same. The reason of course is that a household location choice is endogenous, and location and subsequently electricity use is driven by many characteristics that we do not observe. If we can summarise households characteristics by a type θ (this may be a vector), consider types θ_1 and θ_2. Assume that type θ_1 consumes energy more evenly over the course of the day than θ_2. Taken to an extreme, suppose household type θ_1 consumes energy at a constant rate q while household θ_2 consumes energy q_1 for half of the day and q_2 for the other half. The cost of supplying energy varies over the course of the day. Let $c_1 < c_2$ denote the per kWh cost of energy, also splitting the day in two only. This corresponds to the wholesale price at which a retailer procures energy in the spot market – this is the social marginal cost.[6] The procurement cost (PC) of supplying energy to household θ_1 is

$$PC_1 = q(c_1 + c_2),$$

while the procurement cost of supplying household θ_2 is

$$PC_2 = q_1 c_1 + q_2 c_2.$$

The average wholesale procurement cost (AW) of supplying energy to household θ_1 is

$$AW_1 = (c_1 + c_2)/2,$$

while the average cost of supplying household θ_2 is

$$AW_2 = (q_1 c_1 + q_2 c_2)/(q_1 + q_2).$$

Denote AS as the socialized price a retailer would need to charge to recover wholesale procurement costs

$$AS = [(q + q_1)c_1 + (q + q_2)c_2]/(2q + q_1 + q_2).$$

As long as $q_1/q = q_2/q$ there is no cross-subsidy; the normalised cost $AW_1 = AW_2 = AS$. But suppose now that $q_1 < q_2$, then clearly $AW_1 < AS < AW_2$ and under the same, unique fixed-rate tariff, household

[6] Wholesale prices equate to social marginal costs if the markets are well-functioning, with externalities priced and adequate competition.

θ_2 benefits from a subsidy funded by household θ_1. The empirical exercise in this paper is concerned with estimating these objects for a variety of population types.

If one continues to ignore household response to prices, there exists a solution to limit these cross-subsidies: the cost of supplying the different types θ_1 and θ_2 is easy to compute. So, ignoring concerns of adverse selection, a retailer can offer them different flat rates $r(\theta_1) < r(\theta_2)$. However this fails to take advantage of the fact that the cost of supplying varies over time. By offering a tariff $r(c_1) < r(c_2)$ instead, the retailer not only solves the problem of cross-subsidies – households consuming more of the expensive energy pay a high price for it, and conversely for the cheaper energy – it gives household θ_2 the right price signal to entice them to decrease peak consumption q_2, and household θ_1 a similar incentive to reduce their consumption during that period. Absent this price signal, households have no cost incentives to consider the timing of their consumption – this is a classic case of moral hazard. A real-time pricing plan achieves just that, and also overcome the adverse selection problem.

4 Statistical framework

We develop a statistical model to identify the household and area characteristics linked to electricity usage throughout the day, and the wholesale procurement costs for that usage. This model is developed with consideration to data availability that is described in the next section – we observe load (electricity use) at high frequencies at a substation level, where each substation connects to many houses and businesses in the distribution network. The method we develop can be applied to settings with (a) census or equivalent data on dwelling stocks and household demographics at a neighborhood level, (b) a high frequency substation panel for electricity use, and (c) high frequency wholesale electricity price data. Conveniently for many jurisdictions that largely use mechanical meters, the method does not require the rollout of interval ("smart") meters throughout the State or Country of study. Indeed, the methodology may prove useful for regulators examining the case for the adoption of interval meters, as it helps demonstrate a dimension of the heterogeneity of energy use across the day across businesses and households.

Consider the following simple (latent) linear model for household load profiles, where there is a separate equation for each half hour of day (48 equations):

$$Q^H_{i,t} = \beta_h \cdot Z_{s(i)} + \nu_{i,t}, \tag{1}$$

where i denotes the household, t the day, h the half hour of day that defines the model, where there are 48 models (for example 00:00, 00:30, etc.). $s(i)$ denotes the substation to which household i is connected, and $Z_{s(i)}$ a vector of demographic and dwelling characteristics for the area covered by the substation $s(i)$ that connects household i to the distribution network. β_h is a vector of parameters, $\beta_h \cdot Z_{s(i)}$ the expected electricity use in half-hour h for a household in an area with characteristics $Z_{s(i)}$, and $\nu_{i,t}$ a mean zero error term.

Likewise, consider the following latent single parameter model for business profiles:

$$Q^B_{j,t} = \gamma_h + \eta_{j,t}, \tag{2}$$

where j denotes the business, γ_h is a single parameter representing the expected electricity use in half-hour h for a business and $\eta_{j,t}$ a mean zero error term.

Aggregating household and business electricity use (equations 1 and 2) to the substation-level gives:

$$\begin{aligned} Q_{s,t} &= \alpha_h + \sum_{i \in I_s} Q^H_{i,t} + \sum_{j \in J_s} Q^B_{j,t} \\ &= \alpha_h + \beta_h \cdot Z_s \cdot |I_s| + \gamma_h \cdot |J_s| + \epsilon_{s,t}, \end{aligned} \tag{3}$$

where $|I_s|$ is the number of households connected to substation s, $|J_s|$ is the number of businesses connected to substation s, α a constant reflecting use by any other load types, and $\epsilon_{s,t}$ is a composite error term, where we assume $E(\epsilon_{s,t}|X) = 0$ with $X = [Z_s \cdot |I_s|, |J_s|]$.[7]

We model wholesale procurement costs for energy delivered via substation s analogously to energy use:

$$PC_{s,t} = \alpha^{PC}_h + \beta^{PC}_h \cdot Z_s \cdot |I_s| + \gamma^{PC}_h \cdot |J_s| + \epsilon^{PC}_{s,t}. \tag{4}$$

From this framework we can identify parameters and expressions with the following interpretations:

[7] Sufficient but not necessary conditions for this assumption to hold is for $E(\nu_{i,t}|X) = E(\eta_{j,t}|X) = 0$. For example, this entails the error terms being uncorrelated with the number of households and businesses connecting to the substation and the substation characteristics.

- $Q_h(Z) = \beta_h \cdot Z$ Average electrical energy use in half-hour of day h for a household connecting to a substation with characteristics Z

- $PC_h(Z) = \beta_h^{PC} \cdot Z$ Average wholesale spot procurement cost for electrical energy use in half-hour of day h for a household connecting to a substation with characteristics Z

- $Q(Z) = \sum_{h=1}^{48} Q_h(Z)$ Average daily electrical energy use for a household connecting to a substation with characteristics Z

- $PC(Z) = \sum_{h=1}^{48} PC_h(Z)$ Average daily wholesale spot procurement cost for electrical energy use for a household connecting to a substation with characteristics Z

- $AW(Z) = \frac{PC(Z)}{Q(Z)}$ Average wholesale spot procurement cost per kWh for households connecting to a substation with characteristics Z

Further, restricting the model such that Z is a constant ($Z = 1$), gives $AW(1) = AS$, the average wholesale spot procurement cost for all households. We consider AS the *socialized* procurement price per kWh, because if all households are to face a fixed volumetric charge for their electricity use regardless of contemporaneous wholesale spot prices, AS must be charged if the retailer or utility is to recover their wholesale procurement costs.[8]

4.1 Interpretation in contestable retail settings

The Victorian setting we study has a contestable retail electricity market. Unlike many jurisdictions (such as Western Australia, Tasmania and many U.S utility settings), prices are not strictly regulated nor required to be uniform across broad classes of customers.

Our estimates of electricity use profiles and the main object of interest, $AW(Z)$, the average wholesale spot procurement cost per kWh for households connecting to a substation with characteristics Z, are invariant to the retail / utility setting. What might differ is the cross-subsidy interpretation. Under a regulated, fixed-price setting, then it is apparent that there is an implicit cross-subsidy away from groups with lower values of $AW(Z)$ to those with a higher values of $AW(Z)$.

[8] In practice retailers enter into forward contracts to cover some or all of their wholesale procurement exposure, however the principle still applies that under fixed-rate pricing, the price must be set at or above a given level if retailers are to recover their total procurement costs.

In contestable retail settings, the cross-subsidy interpretation requires some qualification since retailers can offer different products, and customers can select into retail plans. Those with lower values of $AW(Z)$ are cheaper to service when compared to those with a higher values of $AW(Z)$. Although it may be that these groups face different prices within and across groups, there is likely to be a meaningful degree of cross-subsidization away from groups with lower values of $AW(Z)$ to those with a higher values of $AW(Z)$ in the Victorian setting for three reasons. First, most retailers offer homogeneous menus to coarse household groupings.[9] Second, the large majority of households are on fixed-price tariffs without facing differential usage incentives in real-time or at different times-of-day. Indeed, no retailer *offered* real-time tariffs to households during our sample window. Finally, the majority of households infrequently switch retailer.[10] Therefore, it is likely that there are tariffs offered by retailers that serve a substantial collection of households that remain for multiple years – and within these groupings there will be heterogeneity in consumption profiles and therefore wholesale procurement costs. We implicitly make this qualification to our discussion of cross-subsidization in the commentary that follows.

5 Data and variable construction

We implement the statistical models outlined in section 4 using (a) half-hourly electricity data sourced from each substation in the state of Victoria, Australia for the year 2018, (b) half-hourly wholesale spot electricity prices, and (c) postcode-level demographic and area data from the Australian Bureau of Statistics.[11] We link these data series together by matching the frequency of the electricity use and wholesale price data, and then by matching location data on the substations and demographic data.

Data from (a) form a panel (substation × time) for electricity use ($Q_{s,t}$). Data from (b) form a time series

[9] Victoria has five contiguous regions serviced by separate Distributed Network Supply Providers (DNSPs). The network fee structures differ across these DNSPs but are the same within each DNSP for a given class of customer, so usually retailers offer a common menu to customers within a given DNSP. Although menus are largely fixed, there are some off-menu items that can be offered via negotiation, see Byrne et al. (2019) for an overview.

[10] See CME (2017) for summary statistics on the characteristics of Victorian retail tariffs, rates of uptake across different tariff structures, and a discussion on switching rates. They report 87% of metered household loads facing a tariff with no time-of-use characteristics, and switching rates of around 15-20% per year (or customers switching on average every 4-6.7 years).

