Is the clean energy transition making fixed-rate electricity tariffs regressive?

Gordon W. Leslie* Armin Pourkhanali Guillaume Roger†

September 7, 2023

Abstract

Wholesale electricity prices can rapidly change in real-time, yet households usually face fixed-price electricity tariffs. In markets with large amounts of solar electricity generation, households that predominantly use energy in the daytime when wholesale prices are low implicitly cross-subsidize households with energy use that is more weighted to the higher-priced evening. We map substation data on electricity use to demographic data, to identify the household characteristics associated with this cross-subsidization in a high-solar setting. We find that households in areas with low house prices and high levels of renters are the net funders of this implicit subsidy. These households currently have the lowest average energy cost for retailers to service, and could be the greatest immediate beneficiaries if real-time retail tariffs are made available, before accounting for price-responsiveness. Finally, we present evidence that cross-subsidy magnitudes have grown significantly in recent years, coincident with rapid solar generator penetration.

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

1 Introduction

Since the restructuring of electricity sectors in many countries there has been a disconnect between 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 wholesale 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

*Corresponding author: Gordon.Leslie@monash.edu.

†Leslie and Roger: Monash Business School, Monash University, Australia. Pourkhanali: School of Economics, Finance and Marketing, RMIT University, Melbourne, Australia. We thank Natalia Fabra, Catie Hausman, Mar Reguant, Joe Shapiro, Frank Wolak, Catherine Wolfram and participants at seminars at the Monash Energy Institute, the Australian Energy Market Commission, and the Markets, Contracts and Organisations Conference at ANU for insightful comments and helpful advice. We are grateful to The Melbourne Experiment at Monash University for providing research support.

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 wholesale prices, and others use energy when the fixed price is relatively high when compared to wholesale 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 in a setting where substantial solar power penetration depresses daytime wholesale prices, with evening prices significantly higher (described later in Figure 1). 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 (a) demonstrates the interplay between fixed-rate tariffs, solar power penetration and cross-subsidies, and (b) provides distributional guidance for who may be more likely to benefit or be harmed by transitioning to cost-reflective pricing (in real-time). While real-time pricing is known to be efficient (Borenstein, 2005a,b), and expected to become increasingly important to encourage valuable demand flexibility as generation shares from intermittent resources increases (Cramton, 2017; Wolak, 2019; Leslie et al., 2020),[2] it is often feared to be distributionally unacceptable because it is said to be too costly to vulnerable households.[3] We can inform this question by examining the distributional aspects of the existing fixed-rate tariff paradigm, documenting – before accounting for price responsiveness – the nature of the cross-subsidies that can be unwound by having more cost-reflective tariffs.

The novelty of our study relates to the method that maps local dwelling, demographic, and area characteristics to real-time electricity use to allow for the study of electricity cross-subsidies. The ideal (but seldom obtainable) data to study electricity cross-subsidies is high-frequency, population-wide, disaggregated by household, and linked to individual demographic information. Prior studies of electricity usage that utilize high frequency data are unable to examine the issue of cross-subsidization because that data are aggregated over large geographical regions (Cicala, 2020, for example). If the electricity data are disaggregated, it is usually only for an experimental or an otherwise selected sample of households (for example,

[1] See, for example, Borenstein (2005b,a); Borenstein and Holland (2005). Borenstein and Bushnell (2018) document the differences between social marginal costs and the private marginal costs faced by users across the United States.

[2] See Holland and Mansur (2008) for an examination the environmental impacts from introducing real-time pricing via decreasing the variance of demand.

[3] 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).

Allcott, 2011; Jessoe and Rapson, 2014; Wolak, 2015; Lynham et al., 2016; Simshauser and Downer, 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; Borenstein, 2012b; Lyubich, 2020).

Our data deviate from the ideal too: they are not disaggregated by household. But unlike the data sources in the aforementioned studies they do allow for estimation of cross-subsidies across key demographic features in a region. We examine electricity use at 161 electrical substations that span a region – so aggregation takes place at the substation level only. We calculate the average (per kWh) wholesale procurement costs for all energy that passes through each substation, and identify the best predictors for these costs from census characteristics of the surrounding neighborhood. This method 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. Hence the method overcomes the absence of ideal household-level data and does not require the availability of interval ("smart") meters throughout the area of study.

We find that in our setting of Victoria, Australia (population 6+ million, and among world-leaders in solar power penetration rates[4]), households in areas with low house prices, low density housing, high levels of renters, and more people that work from home are the net *funders* of this implicit subsidy. These groups either have a higher share of their electricity use in the daytime (where the sun is shining, solar panels generating, and wholesale prices are low); a lower share in the evening (where wholesale prices are usually significantly higher); and/or, a lower share during the few hours in the year with the highest wholesale prices. For example, to isolate one characteristic in 2018, we estimate that the average wholesale procurement cost for households in the highest rental neighborhoods is 1c/kWh less than in the highest owner-occupier neighborhoods all else being equal, with the mean cost 10c/kWh. This represents a 10% difference and an average annual implicit transfer of $44 away from each household in high rental neighbourhoods, all other characteristics held equal. This transfer arises because households in high-rental neighborhoods consume relatively less energy during the higher-priced evening peak hours.[5] This is a large annual redistribution

[4]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).

[5]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),

when compared to existing energy subsidies. For example, Victoria's major rooftop solar subsidy program amounts to $35 per non-recipient household in 2018.[6]

Further, we demonstrate that the cross-subsidies from day-trough-heavy users to evening-peak-heavy users have increased from almost zero in 2011-12, to the significant amounts we compute in 2018, and further again by 2022. This increase is rooted in solar penetration, which exacerbates the wholesale price differences between the daytime trough and the evening peak. That difference increases from an average of $40/MWh in 2017-18 to a $160/MWh in 2021-21. Therefore, the relevance of our work is increasing with the (large-scale) adoption of solar power.

Finally, these results provide an early empirical platform to consider the distributional consequences from a large-scale adoption of real-time pricing. The immediate consequence of real-time pricing is the unwinding of the cross-subsidies entailed in fixed-rate pricing, with distributional impacts from this mechanism expected to initially exceed distributional impacts from price responsiveness. Indeed, empirical evidence from Spain suggests that there is at least initially little household behavior change from transitioning to real-time pricing (Fabra et al., 2021). 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.[7] Our estimates show that households in more vulnerable neighborhoods (renters in Australia have approximately one-tenth the net wealth of non-renters) would on average pay *less* under real-time pricing in the absence of behavior change. The reason is that the *timing* of consumption matters a great deal, especially in settings with substantial amounts of solar energy resources. 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 may speculate they are best equipped to be price-responsive and deliver economic efficiency gains. Jurisdictions with flat-rate electricity prices may be able to – at least initially – redistribute payment shares away from more vulnerable segments of the population with the adoption of real-time pricing, perhaps then improving economic efficiency as user-responsiveness to price variation develops.

The paper proceeds by reviewing the relevant literature on retail electricity tariffs before outlining a

---

Figure 1.5.

[6]Calculations outlined in Section 5.

[7]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).

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 three areas of study. Our first contribution is to develop measures to inform the distributional impacts of real-time and fixed-rate pricing on households across a large population. There are two settings that can be used to study the distributional impacts of real-time pricing (now RTP) on households. The first one consists in examining the billing and consumption responses of households that have transitioned to real-time pricing. Fabra et al. (2021) take advantage of a large RTP transition event in Spain to study price responsiveness of households, but without consideration to distributional impacts. The second setting is ours. We approach this 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. Fabra et al. (2021) find households were not price-responsive following the initial switch to RTP, so we use this result to interpret ours as providing insight to initial, first-order, distributional consequences from making RTP tariffs available to households in our dataset.[8] Cahana et al. (2021) apply the Fabra et al. (2021) finding to suggest that RTP is regressive in Spain across seasons (low-income households use more during the more expensive Winter months) but progressive within seasons (low-income households use relatively less at peak times of the day). Taken together with our findings, this demonstrates the empirical nature of the question; ultimately the results depend on the details of wholesale price variation, and how the timing of use varies across household demographics.

Borenstein (2012b) examines the distributional impacts of *increasing block pricing tariffs* (tariffs where the marginal price increases with usage) relative to flat-rate tariffs in California. Simshauser and Downer (2016) instead examine the distributional impacts of *time-of-use* pricing tariffs (4 price levels based on on- and off-peak timing of consumption) relative to single-rate tariffs in Australia. Both analyses use confidential household level data, with Simshauser and Downer (2016) using a sample of meter-level data to simulate

[8] As concluded in Fabra et al. (2021), the low price elasticities they estimate "does not call into question the usefulness of dynamic pricing, but rather highlights aspects of the setting that may allow RTP programs to be effective: consumer awareness, low-cost information, and automation of demand response." For example, non-zero real-time price elasticities are identified and accentuated with in-home monitoring displays in field experiment settings (Jessoe and Rapson, 2014); and price elasticities have been documented to increase over the long-run in the context of flat-rate electricity prices (Deryugina et al., 2020).

use for what they deem to be representative households in the characteristics at their disposal – family size/composition and concession/hardship status, whereas Borenstein (2012b) maps households electricity use over monthly billing intervals to income measures at a census block level. Levinson and Silva (2022) examines the redistributive properties of increasing block tariffs at a Utility unit of analysis to construct an "electric gini" that documents which areas shift more costs from households using little electricity to those households using more, but raise that electricity demand is not strongly correlated with income. We extend these works by studying the redistributional impact of *real-time pricing tariffs* relative to flat-rate tariffs when assuming no demand responsiveness. We map publicly available substation-level electricity data to a broader set of demographic and housing characteristics (for example, rental status and house values). Similar to Borenstein (2012b) and Levinson and Silva (2022), we source our demographic information at an aggregate level but instead use the high-frequency electricity use data that is necessary to examine the cross-subsidies inherent to flat-rate pricing relative to real-time pricing.[9] Examining observational data in the context of real-time pricing directly links to the marginal wholesale procurement costs of servicing households; this can identify groups of customers that are cheaper or more expensive for retailers or utilities that offer population-wide fixed-rate plans.[10]

Our second contribution informs the distributional impacts from the clean energy transition. Our results show that solar power penetration induces a different profile of wholesale procurement costs, due to additional solar power accentuating price dynamics over the course of a day. Distributional concerns across households manifest not only due to the well-documented redistribution tied to net-metering (for example, Borenstein, 2012a, 2017; Borenstein et al., 2021); we demonstrate the extent to which households with higher consumption weights in the middle-of-day cross-subsidise those who consume mostly at the sunset peak is also increasing.[11] We provide the first documentation of heterogeneity in consumption-timing across broad demographic lines in a large population, and our results are a first pass to identify households that may benefit or lose out under fixed-rate tariff regimes as solar power penetration rates increase.

Finally and most broadly, we contribute to the vast literature on welfare economics in electricity markets.

[9] Borenstein (2012b) and the data we use aggregate in different dimensions. Borenstein uses household-level billing data to study monthly usage, whereas we have high frequency use (30 minute increments) aggregated to a substation level.

[10] We focus on the energy procurement cost component of electricity service, not the recovery of regulated asset costs (such as network costs) built into electricity tariffs. See Simshauser (2014) for a study of network tariffs (not energy).

[11] Other programs related to the clean energy transition (for example energy efficiency subsidies) also have distributional impacts, see Borenstein and Davis (2016).

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 RTP better serves consumers and society, precisely because these marginal benefits and costs can align under 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 before accounting for any price-responsiveness. 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 wholesale electricity market in the United States and find results that are consistent with the efficiency results put forth by theory. Our paper stops short of efficiency claims.

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

Take $D(p)$ as a vector of demands over time for a user (or group of users) given a price vector p. Suppose customers face some constant price for energy used ($\overline{p}$), but the retailer must procure energy at wholesale prices $\tilde{p}$. $C(a,b)$ is the electricity expense associated with a user facing prices a, with the prices paid by either that user or their retailer being b. Therefore the wholesale procurement cost for this user is therefore the following dot product:

$$C(\overline{p}, \tilde{p}) = D(\overline{p}) \cdot \tilde{p}, \tag{1}$$

where demand $D(\cdot)$ is conditioned on the vector of prices $\bar{p}$ faced by consumers, but the retailer pays real-time wholesale prices $\tilde{p}$. The average wholesale procurement cost (c) *for this group of consumers* is therefore C divided by total usage, or

$$c(\overline{p}, \tilde{p}) = \frac{D(\overline{p}) \cdot \tilde{p}}{D(\overline{p}) \cdot 1} \tag{2}$$

Typically $\overline{p}$ is a socialized price that allows (at least) cost recovery of energy charges across the population; in this model and in our data, this excludes transmission and distribution charges. Then the extent that any one user benefits or funds a cross-subsidy (S) from the fixed price can be represented in c/kWh by:

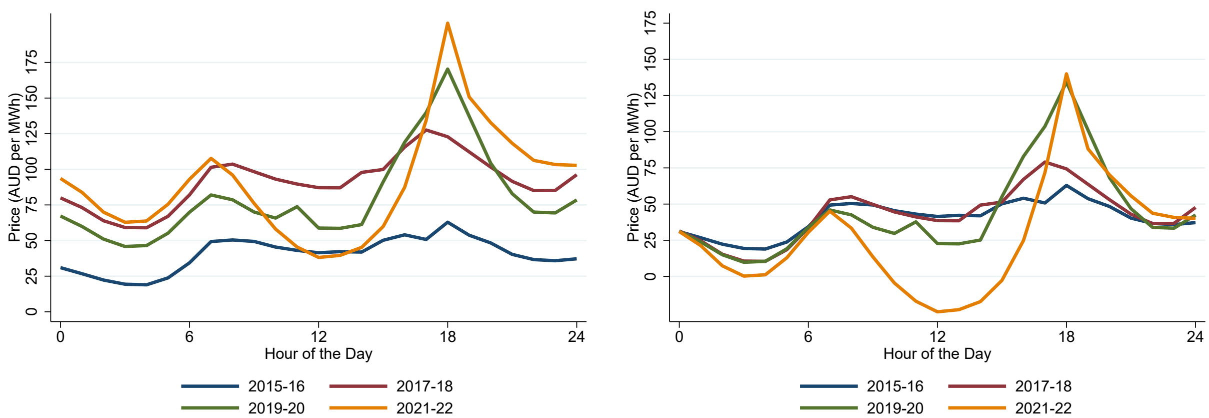
$$S(\overline{p}, \tilde{p}) = c(\overline{p}, \tilde{p}) - c(\overline{p}, \overline{p}) \tag{3}$$

where for expositional reasons we will now consider $c(\overline{p}, \overline{p})$ as the cost incurred by the user at the socialized price. Clearly $S < 0$ means that customers funds the subsidy of other customer(s) for whom $S > 0$. A consumer for whom $S < 0$ is cheaper to service than the aggregate and so is labeled "low cost" and if $S > 0$, that consumer is a "high cost" consumer.

Our empirical exercise identifies groups of these low cost and high cost consumers given their electricity usage by first constructing the cost $c(\bar{p}, \tilde{p})$ at a substation level. This object reflects the wholesale energy cost to the retailer or utility selling energy to its end user, and therefore can be constructed regardless of the existing tariff regime. Then we examine how it correlates with local area housing and demographic characteristics. Low-cost customers are those with a relatively low share of their energy use in the evening peaks and/or most extreme weather/electricity grid conditions (usually Summer in Australia). Equivalently, those with a high share of use during off-peak times are cheaper to service – and more profitable to retailers offering a flat-rate tariff to all their customers. We discuss in further detail the tariffs offered in our setting in Section 4.

When wholesale price variation is low, the question of which population segments fund and which receive the cross-subsidies inherent to fixed-rate prices is perhaps of little importance. However, the nature of modern clean energy technologies such as wind and solar generation is that their output is intermittent, which induces more variation and volatility in wholesale prices. When wind and sun are abundant, prices tend to be low; but when conditions are dark and still, prices can get high. To emphasize this (in the case of solar penetration), consider the changes in average price patterns across time-of-day in Victoria from 2015-2022 in Figure 1. The average price difference between the daytime trough and evening peak in 2015-16 was \$21/MWh, approximately a 50% difference. However, six years on, during which there was a 7-fold increase in rooftop solar capacity in Victoria, that difference appears tiny.[12] In 2017-18 (covering the timing of this study), this peak-trough price difference doubled to \$40/MWh, in 2019-20 it grew again to \$110/MWh, and finally in 2021-22, the difference was \$160/MWh an 8-fold increase on 2015-16.[13]

Figure 1: Average wholesale electricity prices by half-hour: Victoria, 2015-16 – 2021-22.



(a) Average prices by hour-of-day

(b) Average prices by hour-of-day (normalised to hour 0, 2015-16)

The normalization in panel (b) shifts all values in the line denoting a year by the same amount so each series starts at the same hour 0 amount, with relative price-differences across hours preserved.

To the extent that a household's energy use correlates with the output of renewables, or is off-beat from the demand of others, then they may be cheaper for a retailer to service. Consider the cost to service for three different consumer types that use the same total amount of energy, but with different use patterns as depicted in Figure 2a. Here, Type 2 is the base case, with usage low overnight and in the middle of day, higher

[12]Source: `https://pv-map.apvi.org.au/postcode`. Rooftop PV capacity increased from 744MW to 5,335MW in Victoria during that time.

[13]The sample window for this study is chosen due to data availability, but at the inception of the analysis, Victoria in 2018 also appeared to demonstrate the impact of solar penetration as well as anywhere in the world. The \$40/MWh average price difference in 2017-18 contained a \$20/MWh price difference for 2017 and an \$80/MWh price difference for 2018 specifically, and had also come on the back of a seven-fold increase in rooftop solar capacity from 2011-2018. These trends have not slowed as of 2022. See Bushnell and Novan (2018); Jha and Leslie (2021) for further description of the mechanisms linking solar penetration to these price patterns.

during the morning hours and highest during the evening hours. Type 1 smooths their usage, increasing their middle-of-day use and decreasing their evening use by an equal amount relative to the Type 2 base. Type 3 does the opposite, using less in the middle of the day, offset by more use in the evening peak, again with no change in total use. Type 1 may correspond to a retiree or shift worker that spends significant time at home during the day, Type 3 perhaps to a full-time worker that is not home during the day. If a socialized flat-rate price is set, whereby a retailer achieves revenues equal to their wholesale procurement costs, then there is little cross-subsidization when wholesale prices display little variation, but potentially significant cross-subsidization if daytime prices differ greatly from evening prices. Figure 2b demonstrates this point by plotting the quantity c in Equation (2) for the three types of consumers – when calculating the wholesale procurement costs under the observed wholesale prices from 2011-12 to 2021-22 (seen in 1a). We see that initially there are little to no cross-subsidies in 2011-12 (because average wholesale prices were relatively flat throughout the day in 2011-12, so each customer type cost roughly the same to service). However, cross-subsidies are rapidly increasing in recent years, with cross-subsidies in this example equating to 10% from Type 1 to Type 3.[14] Figure 2c normalises each series relative to Type 2 to more clearly show the divergence of the cost of service for Type 1 and Type 3. To the extent that Type 1 and Type 3 customers a) exist, and b) are linked to socio-economic characteristics, it is possible that the new wholesale price dynamics associated with markets undergoing a clean energy transition render fixed-rate electricity tariffs more regressive (progressive) if economically vulnerable households are more likely than less vulnerable households to have Type 1 (Type 3) consumption profiles.

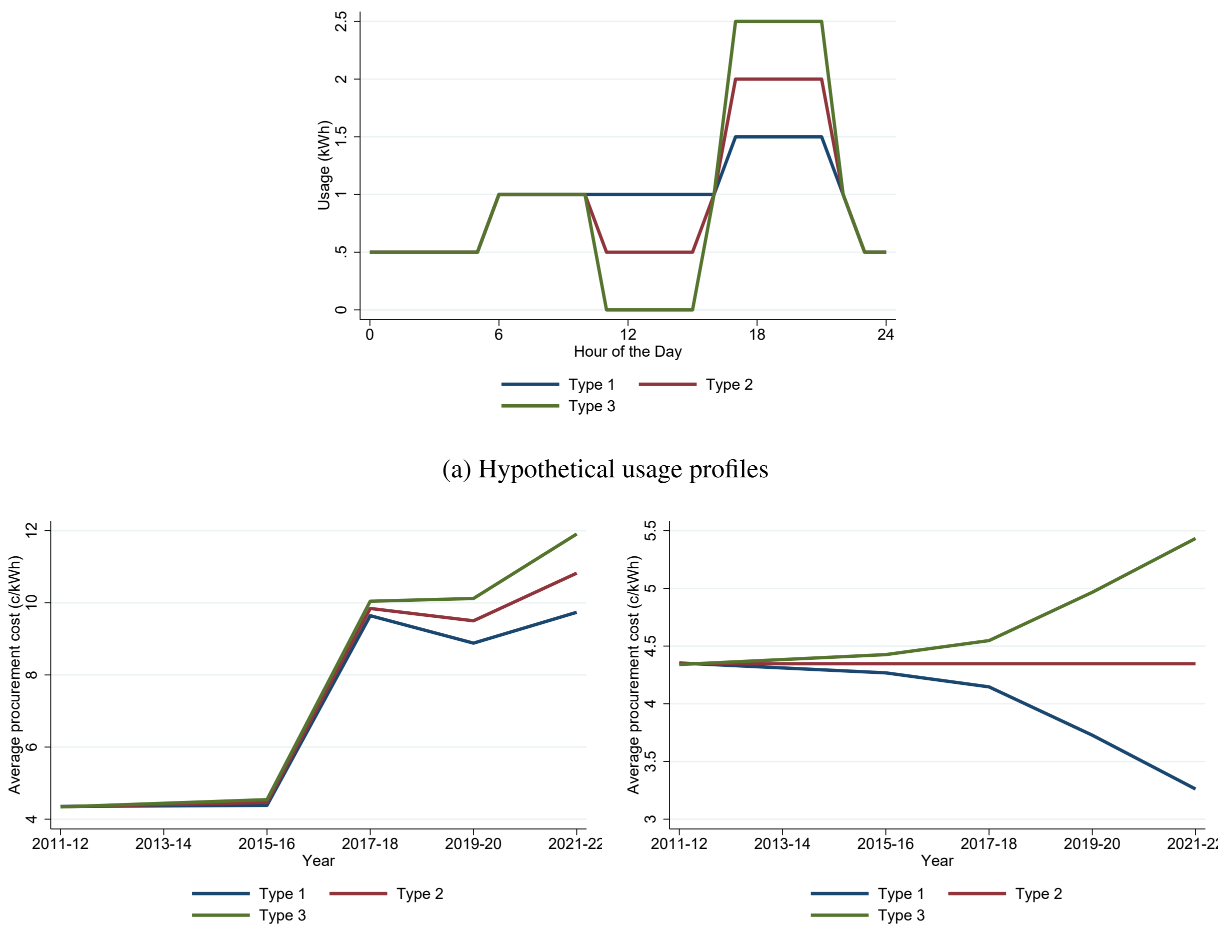
Finally, we note that having consumers face cost-reflective prices does not neatly offset these cross-subsidies. In other words, these measures of procurement costs and cross-subsidies are not equivalent to outcomes if an end-user transitions to cost-reflective prices. The reason is demand response (elasticity). That is, if end-users were to move from facing a flat-rate price ($\overline{p}$) to real-time prices ($\tilde{p}$), then their consumption expense equals:

$$C(\tilde{p}, \tilde{p}) = D(\tilde{p}) \cdot \tilde{p} \tag{4}$$

The difference in the end-users consumption expense when moving from flat-rate and real-time prices is

[14]The average wholesale procurement costs in 2021-22 are 9.7c/kWh, 10.8c/kWh and 11.9c/kWh for Types 1, 2 and 3. This is approximately a 10% cross-subsidy funded and received by Type 1 and 3 relative to the Type 2 baseline.