[11] Victoria is separated into 5 distribution network regions. Each region releases historical substation loads (at half-hour frequency or less) once a year. for more details see following links:
AusNet:[`https://www.ausnetservices.com.au/Electricity/Network-Information/Zone-Substation-Reports`]
Citipower:[`https://www.powercor.com.au/what-we-do/the-network/zone-substation-reports/citipower-zone-substation-reports/`],
Jemena:[`https://jemena.com.au/electricity/network-information/zone-substation-information/`],
Powercor:[`https://www.powercor.com.au/what-we-do/the-network/zone-substation-reports/powercor-zone-substation-reports/`],
United Energy:[`https://www.unitedenergy.com.au/industry/mdocuments-library/`].

of Victorian wholesale electricity prices (P_t). Multiplying $Q_{s,t}$ by P_t forms a panel (substation $\times$ time) containing wholesale procurement costs ($PC_{s,t}$). The substation panel of electricity use contains approximately 2.8 million observations for 2018, reflecting half hourly time periods and 157 substations. Overall there are 5,151,930 people, 1,706,786 residential dwellings and 47,530 businesses that we consider connected to the substations in our Victorian setting.[12]

To construct Z_s in the statistical model – the demographic and area characteristics attached to each substation – decisions are required on what characteristics to include and how to represent them. For expositional reasons we have chosen a broad set of measures that describe the nature of the households and housing stock each substation services, then sort substations into high, medium and low levels of these characteristics (corresponding to the bottom, middle and upper tercile according to their rank in each category). Z_s contains a constant, and then two binary variables for each category, indicating whether the substation falls into the low or high level for that category. We include 12 categories, making Z_s a vector with 25 entries.

The categories we use in our statistical description can be grouped as seven demographic variables, four housing stock variables, and a climate variable. The demographic variables are 1) proportion of people over age 65, 2) average household size, 3) proportion of people that are born overseas, 4) proportion of people that work from home, 5) unemployment rate, 6) average income, and 7) proportion of people with a post-school qualification. The housing stock variables are 8) proportion of dwellings that are rented, 9) median house price, 10) residential density, 11) solar installations per residential dwelling. The climate variable is 12) the number of cooling degree days.[13] Appendix B contains further details of the variable construction, including summary statistics for the characteristics and an overview of the mapping of postcode-level information to each substation to construct Z_s, $|I_s|$ and $|J_s|$.

To demonstrate the link between our characteristic specifications and statistical model, if interested in the average electrical energy use at half-hour 2 (00:30) for a residential dwelling in an area with medium

[12]Victoria's population was 5.9 million, with 2.3 million residences at the 2016 Census, with the population projected to be 6.3m in 2018 (DELWP (2019)). Therefore, our study covers approximately 80-90% of the total population and 75% of residences in Victoria. Some substation data is dropped for data quality reasons, described in appendix B.

[13]We consider cooling degree days (CDD) and omit heating degree days because a) Victoria has a summer peak, and b) there exists a strong correlation between these variables that results in a less transparent model interpretation when both are included. We define CDD to be the sum over 2018 for each substation of $max(0,(T_{max}+T_{min})/2-18)$, where T_{max} and T_{min} are the daily maximum and minimum temperature in degrees centigrade, where we match each substation to the closest weather station using data from the Bureau of Meteorology available at `http://www.bom.gov.au/climate/data-services/station-data.shtml`.

levels of every characteristic, we would use $\beta_2 \cdot Z$, where Z is a vector with (1,0,0,0,....). If instead we were interested in areas with low levels of people aged over 65 and medium characteristics for everything else, then the Z vector would be (1,1,0,0,....). Finally, if we were interested in areas with high levels of people aged over 65 and medium characteristics for everything else, then the Z vector would be (1,0,1,0,....).

Defining each substation based on whether they have low, medium, or high levels of the characteristics in our model is useful to visualize and describe cross-subsidization in a broad sense. Given the obvious heterogeneity in household electricity use patterns, we acknowledge that it is possible that two people with a common set of demographic characteristics may be considered high and low users of energy. Depending on the times of day when they use their energy, they may also be high or low procurement cost customers. Further, it is of course possible that consumption be non-monotonic in some variables of interest. For example low-income households may tend to use little energy due to tight budget constraints; high-income households may also use little energy because they work long office hours or own energy-efficient appliances, and middle-income earners may end up being the largest energy users. However, our modelling choices are a means to bring forward useful insights, where more granular approaches may pick up too much noise to be useful in this statistical exercise. Likewise, a coarser or linear modelling approach may be too blunt to examine whether the energy characteristics we model are broadly monotonic or non-monotonic in the attributes we consider.

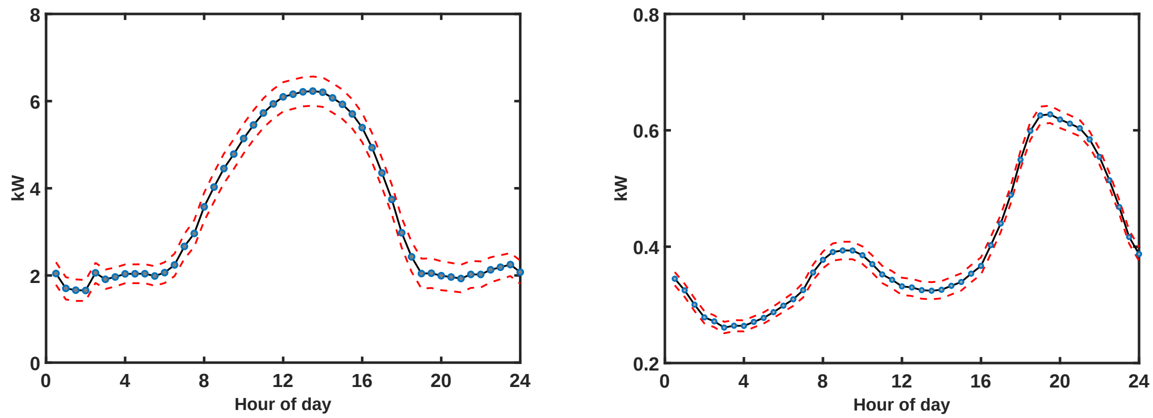
6 Results

6.1 Electricity use profiles

Figure 2 displays the average electricity use profiles for Victorian households and businesses by reporting the estimates for equation (3) when restricting the model such that Z only contains a constant ($Q_h(1)$, where no substation characteristics enter the model). Businesses are estimated to have on higher levels of electricity use to households, and a much different load shape. Average electricity use for businesses is stable at approximately 2 kWh overnight, with this average rapidly increasing as standard business hours begin, hitting a middle-of-day peak at approximately 6 kWh (figure 2a).

In contrast to electricity use for businesses being weighted heavily toward traditional 9-5 business hours, Figure 2b displays average household electricity use as having two peaks and troughs. The global minimum is overnight at approximately 3am, with consumption ramping up toward traditional waking and breakfast

Figure 2: Estimated average Victorian household and business electricity usage by half-hour, 2018



(a) Business (b) Household

Figures report estimates for the 48 half-hourly models described in equation (3) when restricting the model such that Z only contains a constant ($Q_h(1)$). The business figure reports estimates of γ_h, and the household figure reports estimates of β_h. Dashed lines represent pointwise 95% confidence intervals, using a covariance matrix robust to heteroscedastic and autocorrelated standard errors.

hours to a 8-9am morning peak. Then, corresponding to business hours and rooftop solar generation hours, there is a local middle-of-day trough, bottoming out at around 2pm. Finally, there is a steep ramp up to the evening peak at approximately 7pm where traditionally workers have returned home and the sun has set. Average Victorian household load profiles mirror the solar "duck curve" seen at a system level in jurisdictions with high levels of solar energy penetration (Bushnell and Novan, 2018; Jha and Leslie, 2019).

Reassuringly, our estimates of average daily household consumption for the 1,706,786 households we consider as connected to the substations we study compare well to the features described in a sample of 2,926 Victorian households collected in 2016, described in ACIL Allen Consulting (2019). First, the dual peak and trough nature of the load-profile shape is also observed in the ACIL sample. Second, our daily mean is 9.5 kWh, which compares sensibly with the 13.6 kWh mean in the ACIL sample. The ACIL sample has higher response rates among elderly residents, families and larger households that we later reveal are more likely to be higher users of energy.[14] This may also reflect a strength of our study that examines observed electricity use across the whole of Victoria, albeit aggregated to a substation level. Examining the

[14]Figure 4.1 in ACIL Allen Consulting (2019) displays a load profile very similar in shape to those we display in Figure 2b. Table 3.5 in ACIL Allen Consulting (2019) shows their household sample to have average annual electricity consumption of 4,984 kWh, or 13.65 kWh a day. Figure 3.2 reveals the sample contains households with greater proportions of children and elderly than is representative of Victoria, with our calculations of their average household size being at least 2.62 (size is top-coded at 5 in Table 3.2), greater than the 2.54 average reported in the 2016 Census.

individual meter data of respondents to a household energy survey may be prone to some general selection bias, whereby higher electricity users may be more likely to respond to surveys simply by being more likely to be home for a survey, and potentially being more interested in responding to an electricity-themed survey.

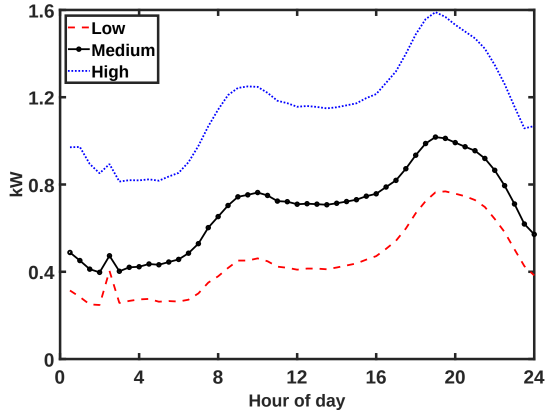
Figures 3a-4f report estimates of the full statistical model, $Q_h(Z)$ as outlined in equation (3) and section 4, that disaggregates household use according to the characteristics of the areas served by the substation. Appendix Table A1 contains the point estimates and standard errors of the model parameters.

Consider Figure 3a. This figure displays the differences in average household electricity uses across areas with different proportions of the population above 65 years old, holding all else in our model equal. The black "medium" line displays our estimate of average household electricity use in areas that are ranked in the middle tercile in each of the 12 categories. The blue dotted "high" line displays our estimate for average household electricity use in areas that are in the top tercile for elderly population share, and middle tercile for all other characteristics. The red dashed "low" line displays our estimate for average household electricity use in areas that are in the top tercile for elderly population share, and middle tercile for all other characteristics. We see households in areas with greater elderly populations have higher average use for all hours of the day, including a 1.6 kW peak at around 7pm, compared to a 1 kW peak for areas with medium levels of the elderly and a 0.8 kW peak in areas with low levels of the elderly. The remaining Figures (3b - 4f) focus on the other 11 characteristics in our model and have the same structure and interpretation as described for 3a.

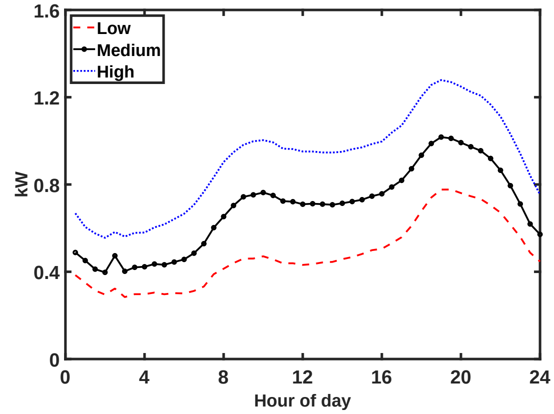
Examining the estimates related to the demographic characteristics in Figures 3a-4a shows that electricity use is higher across all hours of day for households in areas with an older population, larger households, higher proportions of overseas-born. However, there is not an obvious monotonic relationship between the remaining demographic variables and consumption levels. For example, middle tercile areas in terms of income contain the highest average energy users, using more energy than average households in areas that are either first or third tercile. This may capture situations where higher income households spend less time in the home or have more energy efficient appliances, whereas lower income households have tighter budgets and may be likely to use less energy.[15]

[15] See Dubin and McFadden (1984) for early work on the discrete / continuous energy use problem facing households. Appliance decisions impact the intensity of energy use, with high-income households likely to be less capital constrained and more able to purchase energy efficient appliances. Fritzsche (1981) present an early empirical documentation of energy use following an inverted u-shape over the family-life cycle, as one would expect family income to also follow.

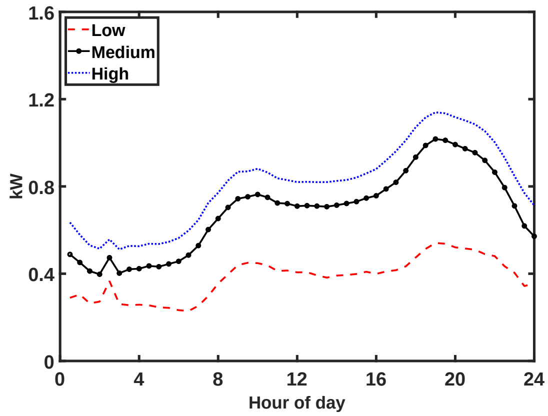
Figure 3: Estimates of household electricity use model (1/2)



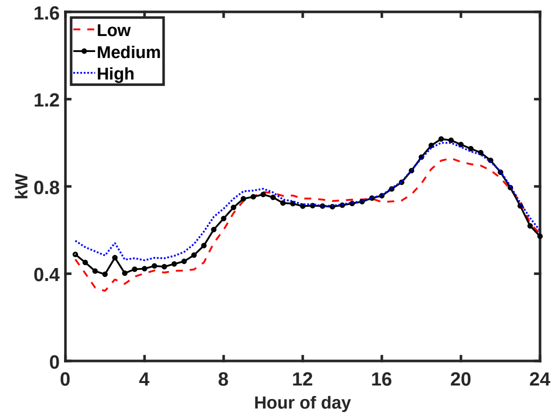
(a) Proportion older than 65



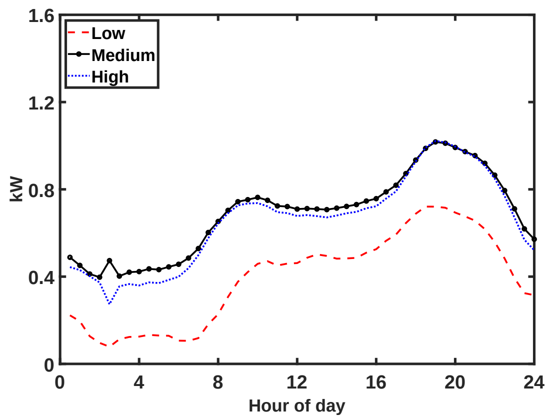
(b) Average household size



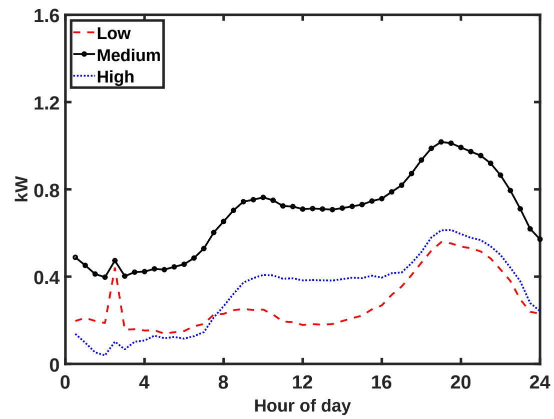
(c) Proportion that are born overseas



(d) Proportion that work from home

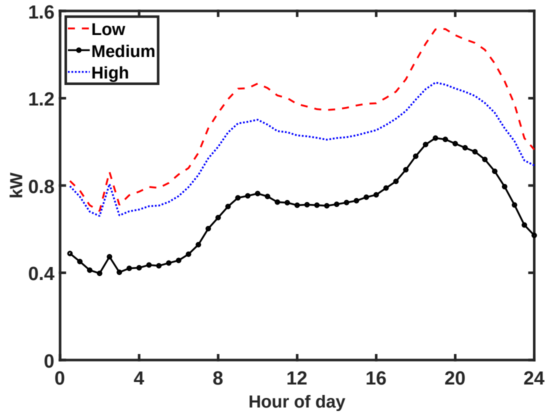


(e) Unemployment rate

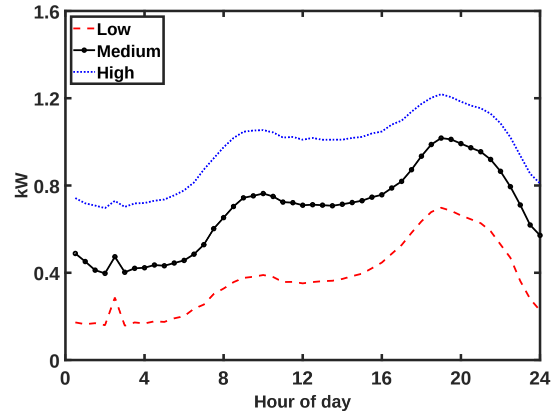


(f) Average income

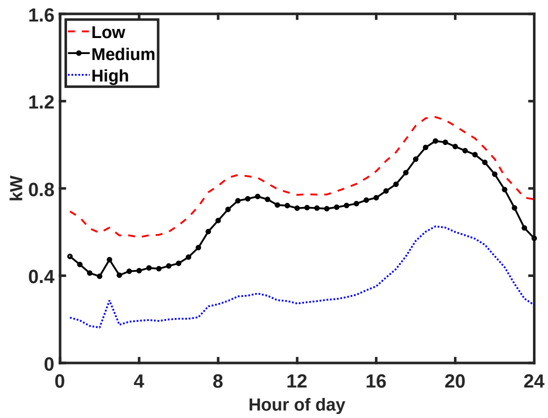
Figure 4: Estimates of household electricity use model (2/2)



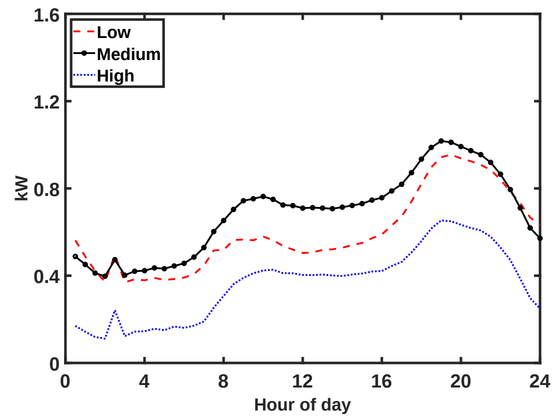
(a) Proportion with post-school qualifications



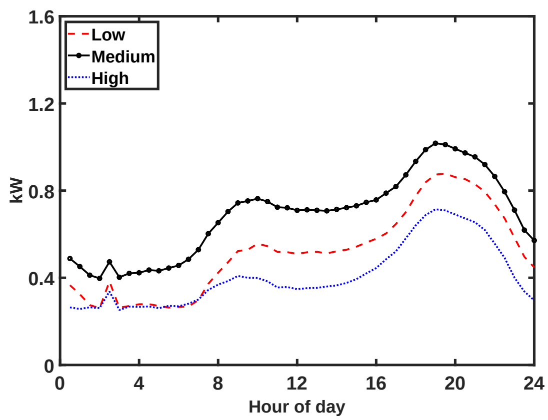
(b) Proportion of dwellings rented



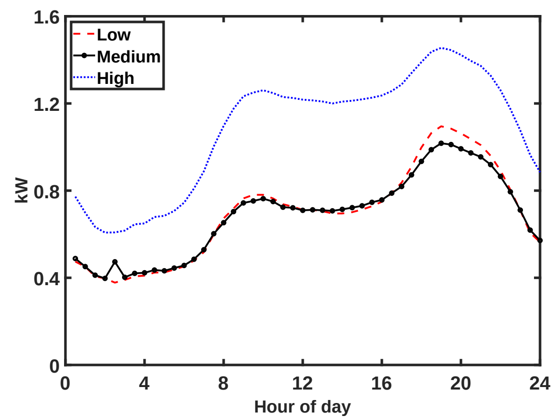
(c) Median house price



(d) Residential density



(e) Proportion of dwellings with rooftop solar



(f) Cooling degree days

For the characteristics relating to housing stock in Figures 4b - 4e, the level of consumption is higher across all hours of day in areas with higher rental rates and higher house prices. These results support evidence in different contexts of owner-occupied houses being more energy efficient than renter-occupied houses (Davis, 2011, for example). Further, it is apparent that high rental areas have a flatter profile relative to lower rental areas, suggesting that households in areas with higher owner-occupier rates weight their consumption more heavily to the evening peak. Finally, in Figure 4f we see that warmer areas tend to have higher levels of energy use.[16]

Curiously, we do not observe monotonic differences in metered electricity use for households across rooftop solar penetration rates. This emphasises the nature of our statistical model – it estimates conditional means, not causal impacts. Although the areas with the greatest solar penetration tend to have lower levels of energy use (especially during the sunny daylight hours), all else is not equal across different solar penetration levels – our measure of solar penetration does not simply capture different levels of behind-the-meter generation. Houses with solar may be in areas with fundamentally different features to areas with less solar that are not captured by our model, and they may also have occupants with different lifestyles and preferences to use energy.

6.2 Wholesale procurement costs and implicit cross-subsidies

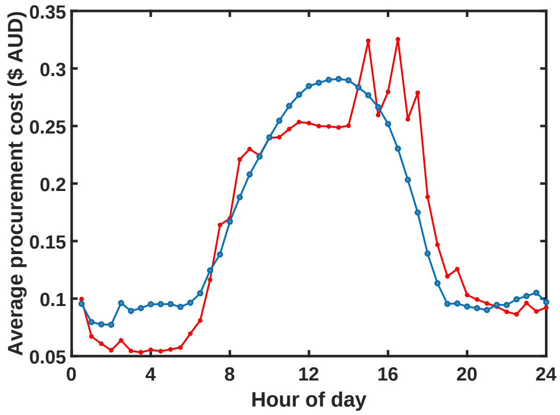
Figure 5 reports the average wholesale spot procurement cost (PC) for households and for businesses, along with the average procurement cost if prices were fixed to be completely socialized within households and within businesses. The per kWh spot procurement cost (which we set as the socialized price) is 9.34 c/kWh for businesses, $\approx$ 10% less than the 10.42 c/kWh socialized price for households.[17] For example, the figures show that at 4am, the average procurement cost for a business is almost 10c if they were to face a socialized price, and 5c if they were to face wholesale spot prices. The average procurement cost for a household at 4am is approximately 1.5c if they were to face a socialized price, and 0.8c if they were to face wholesale spot prices.