Figure 2: Growth in potential cross-subsidies: Victoria 2011-12 – 2021-22



(a) Hypothetical usage profiles

(b) Average wholesale procurement price

(c) Average wholesale procurement price (normalised to Type 2, 2011-12)

Normalisation in panel (c) adds to each data point the difference between Type 2 average wholesale procurement costs in 2011-12 levels and the Type 2 average wholesale procurement cost for the year of the data point.

therefore:

$$C(\tilde{p}, \tilde{p}) - C(\overline{p}, \overline{p}) = D(\tilde{p}) \cdot \tilde{p} - D(\overline{p}) \cdot \overline{p}$$

$$= \underbrace{D(\overline{p}) \cdot (\tilde{p} - \overline{p})}_{\text{first-order cost impact}} + \underbrace{(D(\tilde{p}) - D(\overline{p})) \cdot \tilde{p}}_{\text{demand-response cost impact}} \tag{5}$$

Our framework can only identify the net funders and beneficiaries of the cross-subsidies entailed by fixed-price retail tariffs under existing consumption patterns. That is, in Equation (5), we cannot speak to the demand-response cost impact from end-users facing real-time prices. Quantifying the full impact of cost-reflective pricing would require applying electricity use elasticity (and cross-elasticity) estimates. Although some are identified in the literature (see for a recent example Deryugina et al., 2020), they are specific to the price variation and the household preferences observed in their setting and cannot be reasonably applied to most other settings. Further, we cannot estimate elasticities in settings with fixed-rate electricity prices given that end-users inherently do not face price variation. Consequently, we define the scope of our analysis to understand which consumer segments are cheaper or more expensive to service in terms of wholesale procurement costs. Then, if willing to assume that any demand response is either small or slow, these consumer segments also correspond to the initial beneficiaries from cost-reflective, real-time pricing. As noted elsewhere, Fabra et al. (2021) find this response to be negligible in the short run – so that the first-order effect may be the one that matters most initially, where Deryugina et al. (2020) demonstrate that price responsiveness may develop over years.

4 Data, setting and method

We conduct a simple empirical exercise that constructs the per kWh wholesale procurement cost (c in Equation (2)) at a substation level, and then estimate a linear model that describes the variation in these costs across local demographic and housing characteristics. This approach is developed with consideration to data availability – we observe load (electricity use) at high frequencies at a substation level, where each substation connects to many customers 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 access to interval ("smart") meters located at the premises of each end-user.[15]

Next we describe the data sources, the key variables in the analysis and the empirical model. This is followed by a discussion of the institutional setting and how it impacts interpretation of the model.

4.1 Data and descriptive figures

The primary data sources are (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) Statistical Area 2 (SA2, approximately postcode-level) demographic and area data from the Australian Bureau of

[15]Indeed, our method 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.

Statistics.[16] 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 substation (s) × time (t) panel for electricity use ($Q_{s,t}$). Data from (b) form a time series of wholesale electricity prices (P_t). Multiplying $Q_{s,t}$ by P_t forms a panel (substation × time) containing wholesale procurement costs ($C_{s,t}$). Aggregating $C_{s,t}$ over the year gives a cross-section containing total wholesale procurement costs for the sample year (C_s). The average (per kWh) wholesale procurement cost over the year of study (Y) is:

$$c_s = \frac{\sum_{t \in Y} C_{s,t}}{\sum_{t \in Y} Q_{s,t}}$$

c_s is the primary variable of interest that we seek to link to local area characteristics to understand which characteristics are associated with high or low wholesale procurement costs. To unpack why some areas have higher or lower wholesale procurement costs, we also examine the timing of electricity use. To do so we measure the share of electricity use in substation s over the year that is contained in a) daytime trough hours (11am - 2pm), $\tilde{Q}_s^D$; b) evening peak hours (5pm - 8pm), $\tilde{Q}_s^E$; c) The top 10 highest wholesale price hours (corresponding to P_t >\$1716/MWh in 2018), $\tilde{Q}_s^{t10}$; and d) The hours where wholesale prices exceed \$300/MWh, considered a high-price threshold in Victoria (corresponding to the top 19 highest wholesale price hours in 2018), $\tilde{Q}_s^{p300}$.[17]

Finally, data from (c) are mapped to each substation – these data contain the relevant regressors that will be used to describe how wholesale procurement costs vary across the substations. These data are available at approximately a postcode level, and are mapped to the nearest substation (or collection of substations). This mapping rule is detailed in Appendix B. Although our ability to link sub-regional demographic data to high-frequency sub-regional electricity use data is novel and informative, we still do not have the ideal

[16]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 (all accessed in June 2020):
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/`].

[17]Although somewhat arbitrary, \$300/MWh is a meaningful threshold in the National Electricity Market (NEM). The price ceiling in the NEM is ≈ 15,000/MWh, however, \$300/MWh is the *Administered Price Ceiling*, which takes effect if the rolling average of electricity prices exceeds a pre-specified, regulator-determined *Cumulative Price Threshold*. Second, \$300/MWh is the strike price for the option-style NEM derivative products that are available for trade on a public securities exchange.

data that builds from individual household electricity and demographic data. We discuss this further in the Section 4.2 when discussing the interpretation of the linear model that is estimated. The final data set for analysis contains data for 161 substations, which when mapped to the Census data in aggregate cover 5,348,530 people, 1,780,627 residential dwellings and 175,272 businesses that we consider connected to the substations.[18]

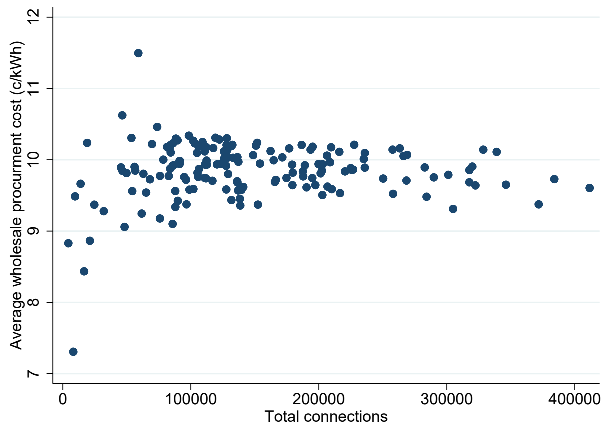
The categories we use in our statistical description can be grouped as six demographic variables, four housing stock variables, two business share variables, and a climate variable. The demographic variables are 1) proportion of people over age 65, 2) average household size, 3) proportion of people that are born overseas, 4) proportion of people that work from home, 5) unemployment rate, and 6) average income. The housing stock variables are 7) proportion of dwellings that are rented, 8) median house price, 9) residential density, 10) rooftop solar installations per residential dwelling. The business share variables are 11) the share of substation connections that are manufacturing businesses and 12) the share of substation connections that are other businesses. The climate variable is 13) the number of cooling degree days.[19] Appendix C contains further details of the variable construction, including summary statistics for the characteristics, their correlations and an overview of the mapping of SA2 information to each substation.

Figure 3 displays the variation in wholesale procurement costs and total usage. Unsurprisingly, the variation decreases with total usage, as one might expect due to the law of large numbers – any end-user with idiosyncratic consumption timing patterns will have more weight in substations with fewer connections than more connections, therefore the variance of wholesale procurement costs can be expected to be greater for smaller substations. In any case, the majority of substations are within 9c/kWh and 10.5c/kWh for wholesale procurement costs, suggesting a 10-15% potential range for cross-subsidies from fixed-rate tariffs at this substation unit of analysis in Victoria, Australia, 2018. We expect more variation at more disaggregated levels of data (usage patterns are more variable the more disaggregated the unit of analysis), and also in the future (prices are fast becoming more variable in line with renewable penetration, discussed in Section 3).

[18]Victoria's population was 5.9 million, with 2.3 million residential dwellings 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 residential dwellings in Victoria. Some substation data is dropped for data quality reasons, described in appendix B.

[19]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`.

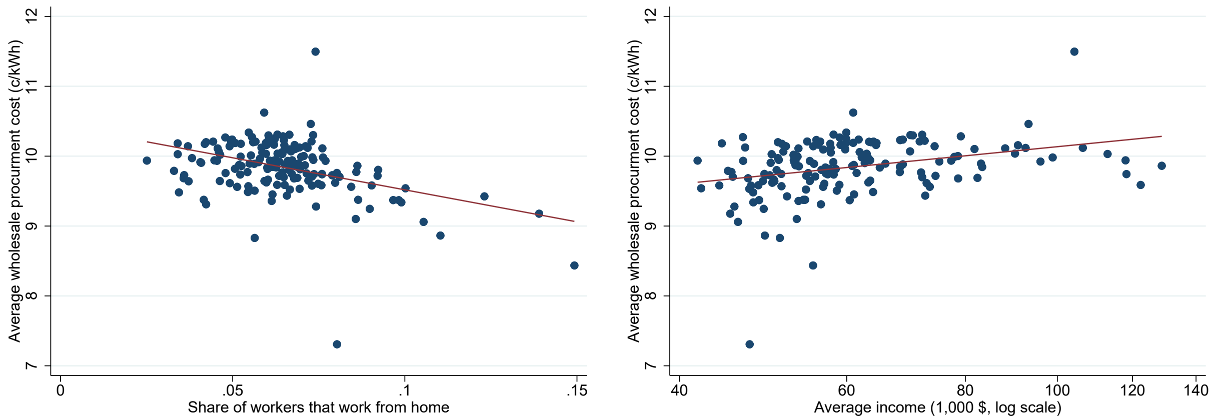
Figure 3: Wholesale procurement costs and substation energy use



We present a series of scatterplots in Figures A1 and A2 to document the univariate relationship between each substation characteristic and average wholesale procurement costs. We bring forward two scatterplots for discussion. Figure 4a displays the scatterplot for the share of workers that work from home, and figure 4b the scatterplot for average income. The correlation with work-from-home share perhaps aligns with intuition: those that work from home will have a relatively larger share of their electricity away from the evening peak, using a greater share of their total energy when wholesale prices are low. The correlation with income is revealed to show fixed-rate tariffs are on-average regressive in this setting and measurement – those in areas with higher incomes tend to have higher average wholesale procurement costs. However, in the next section we will estimate a multivariate linear regression model, which can identify the variation in average wholesale procurement costs jointly across all factors, and will not identify income as a driver after controlling for other factors. Appendix Table A2 reports the correlations between characteristics, revealing that income is positively correlated with house prices, which is also likely to have predictive power on electricity consumption patterns.

Finally, Figure 5a displays the average usage across the day for end-users connected to substations with high-, medium- and low-rental shares, and Figure 5b is equivalent with the exception that it plots the share of all usage in each half hour. This displays two relevant features. First it returns a finding in-line with the split-incentives literature on renter vs owner-occupier homes; usage on average is higher in high-rental neighborhoods, perhaps due to less investment in energy-efficient appliances and building materials. However, for the purpose of this paper, the relevant metric to relate to a flat-rate electricity price is the

Figure 4: Average wholesale electricity procurement costs for substations, 2018



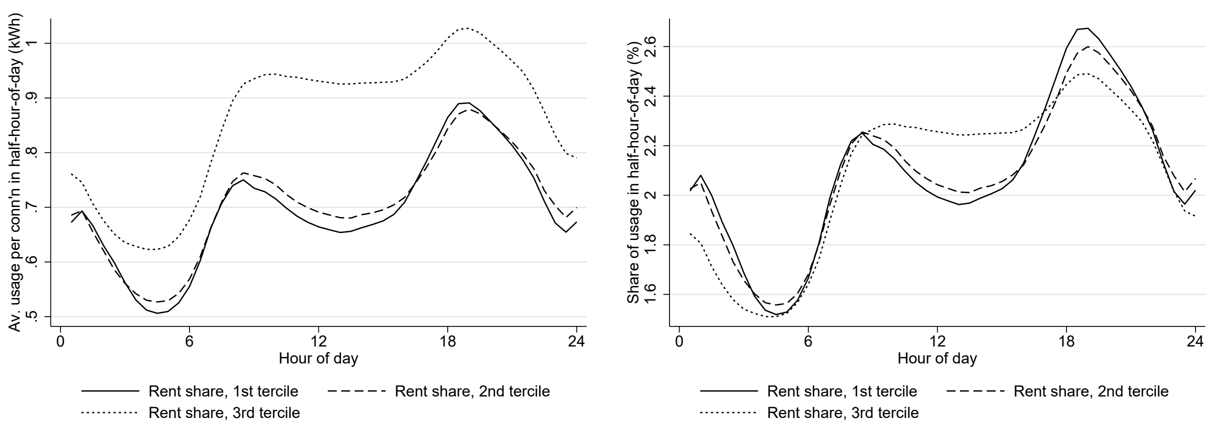
(a) Work-from-home share

(b) Average Income (log)

Each point is the average procurement cost of electricity for a substation (c/kWh) on the y-axis and that substation's value of the listed characteristic on the x-axis. A linear line-of-best-fit is also displayed.

share of usage at any time of day, and what is revealed is that high-rental neighborhoods tend to have a relatively higher share in the (cheaper) daytime and a lower share in the (expensive) evening. This suggests that average wholesale procurement costs in high-rental share areas will be lower than in areas with high owner-occupier shares.

Figure 5: Usage for substations in high-, medium- and low- rental share neighbourhoods, 2018



(a) Av. usage per connection

(b) Share of all usage

Each substation is ranked in the 1st (low) 2nd (medium) or 3rd (high) tercile with regard to the share of properties that are rented in their neighborhood. Within these groups, the average usage per connection (left panel) and share of all usage (right panel) is reported for each half-hour-of-day.

4.2 Empirical Model

We describe the variation in wholesale procurement costs at a substation level by estimating the following linear model:

$$c_s = \alpha + \beta.X_s + \epsilon_s \tag{6}$$

The 13 elements of the vector X_s are described in the previous subsection. They cover demographic, housing, business, and climate characteristics surrounding the substation. The variables that relate to shares (share of rental houses, etc.) take values between zero and one, whereas the unbounded variables (house prices, etc.) enter the model with a log transformation. The model is estimated using Weighted Least Squares, where observations are weighted in proportion to the square root of the annual usage at the substation. This reflects that substation-level observations aggregate the behavior (usage) of the end-users connected to it, with the variance of the idiosyncratic term expected to be smaller for substations with more usage because the dependent variable is the mean wholesale procurement cost of energy at a substation, as seen in Figure 3.[20] Standard errors are constructed using the White (1980) covariance sandwich matrix robust to heteroskedastic standard errors.

Interpretation of model coefficients

We stress that this model is suitable for describing the end-user groups that are lower- and higher-energy procurement cost customers. The estimates do not have a causal interpretation; for example, as a best linear predictor function it describes how procurement costs vary across areas with different existing rates of renters, but does not speak to how swapping a renter in a home to an owner-occupier may alter these costs. To this end, identifying the characteristics of low- and high-procurement cost groups correspond to the groups that fund or benefit from the implicit cross-subsidies entailed in fixed-rate electricity tariffs during the study window. Equivalently, these are the first-order winners and losers that could be expected from adopting real-time pricing, noting that this measurement does not account for any subsequent demand response as discussed in Section 3.

The descriptive interpretation of the model also relates to the measurement of the regressors – it returns the best linear predictor function given the as-measured data at our disposal. As mentioned, we do

[20] See page 511 of Greene (2003) for a demonstration of the suitability of Weighted Least Squares when estimating linear models where the dependent variable is a mean, whereby the variance of each observation is proportional to the inverse of the square root of the denominator.

not have ideal, unit-level data on electricity consumption or household characteristics. Instead we match the characteristics of the nearest census regions to each substation. Although our mapping is designed so that there is no double-counting (there are more census regions than substations, so some substations are matched to multiple census areas, and occasionally two substations merged to match a census area), these average characteristics will likely have some departure from the actual average characteristics of the properties and occupants connected to the substation. Connections to substations are determined by the paths of the poles and wires, not by zipcode or other administrative borders; although all are contiguous catchment areas, perfect overlap is not guaranteed. Therefore, there is likely to be some attenuation bias to the extent that neighboring substations or census regions have different characteristics, and the overlap between a substation's catchment misaligns with the census region.

In particular, we note two items relating to businesses. First, we take all listed residences and businesses in the census data and consider this the potential number of connections to a substation. Then we take the share of these potential connections that are manufacturing businesses for our first industry descriptive regressor, and the share of that are non-manufacturing businesses for our second industry descriptive regressor. We make this distinction because their operating hours and intensities are likely distinct, with manufacturing businesses more likely to have a near-constant load shape 24/7 or be near-constant during worker shifts, whereas other businesses may vary more with the habits of their customers. Second, we stress again the nature of the model not being causal, as areas with higher shares of businesses may attract households with particular electricity consumption profiles, which cannot be separately identified in our study.

Finally, the aggregation of our unit of observation gives a depiction of the variation in average wholesale procurement costs across neighborhoods, not individual households. For example, we cannot identify how the consumption profiles of households with low incomes located in low-income neighborhoods compare to households with low incomes located in high-income neighborhoods. Instead, we can only describe the differences in average consumption profiles of energy users connected to substations with low- and high-average incomes.

4.3 Institutional Setting

Energy losses and the costs incurred by retailers serving end-users:

Wholesale prices in Victoria are set under a *zonal* market design, meaning they vary over time but remain uniform across location. Transmission losses are attributed to the price received by generators; therefore, the procurement cost of energy passing through each substation is captured by the prevailing wholesale price and a transmission loss adjustment is not needed.[21] Although there are downstream distribution losses from the substation to the end-user, these are ultimately paid for by retailers. Therefore the energy passing through substations closely approximates the quantity of energy that must be purchased by retailers on behalf of their customers.[22]

Contestability of retail markets and cross-subsidy interpretation: The retail electricity market in Victoria is fully contestable, where households can choose from products offered by competitive retailers. Unlike many jurisdictions (such as Western Australia, Tasmania and many U.S regulated utility settings), there are no regulated geographical retail monopolies and prices are not strictly regulated.[23]

Our measures of wholesale procurement costs and the shares of electricity use at various times are accurate and suitable regardless of whether the industry contains a regulated regional utility service or is subject to retail competition. What may differ are the conclusions that can be formed on how wholesale procurement costs map to cross-subsidies. Under a regulated, fixed-price setting where prices are set to recover some multiple of costs, then it is apparent that there is an implicit cross-subsidy away from groups with lower wholesale procurement costs to those with higher values.

Despite end-users having retailer choice in Victoria, the nature of the retail offerings still justifies the same interpretation of the link between wholesale procurement costs and cross-subsidies. First, the vast majority of households are on fixed-price tariffs without facing differential usage incentives in real-time or at different times-of-day. Therefore, the retail price faced by an end-user in high- or low- wholesale price periods is the same, and any differences in their share of energy use at different times are not driven by price variation.[24] Second, retail competition is concentrated with 80% market share among 4 firms (Australian

[21] That is, if generator i sends out $Q_{i,t}$MWh of energy at time t, they receive $Q_{i,t} * LF_i * P_t$, where LF_i is that generator's loss factor set by the system operator, and P_t is the wholesale energy price at time t (Australian Energy Market Commission, 2019).

[22] Each network service provider lists "Distributional Loss Factors" (DLFs) for the different classes of connection in their network. That is, a retailer is charged a constant loss factor for the energy used by its customers (approximately 5% for most household connections in Victoria), regardless of time-of-day. Although in practice losses are not constant, the aggregate loss-adjusted energy at customer meters will on-average equate to the reading at the substation. For this reason we do not adjust the substation data to account for distribution losses in this study. See Australian Energy Market Operator (2018) for a list of DLFs by customer connection type.

[23] This is not to say the market is unregulated, for example there exists a default offer that acts somewhat as a price ceiling for customers getting rolled over onto new plans when their contracts expire.

[24] Indeed, no retailer *offered* real-time tariffs to households during our sample window. See CME (2017) for summary statistics on the characteristics of retail tariffs in Victoria, 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

Competition and Consumer Commission, 2018, p134), and retailers offer homogeneous menus to coarse household groupings, meaning that there are large groups of customers facing the same flat price.[25] Tariff offerings do not price discriminate based on consumption patterns, so if a tariff is offered by a retailer to achieve and expected aggregate profit margin, then customers with consumption patterns that lead to lower average wholesale procurement costs cross-subsidize those on the same plan with higher average costs.

5 Results

5.1 Wholesale procurement costs

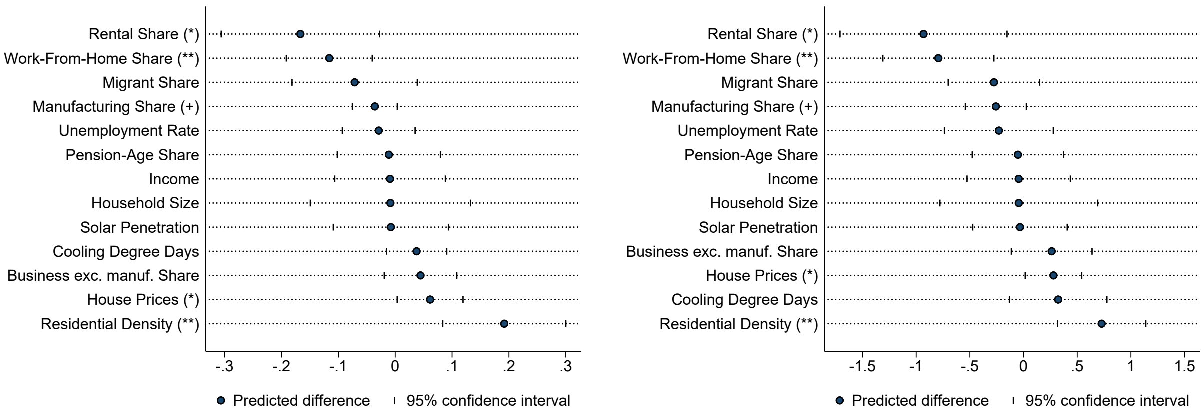
Estimates for Equation (6) that describe the variation in average wholesale procurement costs (c_s) across substations are reported in Column 1 of Table 1. Figure 6 displays these estimates and their associated 95% confidence intervals from least to greatest value for a common deviation in the value of that characteristic. That is, it reports $\hat{\beta}_j * \Delta_j \pm 1.96 * se(\hat{\beta}_j) * \Delta_j$, where $se(\hat{\beta}_j)$ is the standard error of the estimate for β_j, and in the left panel Δ_j is 1 standard deviation of characteristic j in the sample, and in the right panel Δ_j is the difference from maximum to minimum observed value in the sample.