We observe from Figure 5 that for both businesses and households, users that have higher weights of

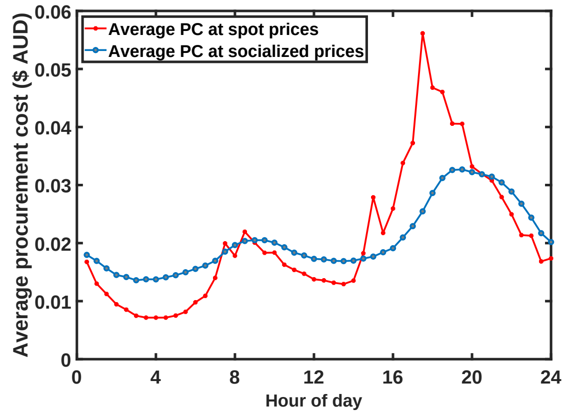
[16]Appendix Figures A3a - A4f display the results when restricting the sample to the summer months, which in Victoria have average maximum temperatures 10 degrees Celsius or more higher than the yearly average. These results display similar qualitative patterns by characteristics across the board, but with higher baseline levels of electricity use and a flatter load profile.

[17]The socialized price for households is AS as defined in section 4. The socialized price for businesses is similarly defined, except replacing the β variables that apply to households with the γ variables that apply to businesses as appropriate.

Figure 5: Estimated average electricity procurement costs at spot and socialized prices, 2018



(a) Business



(b) Household

Each point is the estimated average procurement cost of electricity for a Victorian business (panel a) or household (panel b) for a **half hour**. The spot price series reports estimates from the simplified version of the 48 models defined by equation (4), $PC_h(1)$. The socialized price series displays the product of the socialized price with estimates from equation (3), $Q_h(1).AS$. Business estimates are calculated analogously to households using the γ coefficients defined in section 4.

energy use in the middle-of-day and overnight would face lower costs if spot-exposed, because the spot procurement cost series is below the socialized procurement cost series. Therefore, these groups are funders of a cross-subsidy if costs are socialized via a flat-rate tariff. Likewise, users with higher weights of energy use at the evening, and to a lesser extent, the morning peak face lower costs under socialized prices and would be the beneficiaries of such a cross-subsidy.

Appendix Figures A1a - A2f and Table A2 report estimates of the full statistical model, $PC_h(Z)$ as outlined in equation (4) and section 4, that disaggregate wholesale spot procurement costs according to the characteristics of the areas served by the substation. These figures largely reflect the wholesale price series in Figure 1b and disaggregated demand figures presented in Figures 3a - 4f.[18] We choose not to discuss these results, but instead to discuss the subsequent calculations that use this output in Table 1, $AW(Z)$, the average wholesale spot procurement cost per kWh for households connecting to a substation with characteristics Z.

The "medium" column of Table 1 reports our estimates of the average wholesale spot procurement cost per kWh for households that are connected to a substation that is the middle tercile for each of the 12 characteristics in our model. The "low" and "high" columns reports the average wholesale spot procurement cost

[18]The $PC_h(Z)$ estimates are the average procurement cost of energy which is not the product of average price and average energy use. This distinction is important because there may only be a few times per year when wholesale prices spike to orders of magnitude above their mean, and therefore the average procurement cost measures will be heavily influenced on energy use in those hours, not year-long averages of energy use at that time of day.

Table 1: Average cost per c/kWh if procuring energy at spot prices, assuming all other characteristics of the residence location are ranked in the middle tercile.

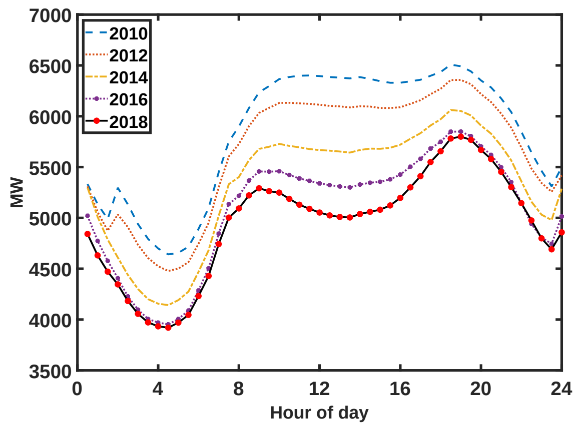
Characteristic	Low	Medium	High	Socialized price
Proportion older than 65	10.71	10.40	10.18	10.42
Average household size	10.38	10.40	10.26	10.42
Proportion that are born overseas	10.27	10.40	10.20	10.42
Proportion that work from home	10.40	10.40	10.20	10.42
Unemployment rate	11.07	10.40	10.56	10.42
Average income	11.27	10.40	11.29	10.42
Proportion with post-school qualifications	10.24	10.40	10.08	10.42
Proportion of dwellings rented	11.15	10.40	9.91	10.42
Median house price	10.04	10.40	10.98	10.42
Residential density	10.33	10.40	11.07	10.42
Proportion of dwellings with rooftop solar	10.76	10.40	10.77	10.42
Cooling degree days	10.42	10.40	10.27	10.42

per kWh for households that are connected to a substation that is the first tercile (low) or third tercile (high) for the characteristic denoted in the row, and the middle tercile for each of the remaining 11 characteristics in our model.[19]

We see that the average spot procurement price per kWh AW is $\approx 5\%$ lower for houses in older neighborhoods (10.18 c/kWh) than in younger neighborhoods (10.71 c/kWh). Similarly, AW is $\approx 11\%$ lower in areas with high proportions of renters (9.91 c/kWh) compared to low levels of renters (11.15 c/kWh). Further, areas with low house prices and low residential density have $\approx$ 7-10% lower average spot procurement prices per kWh than the areas with higher levels of these characteristics. For all other characteristics, there is not a monotonic relationship between AW and the prevalence of that characteristic in a substation's area. This suggests that there is not a monotonic relationship between characteristics such income, work-from-home status, household size, etc. and the share of consumption that occurs in high wholesale price periods and low wholesale price periods. These observations largely hold when restricting the sample to the Summer months, with the magnitudes larger, reflecting the higher energy use and price volatility in the Summer (Table A3).

[19]This is equivalent to $AW(Z)$ where Z is a vector of zeros with the exception of the constant and the element relating to the first or third tercile of the characteristic taking the value 1.

Figure 6: Average electricity use for Victoria, 2010 - 2018.



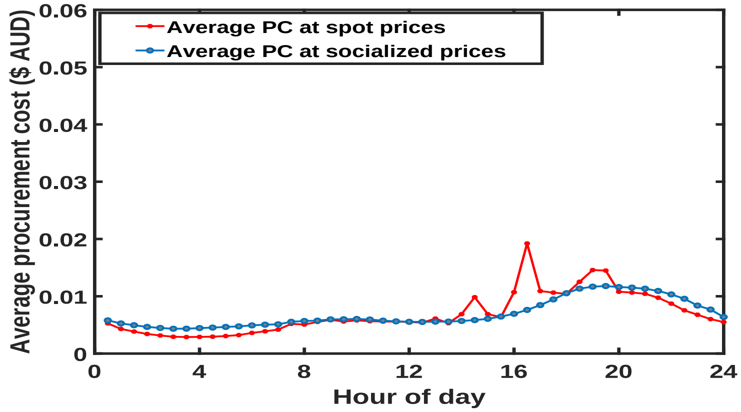
7 Extension - longer run trends in within-day cross-subsidization

The observed cross-subsidization of energy procurement costs across households is driven by the share of energy used in high wholesale spot price periods (usually the evening demand peak) and low price periods (usually overnight or in the middle of the day). Bushnell and Novan (2018) and Jha and Leslie (2019) document that coincident with increased solar generation penetration lower daytime prices and higher evening peak prices in both California and Western Australia. Solar penetration in Victoria has rapidly increased from 734 MW in 2014, to 1,152 MW in 2016, to 2,039 MW in our sample year of 2018, and Figure 6 displays the hollowing out of Victorian daytime electricity use relative to other times of day since 2010.[20] In this extension, we collect and organize data on housing and business substation electricity data for 2014 and 2016, matching these sets of substations to census data on housing and businesses to estimate the average electricity use profiles for Victorian households and businesses. With this information we can estimate equation (3) and (4) when restricting the model such that Z only contains a constant, and recover the average procurement costs at wholesale spot prices and at socialized prices for households in 2014 and 2016.

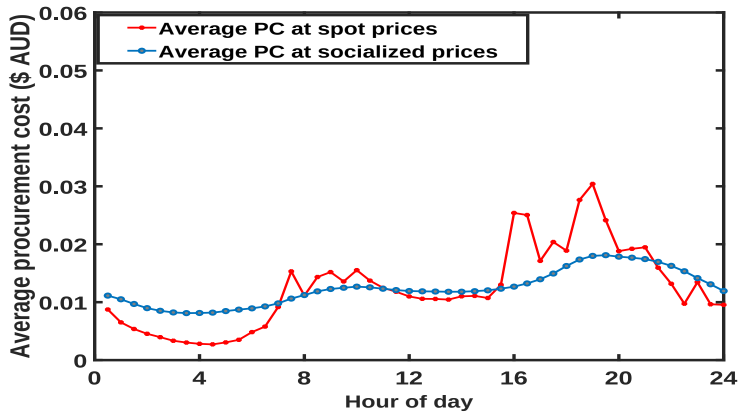
Figure 7 displays the output from the cross-subsidization trends analysis. Panel (a) displays little deviation between the average procurement cost for household electricity use when assuming socialized or wholesale spot prices. The exception is spot procurement on average being slightly cheaper throughout the night, but higher for some of the half-hour intervals between 5-8pm. This pattern is more pronounced in 2016 (panel b), with spot procurement in the middle-of-day hours also becoming slightly cheaper. Finally,

[20]Solar penetration figures obtained from `https://pv-map.apvi.org.au/postcode`.