We observe that the largest predictors of wholesale procurement costs for a 1 standard deviation change in a characteristic are rental shares, work-from-home shares, house prices and residential density; all other characteristics are not detected to differ from zero for hypothesis tests at a 5% level. That is, cheaper areas to service tend to be areas with higher rental shares, higher work-from-home shares, lower house prices and lower residential density. Earlier, we saw in Figure 4b that wholesale procurement costs were unconditionally positively correlated with income, suggesting that fixed-rate tariffs are regressive. However, in this model, income is not detected to predict wholesale procurement costs after controlling for other neighbourhood characteristics. Instead, flat-rate tariffs appear to be regressive in terms of wealth measures, because the wealth of households in areas with low house prices and with high rental rates are generally much lower than those in areas with high house prices and owner occupancy rates. For example, in Australia the median household net wealth for owner occupiers without a mortgage is \$1.1m, with a mortgage is

15-20% per year (or customers switching on average every 4-6.7 years), meaning that most customers stay on the same fixed-rate plan for many years.

[25] 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.

Figure 6: Predictors of average wholesale procurement cost



(a) Change in characteristic: 1 std. dev.
Mean 9.84c/kWh

(b) Change in characteristic: Min to Max value
Mean 9.84c/kWh

Estimates of Equation (6). See Table 1 for parameter estimates, standard errors and estimation information. Reported values transform coefficient estimates and standard errors to report an X unit change in the regressor of interest, where X is the sample standard deviation of that regressor in the left panel, and the sample maximum to minimum difference for that regressor in the right panel, reported in Table A1. Regressors listed from lowest estimated value to highest value. Key relates to p-values for the test that coefficient is equal to 0. ** p-value < 0.01, * p-value < 0.05, $^{+}$ p-value < 0.10.

$0.8m, and for renters is $0.1m.[26]

Households in low density areas tend to be cheaper to service, and graphically the magnitude seems large when compared to other factors, but this reflects the immense variation in residential density in our sample spanning rural areas and high-density cities. Finally, areas with greater shares of work-from-home shares are cheaper to service, ostensibly because they use more energy during the daytime when energy is cheap, however we will see the explanation is more nuanced in the next section that examines the timing of energy use.

Finally, similar to income, we do not see that rooftop solar share is a significant predictor of wholesale procurement costs in this model. This emphasizes that the interpretation of the estimates is not causal but descriptive – it helps describe where the areas with the lowest wholesale procurement costs are but not necessarily why. Given the energy price patterns in Victoria, adding rooftop solar increases average wholesale procurement costs because households adding solar decrease their share of energy procured from the grid at the lowest cost times of day (see Figure 1). Yet unlike rental status and house prices, solar is not detected as a significant predictor of wholesale procurement costs, likely because solar uptake in Australia

[26]See Table 8.2 Household Assets and Liabilities, Tenure and Landlord Type in Australian Bureau of Statistics (2019-20).

is strongly correlated with owner-occupancy status and net wealth, as documented in Best et al. (2019).

Context for magnitudes: These average procurement costs inform the direction of cross-subsidies, but only describe heterogeneity in dimensions that relate to census-level characteristics. Small differences in these procurement costs are of substantial economic magnitude for some customers, with energy expenses proportionally a large amount of all expenditures among low-income households in Australia (6%, see Phillips, 2018, page 15). Further, expenditure shares on energy are 10% or higher for a quarter of welfare recipients.[27] To demonstrate, comparing the average procurement cost for households in the highest rental neighborhoods to the procurement costs for households in lowest rental neighborhoods (holding other characteristics equal) implies that per kWh procurement costs are about 9.5% lower in the highest rental neighborhood (which is within the variation we see in wholesale procurement costs across substations reported in Figure 3). At average annual household usage levels, this implies an (average annual) implicit transfer of $44 away from each household in high rental neighborhoods, all other characteristics held equal.[28] This represents 3% of the $1,457 average electricity bill for Victorian households in 2018 (Australian Competition and Consumer Commission, 2018). This is a large annual redistribution when compared to existing energy subsidies, with expenditures from Victoria's major rooftop solar subsidy program equating to $35 per non-recipient household in 2018.[29] However, it is a smaller (but non-negligible) fraction in comparison to major welfare policies; total expenditure on unemployment benefits in Australia equated to approximately $420 per non-recipient or $780 per employed person in 2018.[30]

Finally, noting that the setting for this analysis is 2018, and that Section 3 demonstrated the extreme increase in the gap between daytime and evening wholesale prices, the extent of the cross-subsidy potential described in this section may have increased multiple times by 2022. So the results in this paper will only be more relevant going forward with even more renewable penetration, all else being equal.

[27]See page 19 of Phillips (2018). Note these are energy expenses that include natural gas expenditure.

[28]Our estimates of Equation 6 return the average wholesale procurement cost, with this predicted to be 0.93c/kWh less for the lowest vs highest rental neighbourhood, all other characteristics held equal. Taking this from the mean wholesale procurement cost of 9.84c/kWh, this reflects a 9.5% difference in prices, and gives a back-of-the-envelope estimate of these households losing $44 per year via cross-subsidies at an average annual household energy use of 4,727kWh.

[29]Phase 1 of Victoria's Solar Homes Program delivered 36,704 subsidies of $2,225 to eligible households in the 2018-19 financial year, totalling $82m (Victorian Auditor-General's Office, 2021). Across the 2.3m residential dwellings in Victoria, this equates to approximately $35 per household.

[30]Expenditures on unemployment benefits in 2018 were $10 billion, with 1.1 million people receiving an unemployment or parenting payment (figures sourced from Australian Institute of Health and Welfare, 2019), leaving a lower bound of 25.0 - 1.1 = 23.9 million non-recipients of unemployment benefits in Australia, approximately $420 per non-recipient. This corresponds to $780 per employed person if instead scaling by the 12.7 million employed in December 2018.

5.2 Timing of energy use

We extend our analysis to better understand the drivers of the variation in average wholesale procurement costs (c_s) across substations. We do this by examining how the share of energy usage varies with substation characteristics, estimating Equation (6) now with dependent variables $\tilde{Q}_s^D$ (share of use between 11am-2pm), $\tilde{Q}_s^E$ (share of use between 5pm-8pm), $\tilde{Q}_s^{t10}$ (share of use in 10 most expensive hours), and $\tilde{Q}_s^{p300}$ (share of use in hours with wholesale prices >$300/MWh). Estimates for these models are reported in Columns 2-5 in Table 1. Again, Figure 7 displays these estimates and their associated 95% confidence intervals from least to greatest value for a common deviation in the value of that characteristic. That is, it reports $\hat{\beta}_j * \Delta_j \pm 1.96 * se(\hat{\beta}_j) * \Delta_j$, where $se(\hat{\beta}_j)$ is the standard error of the estimate for β_j, Δ_j is 1 standard deviation of characteristic j in the sample, with the four panels corresponding to $\tilde{Q}_s^D$, $\tilde{Q}_s^E$, $\tilde{Q}_s^{t10}$, and $\tilde{Q}_s^{p300}$.

The predictors of wholesale procurement costs (Figure 6) align with the predictors of timing (Figure 7) in an intuitive fashion. First, examining rental shares, we see that high rental share neighborhoods are associated with lower shares of energy in 5pm-8pm evening peak hours (Panel a), which on average sees the highest wholesale energy prices. Further, their usage at the few peak times across the whole year (Panels c and d) are significantly lower, perhaps reflecting that rental properties are less likely to have air conditioning and the most extreme price times over a year are typically times of extreme heat. Similar patterns in usage are found in residential density, where low-density households are found to use less at expensive times throughout the year, again perhaps reflecting that high-density areas with many apartments could be more modern and more likely to have air-conditioning. Areas with high house prices instead only are found to have *higher* shares of energy use during 5pm-8pm windows, which on-average are higher priced.

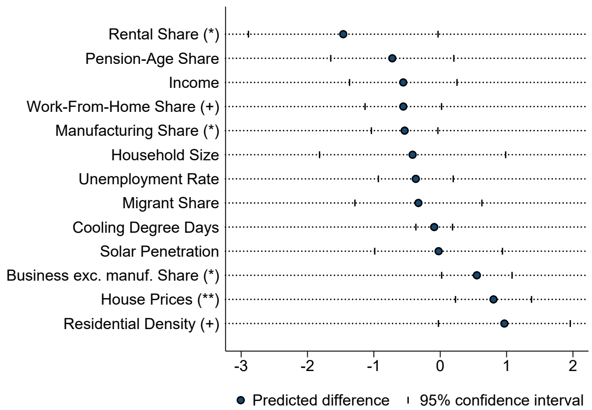
Curiously, we find that the driver of low wholesale procurement costs for areas with higher work-from-home shares is not because they have a higher share of usage in the daytime. Instead, they tend to have higher shares of energy use overnight (which is essentially the omitted category in the reported figures, and corresponds to another time of day with low wholesale prices) and low usage shares in the most extreme priced hours of the year. At the time of the study (pre-Covid pandemic) it may have been that those that reported working from home did not tend keep traditional daytime working hours.

Table 1: Estimates of substation wholesale procurement costs and usage profiles

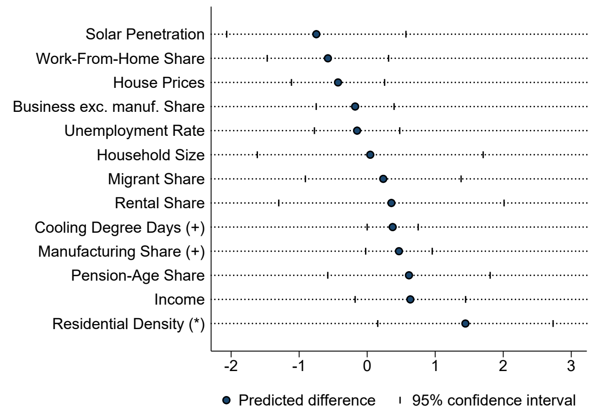
	(1) c_s	(2) $\tilde{Q}_s^E$	(3) $\tilde{Q}_s^D$	(4) $\tilde{Q}_s^{t10}$	(5) $\tilde{Q}_s^{p300}$
Solar Penetration	-0.079	-0.253	-7.737	-0.017	-0.046
	(0.535)	(5.080)	(6.955)	(0.065)	(0.103)
Rental Share	-1.327*	-11.626*	2.832	-0.210**	-0.344**
	(0.565)	(5.798)	(6.723)	(0.065)	(0.110)
Income (log)	-0.040	-2.447	2.787	0.000	-0.004
	(0.218)	(1.815)	(1.819)	(0.023)	(0.038)
Work-From-Home Share	-6.392**	-30.655^{+}	-31.828	-0.733**	-1.220**
	(2.125)	(16.196)	(25.073)	(0.240)	(0.373)
Household Size	-0.026	-1.261	0.136	-0.021	-0.035
	(0.218)	(2.167)	(2.565)	(0.026)	(0.041)
Unemployment Rate	-0.012	-0.156	-0.063	0.000	-0.000
	(0.014)	(0.122)	(0.135)	(0.001)	(0.002)
Migrant Share	-0.516	-2.378	1.708	-0.060	-0.093
	(0.407)	(3.532)	(4.224)	(0.047)	(0.075)
Residential Density (log)	0.076**	0.382^{+}	0.570*	0.011**	0.018**
	(0.022)	(0.200)	(0.260)	(0.002)	(0.004)
House Prices (log)	0.071*	0.924**	-0.493	0.005	0.010
	(0.034)	(0.336)	(0.402)	(0.004)	(0.007)
Pension-Age Share	-0.187	-12.040	10.241	-0.051	-0.072
	(0.772)	(7.887)	(10.153)	(0.090)	(0.153)
Cooling Degree Days (log)	0.078	-0.187	0.774^{+}	0.013^{+}	0.016
	(0.056)	(0.291)	(0.395)	(0.007)	(0.010)
Manufacturing Share	-4.717^{+}	-70.558*	61.437^{+}	-0.486	-0.782
	(2.653)	(33.632)	(32.846)	(0.295)	(0.506)
Business exc. manuf. Share	3.424	42.482*	-13.631	0.486^{+}	0.764
	(2.503)	(20.816)	(22.472)	(0.279)	(0.464)
Constant	9.920**	57.058**	-3.612	0.228	0.477
	(2.471)	(20.658)	(20.206)	(0.259)	(0.441)
N	161	161	161	161	161

Estimates of Equation (6). c_s is average wholesale procurement cost (c/kWh), $\tilde{Q}_s^E$ is share of energy use in evening peak hours (5pm - 8pm), $\tilde{Q}_s^D$ is share of energy use in daytime trough hours (11am - 2pm), $\tilde{Q}_s^{t10}$ is share of energy use in the top 10 highest wholesale price hours for 2018, and $\tilde{Q}_s^{p300}$ is the share of energy use in hours where wholesale prices exceed \$300/MWh. Models estimated using Weighted Least Squares, with substations weighted by the square root of their total load over the year – the dependent variables all are averages with total load the denominator. Standard errors using the White Sandwich formula (White, 1980) reported in parentheses. Key relates to p-values for test that coefficient is equal to 0. ** p-value < 0.01, * p-value < 0.05, $^{+}$ p-value < 0.10.

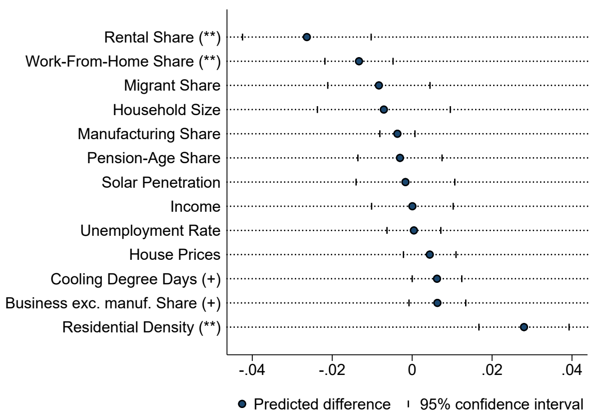
Figure 7: Predictors of usage share timing



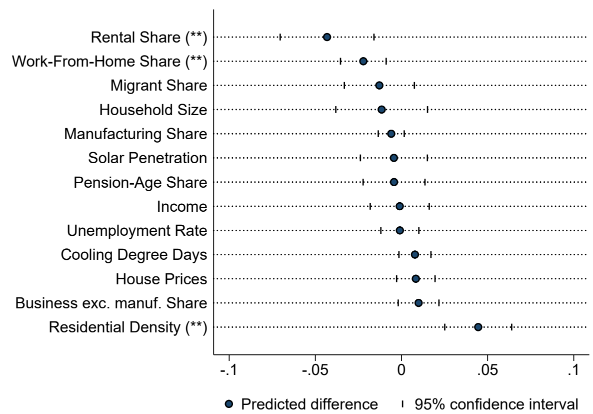
(a) Share of usage: Evening (5pm-8pm)
Mean 30%



(b) Share of usage: Daytime (11am-2pm)
Mean 25%



(c) Share of usage: Top 10 w'sale price hours
Mean 0.20%



(d) Share of usage: W'sale price >300/MWh
Mean 0.35%

Estimates of Equation (6). See Table 1 for parameter estimates, standard errors and estimation information. Reported values transform coefficient estimates and standard errors to report an X unit change in the regressor of interest, where X is the sample standard deviation of that regressor, reported in Table A1. Regressors listed from lowest estimated value to highest value. Key relates to p-values for the test that coefficient is equal to 0. ** p-value < 0.01, * p-value < 0.05, $^{+}$ p-value < 0.10.

6 Discussion

The results from our analysis demonstrate that even at coarse groupings, there can be substantial variation in the wholesale procurement cost of energy users. Households that have relatively higher shares of their energy use away from peak periods are those located in areas with higher shares of renters, those who work from home, and in areas with lower value homes and lower residential density. Renters and people in areas with lower value homes are usually perceived to be more vulnerable (or at least have less net wealth), yet they are the ones essentially cross-subsidising wealthier neighborhoods that have higher rates of owner-occupancy. To the extent that these groups use more energy overall (see Figure 5a), they also contribute a higher share of volumetric network tariffs used in the recovery of network infrastructure and operating costs. Although not that examined in our analysis, this is another form of cross-subsidization. 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.[31]

We now cautiously offer some discussion on what moving customers from fixed-rate tariffs to cost-reflective (real-time) tariffs may entail. In a competitive retail electricity market setting like Victoria, which is characterized by a) mostly time-invariant tariffs (CME, 2017), and b) few customers switching 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. Evidence from Fabra et al. (2021) suggests that at least initially, households (in Spain) do not demonstrate price responsiveness when being transitioned to RTP. Therefore, although we do not estimate the potential behavioral changes that may occur under real-time pricing (RTP), our results suggest that the introduction of RTP may be progressive. This is because some more vulnerable population segments would have lower energy costs if they faced time-varying prices when compared to a flat-rate socialized price at their existing electricity use patterns. However, incumbent retailers do not have any incentives to offer tariffs that may induce any demand response (elasticity) for two reasons. It may increase customer engagement and prompt customers to switch to another retailer (while churn is currently very low). Second, preserving zero elasticity is best for revenue maximisation. Hence RTP penetration likely relies on either new entrants that can reach the consumers that are interested in RTP, or on a regulatory mandate for incumbents to offer RTP tariffs.

Now speaking beyond what the results in this paper can explicitly offer, more cost-reflective retail tariffs have not only distributional consequences. With some demand-side price elasticity there are also implications for economic efficiency, especially under real-time electricity pricing tariffs. An 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 in the long-run 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

[31]For example, network tariff cross-subsidization is an object of study in Simshauser (2014) and Borenstein et al. (2021).

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 or swimming pool pre-cooling or pre-heating devices) and energy management systems to introduce short-run elasticity to the demand-side of electricity markets.

If more end-users adopt real-time pricing, one can expect the prices of fixed-rate plans to increase (Borenstein, 2005b). Starting from an environment in which all households are subject to a flat-rate tariff, households with the lowest average cost of service have the greatest first-order cost saving incentive to switch to RTP, leaving higher cost-to-serve customers 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.[32] This work may inform the implementation of such a policy, or the strategy of an entrant retailer offering a new RTP product to the market, as it identifies locations and customer characteristics for whom switching presents the greatest benefit, and who have the greatest impact on the average cost of supplying a fixed-rate tariff.

We acknowledge that many households may value price certainty and may not wish to be exposed to real-time pricing. Our research shows some population segments that would benefit *on average* from first-order cost savings under real-time pricing, before considering any demand responsiveness. So although some vulnerable population groups may 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, 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

[32]Borenstein (2007) discusses the extent that commercial and industrial customers motivated to shift to real-time-pricing may derive most value from the shape of their natural load shape as opposed to exploiting their price elasticity.

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 if introducing RTP. Finally, technology may also help; it is increasingly possible to delegate the energy management of some appliances in one's house to a computer.

7 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 cross-subsidies received by households that consume relatively more at the evening peaks or the few most extreme price events throughout the year. The extent of these cross-subsidies are increasing with rapid solar power penetration, which is resulting in substantially lower wholesale prices in the daytime and higher wholesale prices at peak times. We find that in Victoria, Australia, areas where relatively more homes are rented and areas where there are relatively more work-from-home households tend to use energy at lower cost times of day, whereas areas with high house prices and high residential density tend to use energy at relatively high cost times of day. Given the median net wealth of renters is approximately 10% of that for homeowners in Australia, it can be viewed that 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 is a prerequisite to providing consumers with the economically efficient price signal. This seems to be a rare instance in which there is potential for efficiency and distributional considerations to be in broad agreement. To be clear, our results do not speak to the long-run welfare impacts from adopting RTP across demographic groups, nor beyond the first-order cost-savings that will result from transitioning away from fixed-rate tariffs, but from our findings we can conclude that incerasing the availability of RTP tariffs may initially benefit the more vulnerable populations. Of course, further research is required to further 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, there is no price variation to drive changes in household demand, which can make for higher revenue. Likewise, incumbents in a market with low levels of customer engagement may have little incentive to promote flexible pricing, which is likely to be less profitable, without capturing larger market shares. This motivates further research into the competitive barriers to RTP, with our findings demonstrating that there is meaningful variation in the cost-to-service households.

References

ACIL Allen Consulting, 2019. Victorian energy usage profiles. Profile calculation methodology and results. Technical Report. Report to Essential Services Commission.

Allcott, H., 2011. Rethinking real-time electricity pricing. Resource and energy economics 33, 820–842.

Australian Bureau of Statistics, 2019-20. Household income and wealth, australia. Https://www.abs.gov.au/statistics/economy/finance/household-income-and-wealth-australia/latest-release.

Australian Competition and Consumer Commission, 2018. Restoring electricity affordability and Australia's competitive advantage. Retail Electricity Pricing Inquiry – Final Report.

Australian Energy Council, 2016. Renewable energy in Australia - How do we really compare? Fact sheet.

Australian Energy Market Commission, 2019. Fact sheet - marginal loss factors. Accessed at https://www.aemc.gov.au/sites/default/files/2019-03/Fact%20sheet%20marginal%20loss%20factors.pdf.

Australian Energy Market Operator, 2018. Distribution loss factors for the 2018/19 financial year. Accessed at https://www.aemo.com.au/-/media/files/electricity/nem/security_and_reliability/loss_factors_and_regional_boundaries/2018/distribution-loss-factors-for-the-2018-2019-financial-year.pdf.

Australian Energy Regulator, 2010. Victorian electricity distribution network service providers, distribution determination 2011–2015, appendices.

Australian Institute of Health and Welfare, 2019. Australia's welfare 2019 in brief. Cat. no. AUS 227. Canberra AIHW.

Best, R., Burke, P.J., Nishitateno, S., 2019. Understanding the determinants of rooftop solar installation: evidence from household surveys in australia. Australian Journal of Agricultural and Resource Economics 63, 922–939.

Borenstein, S., 2005a. The long-run efficiency of real-time electricity pricing. The Energy Journal 26.

Borenstein, S., 2005b. Time-varying retail electricity prices: Theory and practice, in: Electricity deregulation: choices and challenges, University of Chicago Press Chicago, Illinois, USA. pp. 317–356.

Borenstein, S., 2007. Wealth transfers among large customers from implementing real-time retail electricity pricing. The Energy Journal 28.

Borenstein, S., 2012a. The private and public economics of renewable electricity generation. Journal of Economic Perspectives 26, 67–92.

Borenstein, S., 2012b. The redistributional impact of nonlinear electricity pricing. American Economic Journal: Economic Policy 4, 56–90.