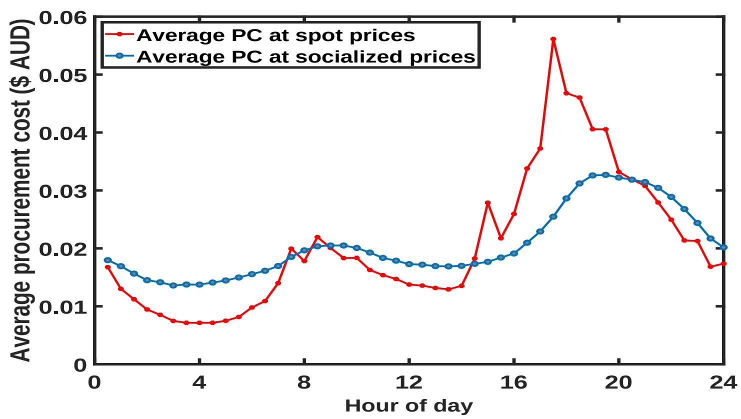
Figure 7: Trends in cross-subsidization, 2014-2018



(a) 2014



(b) 2016



(c) 2018

Each point is the estimated average procurement cost of electricity for a Victorian household for a **half hour**. TThe spot price series reports estimates from the simplified version of the 48 models defined by equation (4), $PC_h(1)$. The socialized price series displays the product of the socialized price with estimates from equation (3), $Q_h(1).AS$.

in 2018 (panel c) we see the largest deviations in both relative and absolute terms, with spot procurement further becoming cheaper in the middle of the day and substantially more expensive in the evening peak. These trends mirror the changing wholesale price trends observed in markets exhibiting a solar "duck curve," suggesting that the cross-subsidization of energy procurement we highlight in our analysis will continue to grow as solar penetration continues. Victoria currently has a suite of policies under its Solar Homes Program that strongly incentivize the continued installation of rooftop and utility-scale solar panels.[21] The link that we propose between renewable penetration and the equity properties of real-time pricing will become of increasing importance to jurisdictions around the world that seek to increase their solar penetration rates toward levels seen in Australia.[22]

8 Discussion

The results from our analysis demonstrate that at even at course groupings, there can be substantial variation in the wholesale spot procurement costs of energy users. At the broadest cut, businesses concentrate their electricity use to the middle of the day – a time that is expected to become cheaper as solar penetration further develops – whereas households have morning and evening peaks that align with higher wholesale prices. However, within households, it is those located in areas with higher shares of elderly residents, higher shares of renters, and in areas with lower value homes that are cheapest to service from wholesale spot market procurement. These three groups are usually perceived to be more vulnerable, yet they are the ones essentially cross-subsidising younger and wealthier neighborhoods that have higher rates of owner-occupancy. Because these groups use more energy overall, they also contribute a higher share of volumetric network tariffs used in the recovery of network infrastructure and operating costs. This is another form of cross-subsidization from socio-economic groups usually considered more vulnerable, toward the more affluent. We note that this cross-subsidisation of infrastructure is not a new concept, although not often empirically identified, and that it can be addressed by a reform of network tariffs.[23]

The results also show non-monotonic relationships between many neighborhood characteristics in both

[21] These policies include subsidies of up to $1850 and interest-free loans through to 2021, on top of the federal subsidies available to both rooftop and utility-scale generators via the Renewable Energy Target. Refer to `https://www.solar.vic.gov.au/` and `https://www.industry.gov.au/funding-and-incentives/renewable-energy-target-scheme` for details of the various schemes.

[22] Australia has the highest rooftop solar penetration rate in the world (Australian Energy Council, 2016). Over 15% of dwellings in Victoria have rooftop solar panels as of the end of 2018 (Roberts et al., 2019).

[23] For example, network tariff cross-subsidization is the object of Simshauser (2014).

their level of electricity use and cost-to-service. For example, middle-income, middle-solar and middle-density areas are high energy users, and middle-education areas are low energy users. Therefore, it is difficult to generalize the electricity use habits of households based on some demographic characteristics that are commonly used in other contexts. Undoubtedly, there is also substantial variation within our coarse grouping with regard to energy consumption and in the timing of energy use at a household level that feed into wholesale procurement costs.

These results have important implications for competitive retail electricity markets and the promotion of demand-side flexibility and real-time, cost reflective pricing. In competitive retail electricity market settings like Victoria, which is characterized by a) mostly time-invariant tariffs (CME, 2017), and b) high levels of customers that do not tend to switch retailer (Mountain and Burns, 2020), the groups identified as low cost-to-service in our analysis are more valuable to retailers that offer a non-discriminatory fixed-rate menu. Therefore, our results suggest that it may be progressive for retailers to offer real-time pricing plans or tariffs that vary with household characteristics or area characteristics. This is because we find that some more vulnerable population segments would have lower energy costs if they faced spot prices when compared to a socialized price at their existing electricity use patterns.

However, more cost-reflective retail tariffs are not only of distributional consequence – with some demand-side price elasticity there are also implication for economic efficiency, especially under real-time electricity pricing tariffs. An optimistic interpretation of our results is that the households that are less likely to benefit from real-time pricing under current consumption patterns are also those that are best equipped to respond to time-varying prices by altering their behaviour and their energy efficiency. That is, according to our results, households in wealthier areas with high rates of home ownership have higher weights of energy use at system peaks, but these are also groups that have been identified in previous studies as being more likely to be energy efficient (Davis, 2011). One reason for this is that owner-occupiers benefit directly from any investment they make in managing their energy consumption, unlike investors who share the return with the tenant. Tenants themselves have weak incentives to invest in energy-saving dwelling improvements due to eviction risks and landlord-tenant split-incentives. Real-time pricing plans may be all the motivation some owner-occupiers need to install load-shifting appliances and fittings (such as home pre-cooling or pre-heating devices) and energy management systems to introduce short-run elasticity to the demand-side of electricity markets. It is likely to also be the cheapest, simplest and least distortionary way to implement "demand response" – unlike, for example, subsidizing consumers to control their appliances directly (AGL, 2018). Borenstein (2005b) however warns that implementing an RTP may engender distributional concerns in the transition phase. Starting from an environment in which all households are subject to a flat-rate tariff and introducing an RTP results in these households with the lowest average cost of service to switch first to the RTP, leaving higher cost-to-serve customer on the fixed-rate plan. Thus customers remaining on a fixed-rate contract may end up paying more. This is akin to the unraveling of insurance markets as in Rothschild and Stiglitz (1976). Borenstein (2005b) also suggests that this phenomenon can be harnessed precisely to promote the switch to RTP: as the fixed-rate plan becomes more expensive, more customers switch to the RTP and so on – see Borenstein (2005b) for details.

Finally, we acknowledge that many households may value price certainty and may not wish to engage in real-time pricing. Our research shows some population segments that would benefit *on average* from real-time pricing if they were to be risk neutral and otherwise unresponsive to prices. So although some vulnerable population groups might benefit from real-time prices in expectation, their welfare may be negatively impacted if they are sufficiently risk averse, or if they have high non-monetary costs associated with paying attention to real-time prices. This motivates further research into the risk preferences and attention costs of households, with our paper suggesting particular value in comparisons between owner-occupiers and renters, elderly and non-elderly, and, occupants of higher and lower valued properties. However we note first that *some* price variation is required to induce price responsiveness; second that not all the variation in wholesale prices is necessary to induce some price responsiveness, especially with risk-averse households; and third that time-varying tariffs with expenditure caps can also be designed to accommodate risk averse consumers. Borenstein (2005b) and Wolak and Hardman (2020) suggest multiple avenues to protect vulnerable populations and to ease the transition. Finally, technology may also help; it is increasingly possible to delegate the energy management of one's house to a computer.

9 Conclusion

This paper studies the implicit cross-subsidies that arise from the widespread use of fixed-rate retail tariffs when wholesale procurement costs are time-varying. These cross-subsidies are rooted in the difference in the timing of consumption across households. With a broad brush, households consuming relatively more in the middle of the day are net funders of households that consume relatively more at the morning and evening peaks. We find that in Victoria, Australia, areas where relatively more dwellings are rented and areas where there are relatively more elderly residents tend to use energy at lower cost times of day, whereas areas with high house prices tend to use energy at relatively high cost times of day. Thus households in areas that are typically described as being more vulnerable cross-subsidize wealthier households. We note that the method we employ is directly applicable to most jurisdictions around the world, as the data requirements match the rudimentary components of electricity system operation and a population census.

The cross-subsidies implicit in the flat-rate tariff can easily be unwound by the use of real-time pricing (RTP). RTP has the added benefit of reflecting the actual cost of procuring energy over the course of the day (absent volumetric network tariffs), and thereby provides consumers with the economically efficient price signal. This seems to be a rare instance in which efficiency and distributional considerations are in broad agreement; to be clear, reforming the market to deliver efficiency gains may benefit the more vulnerable populations. Of course, further research is required to inform this claim and specific tariff designs. Few households may be willing to be exposed to extreme prices (as high as $14,500/MWh, or $14.5/kWh in Australia), but these extreme risks can be insured against without losing the benefits of the price signals that RTP provides (Wolak and Hardman, 2020). Further work that examines strategies to effectively communicate and implement RTP among vulnerable populations may be of substantial value to policy makers and researchers.

In the state of Victoria, which is equipped with interval meters, there are no technological or regulatory barriers to the implementation of RTP. Yet there is almost no RTP penetration, with very few electricity retailers offering such flexible pricing plans. It is easy to understand the reluctance of incumbent retailers to real-time pricing: under a fixed-rate plan, a household demand is completely price inelastic, which makes for higher revenue. Likewise, incumbents in a market with low levels of customer engagement may have little incentive to promote flexible pricing, which is less profitable, without capturing larger market shares. Thus to foster RTP, a regulator may have to foster entry of new retailers, or to mandate that all retailers offer an RTP plan. This is not very different from mandating default price ceilings on fixed-price offers, which are currently in place. This motivates further research into the competitive barriers to RTP and potential regulatory solutions.

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Appendices

A Additional tables and figures

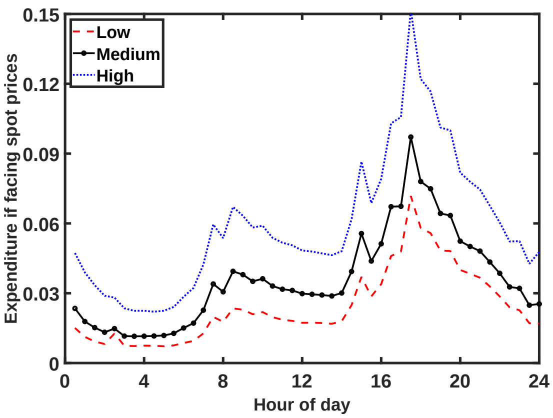
Table A1: Estimates of household electricity use model, equation (3)