Borenstein, S., 2017. Private net benefits of residential solar pv: The role of electricity tariffs, tax incentives, and rebates. Journal of the Association of Environmental and Resource Economists 4, S85–S122.

Borenstein, S., Bushnell, J.B., 2018. Do two electricity pricing wrongs make a right? cost recovery, externalities, and efficiency. National Bureau of Economic Research Working Paper.

Borenstein, S., Davis, L.W., 2016. The distributional effects of us clean energy tax credits. Tax Policy and the Economy 30, 191–234.

Borenstein, S., Fowlie, M., Sallee, J., 2021. Designing Electricity Rates for An Equitable Energy Transition. Technical Report.

Borenstein, S., Holland, S., 2005. On the efficiency of competitive electricity markets with time-invariant retail prices. RAND Journal of Economics 36.

Brounen, D., Kok, N., Quigley, J.M., 2012. Residential energy use and conservation: Economics and demographics. European Economic Review 56, 931–945.

Bushnell, J., Novan, K., 2018. Setting with the sun: The impacts of renewable energy on wholesale power markets. National Bureau of Economic Research.

Byrne, D.P., Martin, L.A., Nah, J.S., 2019. Price discrimination, search, and negotiation in an oligopoly: A field experiment in retail electricity.

Cahana, M., Fabra, N., Reguant, M., Wang, J., 2021. The distributional impacts of real-time pricing.

Cicala, S., 2020. Powering work from home. Technical Report. National Bureau of Economic Research.

CME, 2017. The retail electricity market for households and small businesses in victoria. Report submitted to the Thwaites Review.

Cramton, P., 2017. Electricity market design. Oxford Review of Economic Policy 33, 589–612.

Davis, L.W., 2011. Evaluating the slow adoption of energy efficient investments: are renters less likely to have energy efficient appliances?, in: The Design and Implementation of US Climate Policy. University of Chicago Press, pp. 301–316.

Department of Environment, Land, Water and Planning, 2019. Victoria in Future 2019. The State of Victoria.

Deryugina, T., MacKay, A., Reif, J., 2020. The long-run dynamics of electricity demand: Evidence from municipal aggregation. American Economic Journal: Applied Economics 12, 86–114.

Fabra, N., Rapson, D., Reguant, M., Wang, J., 2021. Estimating the elasticity to real time pricing: Evidence from the spanish electricity market. AEA Papers and Proceedings forthcoming.

Greene, W.H., 2003. Econometric analysis. Pearson Education India.

Holland, S.P., Mansur, E.T., 2006. The short-run effects of time-varying prices in competitive electricity markets. The Energy Journal 27, 127–155.

Holland, S.P., Mansur, E.T., 2008. Is real-time pricing green? the environmental impacts of electricity demand variance. The Review of Economics and Statistics 90, 550–561.

Jessoe, K., Rapson, D., 2014. Knowledge is (less) power: Experimental evidence from residential energy use. American Economic Review 104, 1417–38.

Jha, A., Leslie, G., 2021. Start-up costs and market power: Lessons from the renewable energy transition Working Paper.

Leslie, G.W., Stern, D.I., Shanker, A., Hogan, M.T., 2020. Designing electricity markets for high penetrations of zero or low marginal cost intermittent energy sources. The Electricity Journal 33, 106847.

Levinson, A., Silva, E., 2022. The electric gini: Income redistribution through energy prices. American Economic Journal: Economic Policy 14, 341–365.

Lynham, J., Nitta, K., Saijo, T., Tarui, N., 2016. Why does real-time information reduce energy consumption? Energy Economics 54, 173–181.

Lyubich, E., 2020. The race gap in residential energy expenditures. Energy Institute at Haas, WP 306.

Mercer, D., 2020. WA electricity prices would be slashed during the day, doubled during peak under new Government trial. ABC News Online Wednesday 16 December 2020.

Mountain, B., Burns, K., 2020. Loyalty taxes in retail electricity markets: not as they seem? Journal of Regulatory Economics forthcoming.

Phillips, B., 2018. Trends in Household Energy Expenditure. Technical Report. ANU Centre for Social Research and Methods. Appendix to Energy Stressed in Australia, produced by the Australian Council of Social Service.

Roberts, M., Nagrath, K., Briggs, C., Copper, J., Bruce, A., Mckibben, J., 2019. How much rooftop solar can be installed in Australia? Report for the Clean Energy Finance Corporation and the Property Council of Australia. Sydney.

Rothschild, M., Stiglitz, J., 1976. Equilibrium in competitive insurance markets: An essay on the economics of imperfect information. The Quarterly Journal of Economics , 629–649.

Simshauser, P., 2014. Network tariffs: resolving rate instability and hidden subsidies.

Simshauser, P., Downer, D., 2016. On the inequity of flat-rate electricity tariffs. The Energy Journal 37, 199–229.

Victorian Auditor-General's Office, 2021. Delivering the solar homes program. Independent assurance report to Parliament, PP no 231, Session 2018-21 .

White, H., 1980. A heteroskedasticity-consistent covariance matrix estimator and a direct test for heteroskedasticity. Econometrica: Journal of the Econometric Society , 817–838.

Wolak, F.A., 2015. Do customers respond to real-time usage feedback? evidence from singapore.

Wolak, F.A., 2019. The role of efficient pricing in enabling a low-carbon electricity sector. Economics of Energy & Environmental Policy 8.

Wolak, F.A., Hardman, I.H., 2020. The Future of Electricity Retailing and How We Get There. Technical Report. Program on Energy and Sustainable Development.

Appendices

A Additional tables and figures

Table A1: Descriptive Statistics

	Mean	Std.Dev.	Min.	Max.	Obs
Av. w'sale p'ment cost (c_s)	9.844	0.408	7.308	11.496	161
Solar Penetration	0.178	0.097	0.002	0.422	161
Rental Share	0.290	0.126	0.072	0.774	161
Income (log)	11.014	0.228	10.640	11.766	161
Work-From-Home Share	0.064	0.018	0.025	0.149	161
Household Size	2.554	0.330	1.800	3.524	161
Unemployment Rate	6.746	2.365	2.820	21.560	161
Migrant Share	0.256	0.138	0.050	0.585	161
Residential Density (log)	0.346	2.531	-5.712	3.894	161
House Prices (log)	14.100	0.869	11.775	15.721	161
Pension-Age Share	0.162	0.060	0.035	0.316	161
Cooling Degree Days (log)	5.939	0.484	2.861	7.009	161
Manufacturing Share	0.011	0.008	0.003	0.058	161
Business exc. manuf. Share	0.017	0.013	0.001	0.078	161

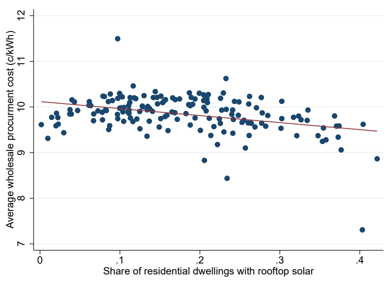
Variable construction described in section 4, and appendix C.

Table A2: Pairwise correlations

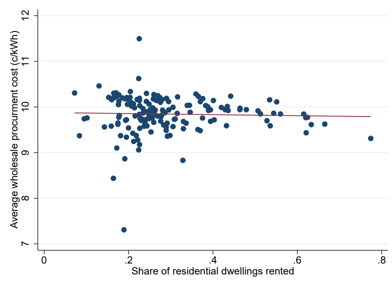
	V1	V2	V3	V4	V5	V6	V7	V8	V9	V10	V11	V12	V13
V1	1.00												
V2	-0.68	1.00											
V3	-0.61	0.33	1.00										
V4	0.39	-0.27	0.07	1.00									
V5	0.16	-0.51	-0.22	-0.40	1.00								
V6	-0.25	0.42	-0.28	-0.67	0.22	1.00							
V7	-0.57	0.44	0.11	-0.71	0.35	0.69	1.00						
V8	-0.77	0.83	0.49	-0.23	-0.40	0.30	0.50	1.00					
V9	-0.48	0.15	0.55	-0.21	0.13	0.03	0.34	0.31	1.00				
V10	0.51	-0.47	-0.20	0.47	-0.40	-0.41	-0.58	-0.47	-0.24	1.00			
V11	-0.09	0.22	0.04	-0.14	-0.15	0.08	0.04	0.18	0.07	-0.03	1.00		
V12	0.06	-0.08	-0.15	-0.13	0.14	0.11	0.13	-0.15	-0.06	0.03	-0.01	1.00	
V13	-0.27	0.38	0.40	0.27	-0.42	-0.12	-0.02	0.24	0.01	0.04	0.12	0.25	1.00

Variable construction described in section 4, and appendix C. V1: Solar Penetration. V2: Rental Share. V3: Income. V4: Work-From-Home Share. V5: Household Size. V6: Unemployment Rate. V7: Migrant Share. V8: Residential Density. V9: House Prices. V10: Pension-Age Share. V11: Cooling Degree Days. V12: Manufacturing Share. V13: Business exc. manuf. Share.

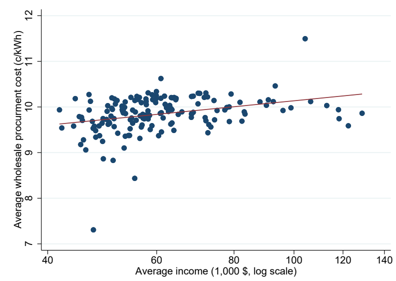
Figure A1: Univariate scatter plots: Average wholesale procurement costs and regressors



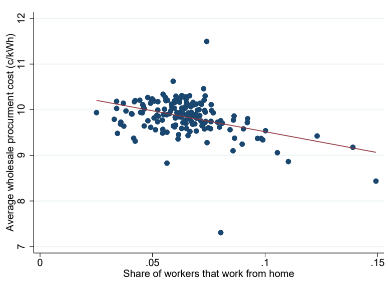
(a) Solar penetration



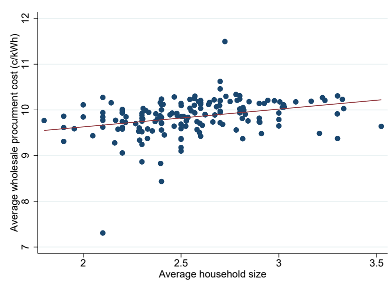
(b) Rental share



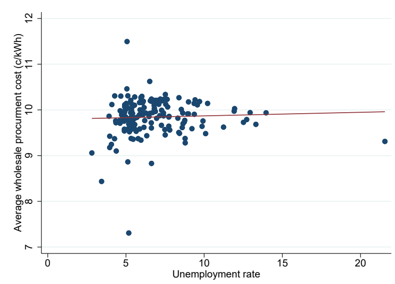
(c) Average income (log)



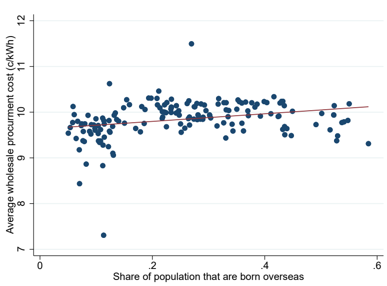
(d) Work-from-home share



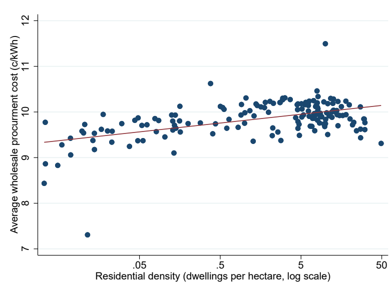
(e) Household size



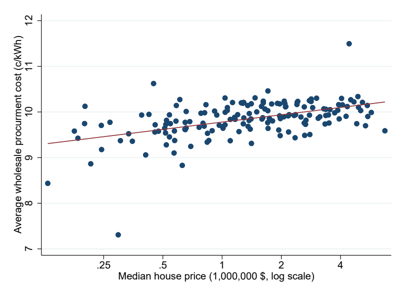
(f) Unemployment rate



(g) Migrant share



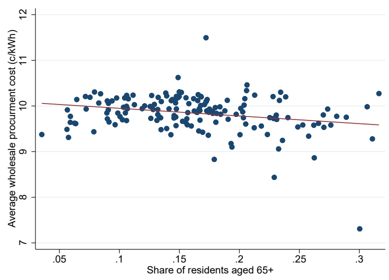
(h) Residential density (log)



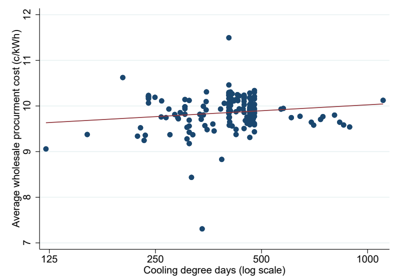
(i) House prices (log)

A linear line of best fit is plotted in each figure.