Variable		2:00 am		6:00 am		10:00 am		2:00 pm		6:00 pm		10:00 pm	
		value	std. error	value	std. error	value	std. error	value	std. error	value	std. error	value	std. error
Proportion older than 65	1^{st} tercile	-0.069	0.006	-0.213	0.007	-0.302	0.010	-0.293	0.010	-0.264	0.011	-0.223	0.009
	3^{rd} tercile	0.420	0.008	0.417	0.009	0.470	0.012	0.441	0.012	0.570	0.013	0.483	0.010
Average household size	1^{st} tercile	-0.150	0.009	-0.173	0.010	-0.293	0.012	-0.254	0.013	-0.248	0.014	-0.194	0.011
	3^{rd} tercile	0.109	0.008	0.222	0.009	0.243	0.012	0.240	0.012	0.269	0.013	0.247	0.010
Proportion that are born overseas	1^{st} tercile	-0.107	0.010	-0.256	0.012	-0.312	0.016	-0.328	0.017	-0.474	0.018	-0.384	0.014
	3^{rd} tercile	0.084	0.007	0.113	0.008	0.114	0.011	0.108	0.011	0.128	0.012	0.137	0.009
Proportion that work from home	1^{st} tercile	-0.100	0.008	-0.066	0.010	0.020	0.014	0.018	0.014	-0.108	0.014	-0.026	0.011
	3^{rd} tercile	0.067	0.008	0.051	0.008	0.023	0.011	0.004	0.011	-0.011	0.012	0.004	0.010
Unemployment rate	1^{st} tercile	-0.395	0.025	-0.379	0.027	-0.279	0.037	-0.238	0.037	-0.267	0.034	-0.307	0.030
	3^{rd} tercile	-0.200	0.009	-0.046	0.009	-0.028	0.012	-0.031	0.012	0.004	0.013	-0.016	0.011
Average income	1^{st} tercile	-0.032	0.010	-0.313	0.010	-0.524	0.014	-0.512	0.014	-0.469	0.014	-0.432	0.012
	3^{rd} tercile	-0.371	0.012	-0.358	0.015	-0.344	0.020	-0.327	0.020	-0.409	0.021	-0.365	0.018
Proportion with post-school qualifications	1^{st} tercile	0.389	0.022	0.395	0.023	0.497	0.031	0.434	0.031	0.462	0.027	0.495	0.024
	3^{rd} tercile	0.333	0.008	0.307	0.009	0.329	0.012	0.300	0.012	0.254	0.012	0.268	0.010
Proportion of dwellings rented	1^{st} tercile	-0.187	0.009	-0.250	0.009	-0.369	0.013	-0.337	0.013	-0.309	0.014	-0.335	0.011
	3^{rd} tercile	0.256	0.009	0.329	0.011	0.293	0.014	0.296	0.014	0.214	0.015	0.220	0.013
Median house price	1^{st} tercile	0.147	0.014	0.183	0.013	0.073	0.017	0.081	0.017	0.134	0.017	0.069	0.014
	3^{rd} tercile	-0.187	0.008	-0.282	0.008	-0.442	0.012	-0.420	0.012	-0.386	0.012	-0.375	0.010
Residential density	1^{st} tercile	0.022	0.011	-0.077	0.012	-0.187	0.016	-0.181	0.017	-0.091	0.018	-0.024	0.014
	3^{rd} tercile	-0.232	0.008	-0.314	0.010	-0.322	0.015	-0.316	0.015	-0.372	0.014	-0.336	0.011
Proportion of dwellings with rooftop solar	1^{st} tercile	-0.090	0.012	-0.216	0.015	-0.205	0.021	-0.193	0.021	-0.149	0.022	-0.128	0.019
	3^{rd} tercile	-0.136	0.008	-0.204	0.009	-0.366	0.012	-0.345	0.012	-0.300	0.014	-0.309	0.011
Cooling degree days	1^{st} tercile	-0.096	0.007	-0.006	0.008	0.014	0.011	-0.021	0.011	0.076	0.012	0.027	0.009
	3^{rd} tercile	0.135	0.006	0.325	0.007	0.498	0.011	0.491	0.011	0.449	0.011	0.396	0.009

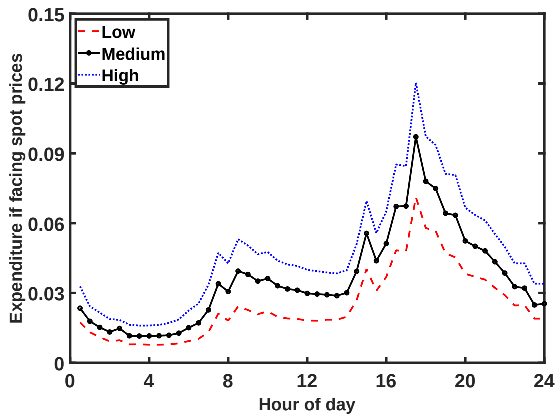
Table A2: Estimates of household procurement cost model, equation (4) All values multiplied by 10^3 (tenth of cents).

Variable		2:00 am		6:00 am		10:00 am		2:00 pm		6:00 pm		10:00 pm	
		value	std. error	value	std. error	value	std. error	value	std. error	value	std. error	value	std. error
Proportion older than 65	1^{st} tercile	-2.128	0.402	-7.639	0.428	-13.375	0.599	-14.435	3.134	-19.068	6.387	-8.764	0.465
	3^{rd} tercile	13.354	0.552	15.138	0.546	20.729	0.784	22.462	4.189	41.796	8.314	19.535	0.575
Average household size	1^{st} tercile	-5.111	0.499	-6.833	0.515	-13.334	0.730	-12.454	3.836	-18.258	7.491	-8.067	0.565
	3^{rd} tercile	3.621	0.465	8.346	0.498	10.836	0.722	11.650	3.624	18.692	7.198	10.019	0.542
Proportion that are born overseas	1^{st} tercile	-3.288	0.704	-9.034	0.707	-13.714	0.956	-17.760	4.846	-36.035	10.781	-14.895	0.747
	3^{rd} tercile	2.629	0.468	3.881	0.462	4.965	0.684	4.449	3.478	8.496	6.661	5.770	0.488
Proportion that work from home	1^{st} tercile	-3.138	0.525	-2.281	0.575	1.054	0.854	0.437	4.079	-7.304	7.862	-0.251	0.588
	3^{rd} tercile	2.296	0.531	1.865	0.481	1.106	0.695	-1.061	3.557	-1.965	6.961	0.538	0.522
Unemployment rate	1^{st} tercile	-12.234	1.282	-14.118	1.367	-12.728	2.010	-13.510	7.862	-19.747	13.558	-12.542	1.433
	3^{rd} tercile	-6.315	0.544	-1.767	0.499	-1.261	0.720	-1.577	3.481	1.054	6.743	-0.941	0.542
Average income	1^{st} tercile	-1.129	0.543	-11.450	0.574	-23.089	0.815	-24.622	3.888	-33.504	7.996	-17.266	0.616
	3^{rd} tercile	-11.759	0.623	-12.946	0.698	-15.236	1.042	-16.308	4.176	-29.202	8.185	-14.643	0.834
Proportion with post-school qualifications	1^{st} tercile	12.472	1.183	14.724	1.194	22.296	1.715	22.476	6.891	35.626	11.610	20.148	1.172
	3^{rd} tercile	10.635	0.543	11.438	0.497	14.702	0.713	14.170	3.585	17.680	6.815	11.178	0.516
Proportion of dwellings rented	1^{st} tercile	-5.976	0.501	-9.040	0.512	-16.252	0.741	-16.227	3.420	-22.351	6.985	-13.537	0.567
	3^{rd} tercile	8.165	0.547	12.127	0.601	13.030	0.847	12.914	3.860	12.686	7.216	9.367	0.634
Median house price	1^{st} tercile	4.729	0.792	6.538	0.689	3.030	0.955	2.903	4.268	6.665	8.148	2.629	0.701
	3^{rd} tercile	-5.997	0.499	-10.536	0.499	-19.802	0.723	-20.609	3.510	-27.840	6.858	-14.956	0.529
Residential density	1^{st} tercile	0.688	0.755	-3.062	0.744	-8.411	1.003	-9.873	5.212	-7.076	11.321	-0.280	0.780
	3^{rd} tercile	-7.249	0.549	-11.197	0.551	-14.219	0.875	-16.212	4.220	-26.947	7.826	-13.175	0.562
Proportion of dwellings with rooftop solar	1^{st} tercile	-2.762	0.704	-7.977	0.771	-9.161	1.178	-9.470	5.201	-9.817	9.847	-4.904	0.894
	3^{rd} tercile	-4.328	0.531	-7.580	0.532	-16.188	0.735	-16.738	3.685	-21.756	7.913	-12.669	0.590
Cooling degree days	1^{st} tercile	-2.945	0.469	-0.237	0.476	0.416	0.685	-1.892	3.425	5.984	6.734	0.511	0.497
	3^{rd} tercile	4.336	0.451	12.073	0.503	22.343	0.709	24.424	3.718	32.095	7.008	16.059	0.490

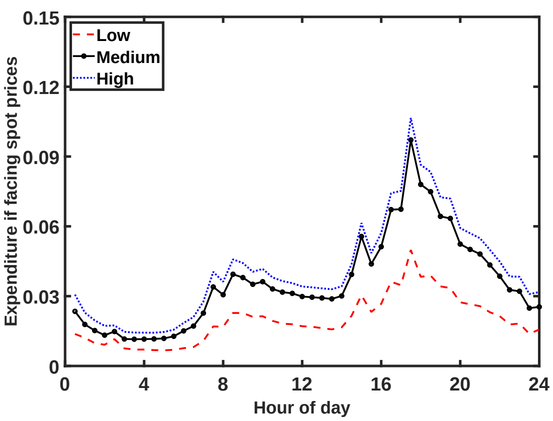
Figure A1: Estimates of household electricity procurement cost model (1/2)



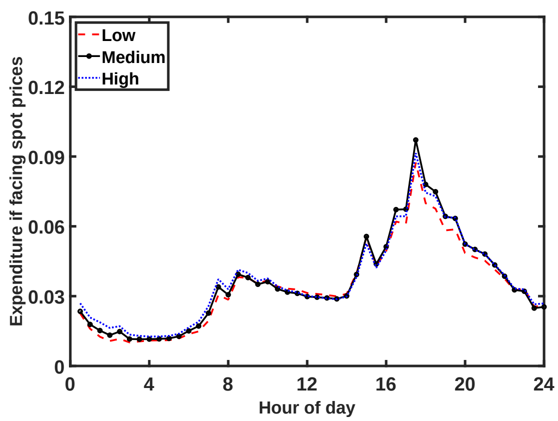
(a) Proportion older than 65



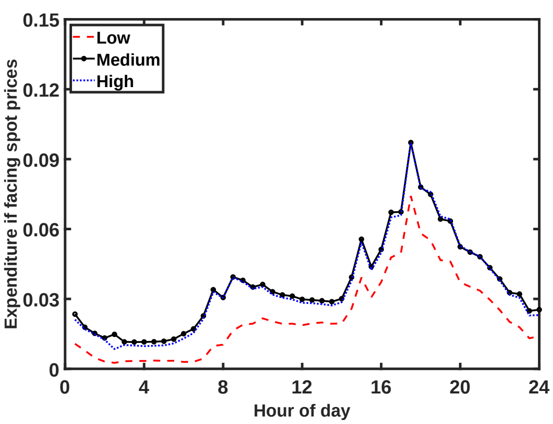
(b) Average household size



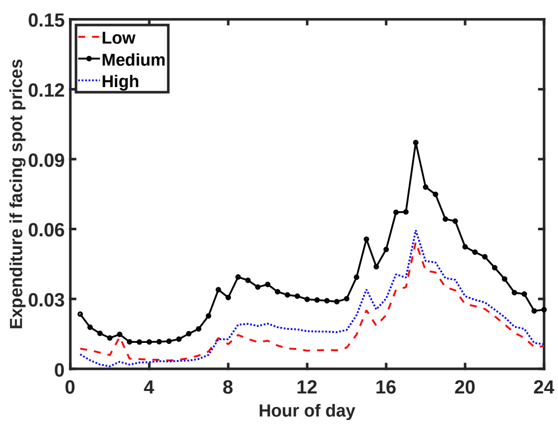
(c) Proportion that are born overseas



(d) Proportion that work from home

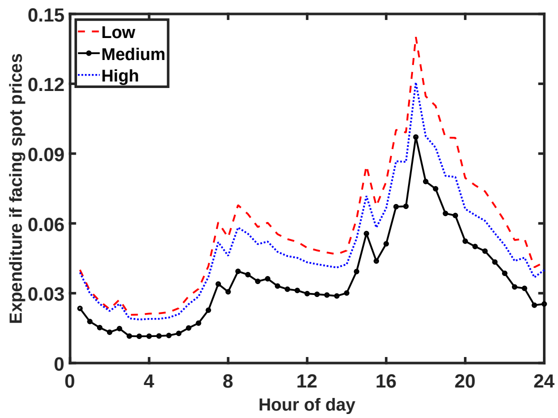


(e) Unemployment rate

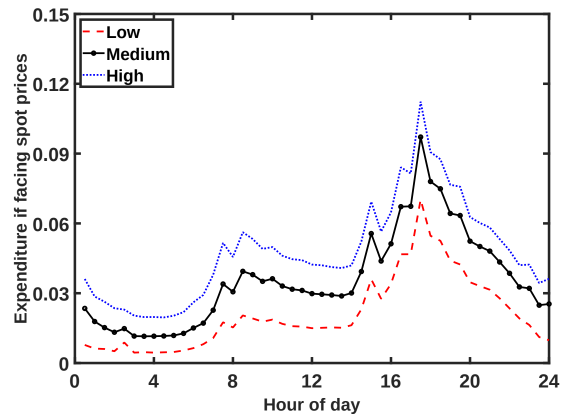


(f) Average income

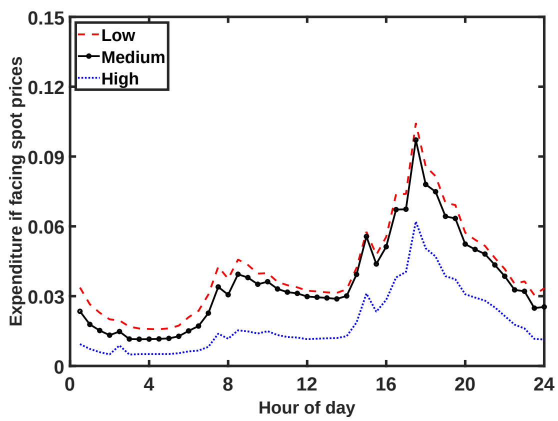
Figure A2: Estimates of household electricity procurement cost model (2/2)



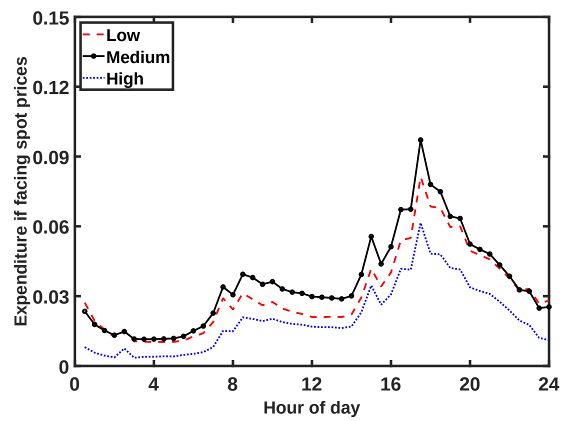
(a) Proportion tertiary education



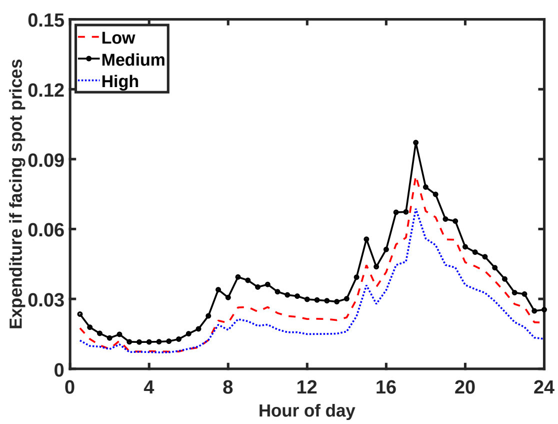
(b) Proportion of dwellings rented



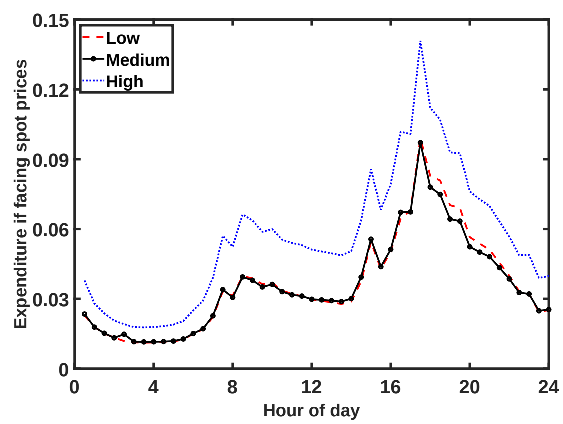
(c) Median house price



(d) Residential density



(e) Proportion of dwellings with rooftop solar

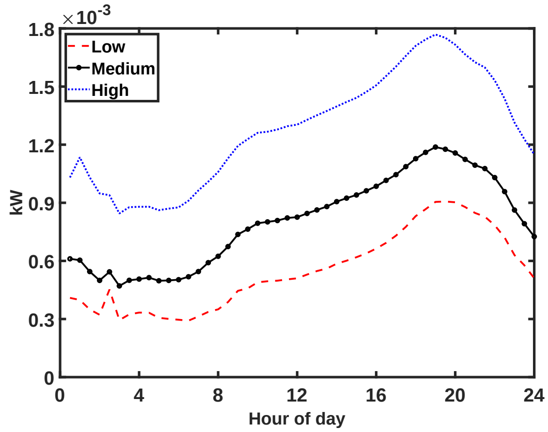


(f) Cooling degree days

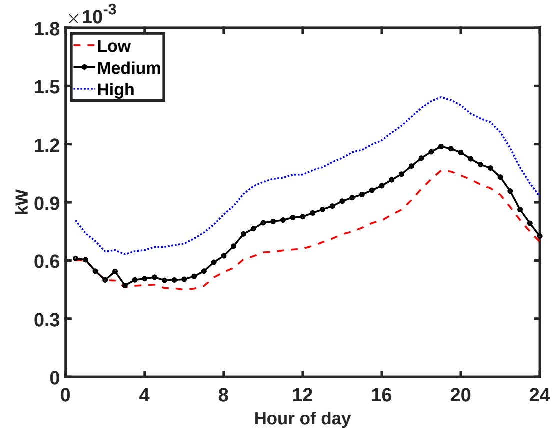
Table A3: Average cost per c/kWh if procuring energy at spot prices, assuming all other characteristics of the residence location are ranked in the middle tercile. (Summer 2018)

Characteristic	Low	Medium	High	Socialized price
Proportion older than 65	16.70	15.75	15.35	16.72
Average household size	14.91	15.75	15.29	16.72
Proportion that are born overseas	15.82	15.75	15.35	16.72
Proportion that work from home	15.72	15.75	15.24	16.72
Unemployment rate	19.42	15.75	16.42	16.72
Average income	17.80	15.75	18.12	16.72
Proportion with post-school qualifications	15.05	15.75	14.93	16.72
Proportion of dwellings rented	17.26	15.75	14.14	16.72
Median house price	14.53	15.75	16.70	16.72
Residential density	15.25	15.75	18.01	16.72
Proportion of dwellings with rooftop solar	16.82	15.75	16.13	16.72
Cooling degree days	16.32	15.75	15.41	16.72

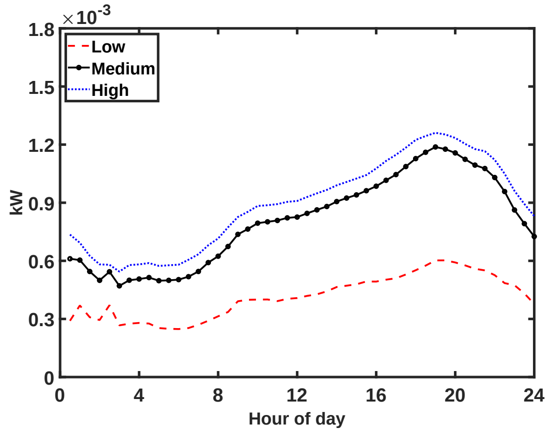
Figure A3: Estimates of household electricity use model, summer months 2018 (1/2)