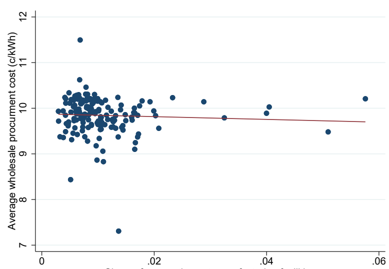
Figure A2: Univariate scatter plots: Average wholesale procurement costs and regressors



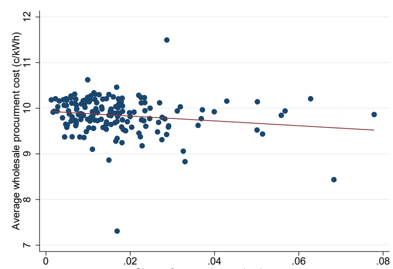
(a) Pension-age share



(b) Cooling Degree Days (log)



(c) Manufacturing business connection share



(d) Non-manufacturing business share

A linear line of best fit is plotted in each figure.

B Data appendix

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

Step 1:

Gather Statistical Area 2 (SA2, approximately postcode-level) data from the Australian Bureau of Statistics (ABS), detailed in section C. These data have SA2 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 $\times$ half-hour as the unit of observation (a panel) and contain demand (in MW) as the variable of interest.

Step 3:

Map SA2s to substations. We consider the centroid of each SA2 and map it to the closest substation. This means getting coordinates for each substation and SA2 centroid.

To map SA2 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.

We then have some ad-hoc reclassifications in the more densely populated areas of Melbourne because the shape of the SA2 and substation regions are not regular polygons, so there is some approximation to the matching method. See for example page 134 in Australian Energy Regulator (2010). For example, for the central business district (CBD, or "downtown") which contains many large towers and is densely populated, there are multiple different zone stations while we have only three suburbs, so we make the following assignments: Merge the substations TP, FR, RP and MP together to cover the southern and eastern part of the CBD; LQ, VM, J and JA to cover the northern and western part of the CBD and BQ is mapped to Carlton (where the substation services Carlton but is located outside of Carlton). Note that some zone stations are omitted due to being decommissioned or having defective data records (for example WA).

These data have SA2 as the unit of observation – with the variable being the closest substation.

Network and connection assumptions

Our mapping algorithm allows us to approximate the average characteristics of the connections in the distribution network. This section briefly explains the source of the approximation and explains why it does not take away from the results in the paper.

The ideal study observes direct connections to each substation and individual characteristics relating to demographics and housing stock, but this information is not available. For example, even in studies with individual electricity data such as Borenstein (2012b), assigning individual demographic information is not feasible and instead characteristics are matched from Census-region data. Although we do not directly observe network characteristics (interconnections and direct dwelling connections), we do observe aggregate electricity use and connections across all substations. There is scope for measurement error insofar as there is not perfect alignment between substation coverage and Census areas (or merged substation / Census groups).

However, because each region is contiguous, there will be no double-counting of characteristics. So there is no reason to expect systematic misallocation error as additional connections attributed to one substation will be matched by less connections at the neighboring substation. Further, the results in the core exercise are driven by relative shares of electricity use at different times of day, again with no reason to expect systematic relative misallocation across time in a manner related to the number of connections or underlying demographic or housing characteristics.

Given there is no expectation for systematic misallocation, we consider this matching to feed into the best linear predictor interpretation of the models estimated. That is, the estimated models describe the variation across substations in wholesale procurement costs, or shares of energy use during specific intervals, conditional on as-measured substation characteristics.

Step 4:

Aggregate SA2 data in step one to a substation unit of observation. Figure B1 shows the location of zone substations and suburbs in Victoria. The middle square on the top plot covers Greater Melbourne, demonstrating that there are usually more suburbs to substations.

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.

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.

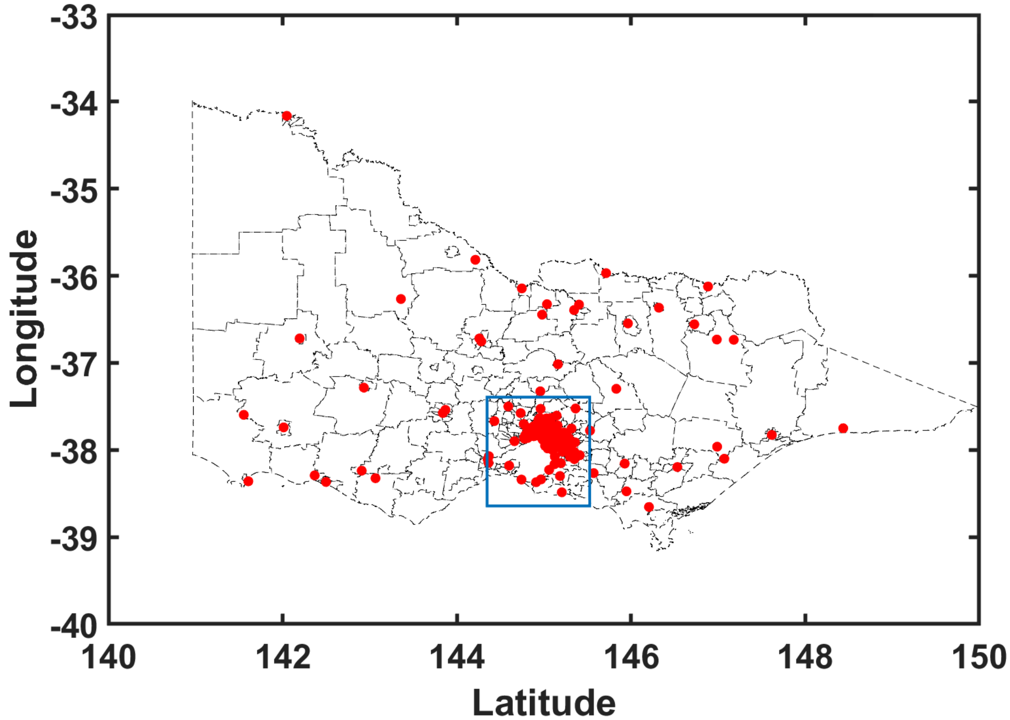
Step 7:

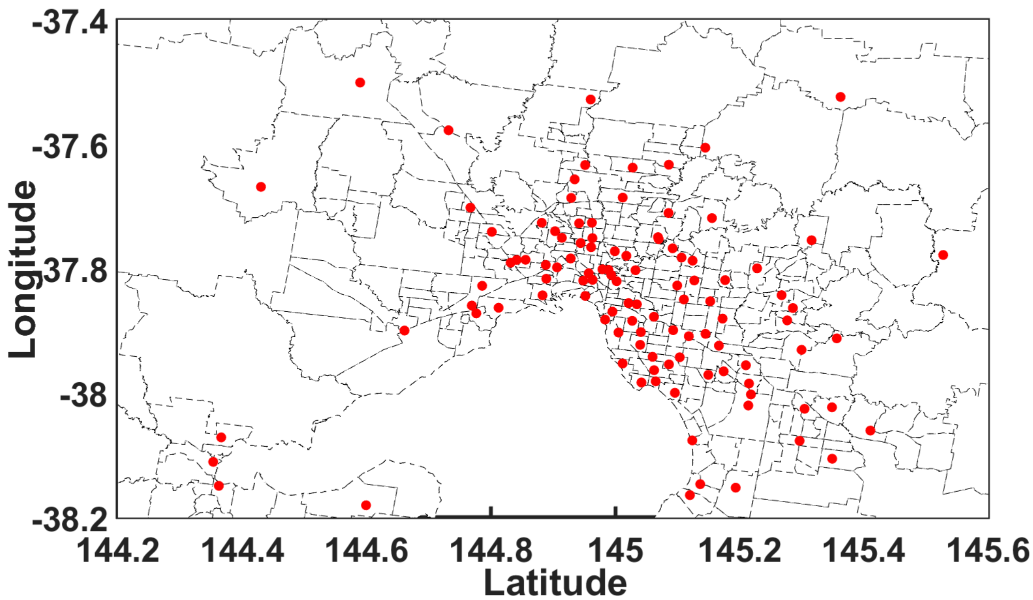
Sample selection: Based on data limitations we omit some suburbs and substations. For example, consider the Cann River substation in the east of AusNet's supply area. We omit this substation because demographic information of the suburbs it services are not available in our data set for 2018. We do not include substations that connect to suburbs that have any missing demographic variable. Further, substations are omitted if they have more than 0.5% of intervals with non-reported electricity values during 2018.

Step 8:

We construct the variables listed in section 4, described in more detail below in section C.

Figure B1: The top plot shows location of zone substations (dots) and SA2 regions (lines) across Victoria and the bottom plot zooms to the Greater Melbourne area





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 C1 provides the ABS variable descriptions.

Table C1: 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) ($)
DWELL–7	Total private dwellings (no.)
DWELL–2	Separate house (no.)
DWELL–3	Semi-detached, row or terrace house, townhouse etc. (no.)
DWELL–4	Flat or apartment (no.)
TENURE–4	proportion of properties rented
HHTYPE–6	Average household size (no. of persons)
WORK-TRAV–14	Other - Worked from home (no.)
WORK-TRAV–15	Other - Employed but did not go to work (no.)
TOTMIG–4	Total number of people born overseas
SOLAR–2	Small-scale solar panel system installations (no.)
CABEE–4	Number of employing businesses: 5-19 employees (no.)
CABEE–38	Number of employing businesses: 20 or more employees (no.)
CABEE–27	Number of employing businesses: Manufacturing (no.)
LF–4	Unemployment rate (%)
LAND	Land area in hectares
HOUSES–3	Houses - median sale price ($)

The variables outlined in section 4 are constructed as detailed below, with raw data sources provided in Table C1 and descriptive statistics and correlations provided in Tables A1 and A2. Note that while most variables are available in 2018, the DWELL, WORK-TRAV and LF variables are only available in the 2011 and 2016 Census years and a linear projection is used for their 2018 values.

- 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–15 +WORK-TRAV–14) / ERP–P–20
- Unemployment rate (LF–4)
- Mean total income (employee and investment) (Income–36)
- 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 4).[33]
- Share of connections that are manufacturing businesses (CABEE–27 / [DWELL–2+DWELL–3+DWELL–4+CABEE–4+CABEE–38])
- Share of connections that are non-manufacturing businesses ([CABEE–4+CABEE–38-CABEE–27] / [DWELL–2+DWELL–3+DWELL–4+CABEE–4+CABEE–38])

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