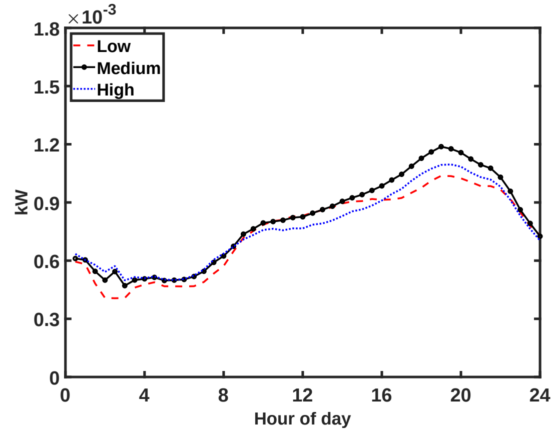
(a) Proportion older than 65



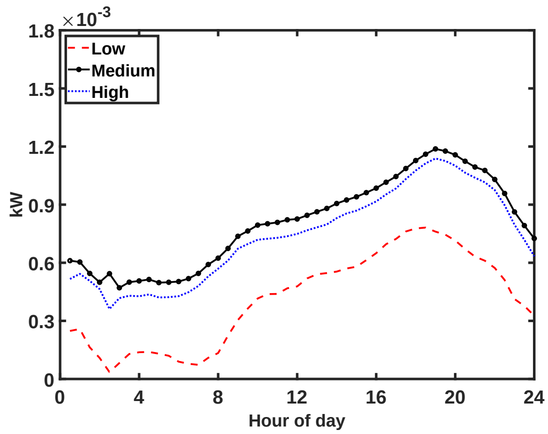
(b) Average household size



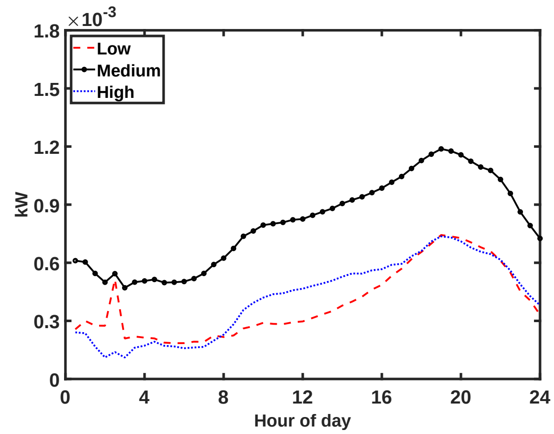
(c) Proportion that are born overseas



(d) Proportion that work from home

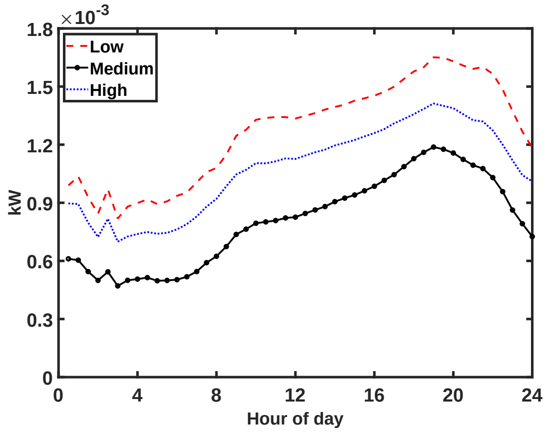


(e) Unemployment rate

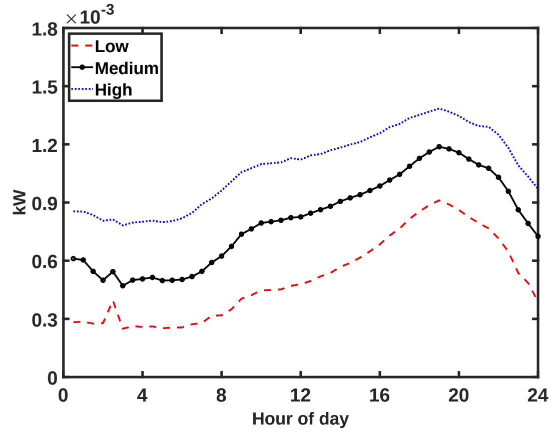


(f) Average income

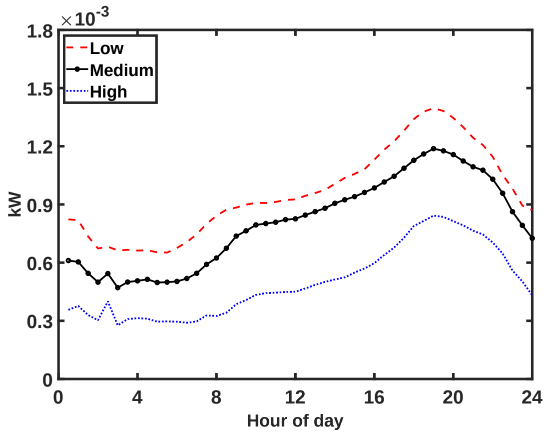
Figure A4: Estimates of household electricity use model, summer months 2018 (2/2)



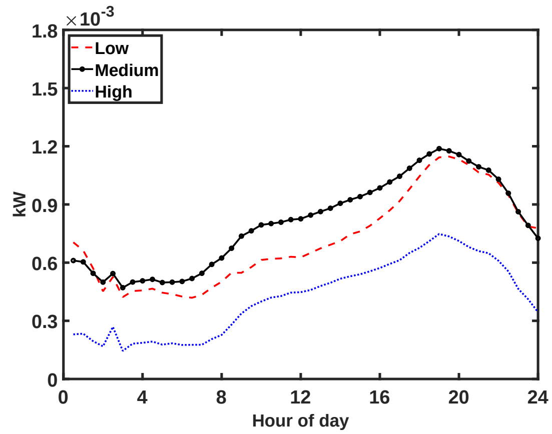
(a) Proportion with post-school qualifications



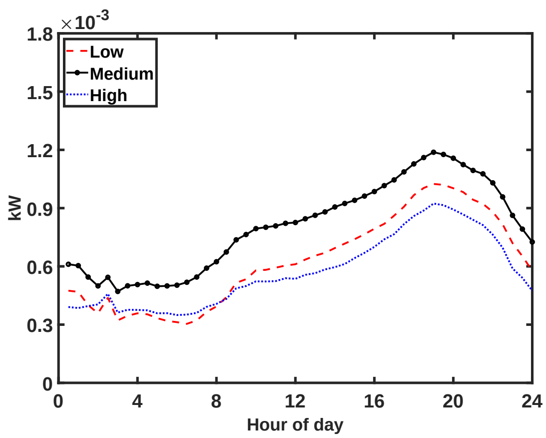
(b) Proportion of dwellings rented



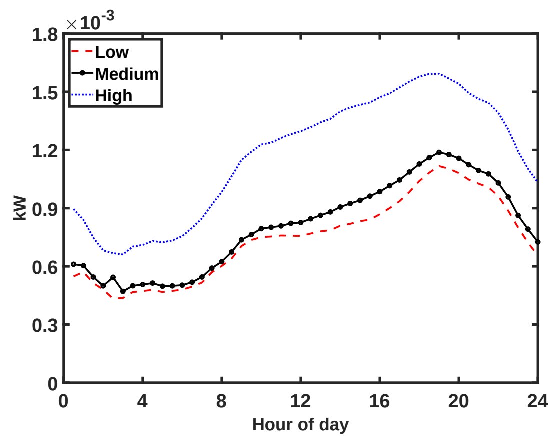
(c) Median house price



(d) Residential density



(e) Proportion of dwellings with rooftop solar



(f) Cooling degree days

B Data appendix

We briefly describe the data organization process behind the statistical analysis in this paper.

Step 1:

Gather postcode level data from the Australian Bureau of Statistics (ABS), detailed in section C. These data have postcode as the unit of observation and contain demographic, housing and area statistics.

Step 2:

Collect substation data from Distributed Network Supply Providers (DNSPs). Each DNSP has a regulatory requirement to provide data for substation-level demand every half hour of the day for the prior financial year. These data have substation × half-hour as the unit of observation (a panel) and contain demand (in MW) as the variable of interest.

Step 3:

Map postcodes to substations. We consider the centroid of each postcode and map it to the closest substation. This means getting coordinates for each substation and postcode centroid. To map postcode to substations we follow two stages, first we use the Haversine formula as follows:

$$d = 2R \times \arcsin\left(\sqrt{\sin^2(\frac{\Delta\phi}{2}) + \cos(\phi_1)\cos(\phi_2)\sin^2(\frac{\Delta\lambda}{2})}\right),$$

where ϕ is latitude, λ is longitude and R is earth's radius (mean radius = 6,371km) to calculate the great-circle distance between two points which is the shortest distance over the earth's surface. We categorise suburbs to the closest substation by this distance measure.[24]

These data have postcode as the unit of observation – with the variable being the closest substation.

Step 4:

Aggregate postcode data in step one to a substation unit of observation. These data have substation as the unit of observation – containing demographic, housing and income statistics.

Step 5:

Collect wholesale price data for Victoria from Australian Energy Market Operator (AEMO). These data have half-hour as unit of observation – containing wholesale price.

[24] Note that the shape of of the postcode and substation regions are not regular polygons, so there is some approximation to this method. See for example Australian Energy Regulator (2010).

Step 6:

Merge data from steps 2, 4 and 5. These data have substation $\times$ half-hour as unit of observation – containing wholesale price, substation load, and substation demographics.

Step 7:

Sample selection: Based on data limitations we omitted some suburbs and substations. For example, consider the Cann River substation in the east of AusNet's supply area. We omit this substation because demographic information of the suburbs it services are not available in our data set for 2018. Further, in the model implementation, we do not include substations or suburbs with missing values for any variable (electricity or demographic). Finally, we merge some substations that only service the same, common suburbs. For instance, in CBD of Melbourne there are six substations that service the single neighborhood as defined by the ABS.

Step 8:

We construct the variables listed in section 5, described in more detail below in section C.

C Variable construction

We outline the key variables used in our analysis from the Australian Bureau of Statistics (ABS), before detailing how they are used to construct the variables we use in our study. The data are publicly available at the Australian Bureau of Statistics website. Table B1, provides the ABS variable descriptions.

Table B1: Names of variables from the Australian Bureau of Statistics that are used in constructing substation-level characteristics

Variables	Descriptions
ERP–P–2	Persons - 0-4 years (no.)
ERP–P–3	Persons - 5-9 years (no.)
ERP-P–4	Persons - 10-14 years (no.)
ERP–P–20	Persons - Total (no.)
ERP–18	Working Age Population (aged 15-64 years) (no.)
INCOME–36	Mean total income (excl. Government pensions and allowances) ($)
SCHOOL–2	Non-School Qualifications (%)
DWELL–7	Total private dwellings (no.)
DWELL–2	Separate house (no.)
DWELL–3	Semi-detached, row or terrace house, townhouse etc. (no.)
DWELL–4	Flat or apartment (no.)
TENURE–4	proportion of properties rented
HHTYPE–6	Average household size (no. of persons)
WORK-TRAV–14	Other - Worked from home (no.)
WORK-TRAV–15	Other - Employed but did not go to work (no.)
TOTMIG–4	Total number of people born overseas
SOLAR–2	Small-scale solar panel system installations (no.)
CABEE–4	Number of employing businesses: 5-19 employees (no.)
CABEE–38	Number of employing businesses: 20 or more employees (no.)
LF–4	Unemployment rate (%)
LAND	Land area in hectares
HOUSES–3	Houses - median sale price ($)

The variables outlined in section 5 are constructed as detailed below, with some descriptive statistics provided in Table B1.

- Proportion older than 65 (ERP–P–20 - ERP–18 - ERP–P–2 - ERP–P–3 - ERP–P–4)/ ERP–P–20
- Average household size (HHTPYE–6)
- Proportion born overseas (TOTMIG–4/ ERP–P–20)
- Proportion of people that work from home (WORK-TRAV–14 +WORK-TRAV–14) / ERP–P–20
- Unemployment rate (LF–4)
- Mean total income (employee and investment) (Income–36)
- Education (School–2)

- Proportion of residential dwellings that are rented (Tenure–4)
- Median House Price (HOUSES–3)
- Residential density (D5 / LAND)
- Proportion of residential dwellings with solar. (SOLAR–2 / [DWELL–2+DWELL–3+DWELL–4])
- Cooling degree days (described in section 5).[25]

Table B2: Descriptive statistics of substation characteristic variables

Characteristic	Mean	St. dev	Min	Max
Proportion older than 65	0.160	0.058	0.034	0.316
Average household size	2.578	0.319	1.900	3.524
Proportion that are born overseas	0.256	0.139	0.050	0.677
Proportion that work from home	0.065	0.018	0.025	0.149
Unemployment rate	15.593	12.285	2.820	81.760
Average income	62409	15867	41789	128831
Proportion with post-school qualifications	140.356	85.519	43.480	491.000
Proportion of dwellings rented	0.284	0.119	0.072	0.698
Median house price	1849512	1416764	130000	5736250
Residential density	6.487	9.034	0.003	79.163
Proportion of dwellings with rooftop solar	0.177	0.093	0.002	0.422
Cooling degree days	413.324	137.739	17.475	1106.583

[25]To compute this variable we use temperature data records via The Bureau of Meteorology in Australia.