The price elasticity of electricity demand in South Australia

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Abstract

In this paper, the price elasticity of electricity demand, representing the sensitivity of customer demand to the price of electricity, has been estimated for South Australia. We first undertake a review of the scholarly literature regarding electricity price elasticity for different regions and systems. Then we perform an empirical evaluation of the historic South Australian price elasticity, focussing on the relationship between price and demand quantiles at each half-hour of the day.

This work attempts to determine whether there is any variation in price sensitivity with the time of day or quantile, and to estimate the form of any relationships that might exist in South Australia.

Keywords: Electricity demand; Price elasticity

1. Introduction

With the deregulation of the electricity market, and especially the gradual evolution of retail competition within the National Electricity Market (NEM), consumers may become exposed to more volatile electricity prices. Meanwhile, the State and Territory Governments are considering a range of policy responses to ensure a flexible way of achieving greenhouse gas abatement in the transition to a carbon-constrained future. One key measure being investigated is a National Emission Trading Scheme (NETS), which may result in higher electricity prices in the future.

Facing possible volatility in electricity prices, consumers may decide to modify their demand profile to reduce electricity costs. Therefore, it will be necessary to estimate how consumers will respond to price changes and to quantify the impacts on both annual energy volumes and peak demand. This work is valuable for policy makers in developing more effective electricity pricing schemes.

According to economic theory, electricity demand will fall as the energy price increases, holding all other factors constant. The consumer's sensitivity to price changes can be measured by the coefficient of **price elasticity**: the percentage change in demand divided by the percentage change in price (holding constant all the other determinants of demand).

Price elasticity is a normalized measure (for the relative price change) of the intensity of how the usage of a good (in this case electricity) changes when its price changes by one percent. It facilitates a comparison of the intensity of load changes among customers, since the price change has been factored out; the price elasticity is a relative measure of response.

Two kinds of price elasticity coefficients are reported in the scholarly literature: own-price elasticity and substitution elasticity.

Own-price elasticity is an useful measure of how customers adjust to increases in the price of electricity by adjusting their consumption of electricity. This is especially useful when evaluating longer-term adjustments to changes in electricity prices. Own price elasticities are typically negative, indicating the reciprocal relationship between demand and price.

Own-price elasticities are generally of two types, inelastic and elastic, and the range of each type differs by region and system. For a commodity, the range of inelasticity is usually between the absolute values of 0 and 1, and the elastic range begins with values greater than 1. Thus, price inelastic demand means a less than proportional change in demand for a given change in the price. In the elastic range, consumer demand responds with a greater than proportional change for a given price change.

On an absolute value basis, ignoring the sign, own-price and substitution elasticities are similar, in that they both measure relative changes, so that a value of zero corresponds to no change in usage, regardless of the change in price (i.e., perfectly price inelastic), and absolute values progressively greater than zero indicate a relatively higher price response. They are roughly similar measures of intensity on a nominal basis --- a substitution and an own-price elasticity of 0.50 both indicate relatively large changes in load in response to price changes. However, because each of these two elasticity values measures a different characterization of how usage is adjusted to price changes (i.e., the price in one period vs. the relative prices in two periods), there is no simple way to cross-map reported values. They should each be used in the appropriate context: the own-price elasticity when the circumstances involve reduced electricity usage, and the substitution elasticity when shifting from one time to another characterizes the price response.

In this paper, we will focus on the own-price elasticity, since our major concern is how the possible changes in retail electricity price will affect the annual and peak electricity demands. For simplicity, we use "price elasticity" instead of "own-price elasticity" in the rest of this paper. Log-linear econometric models of the electricity demand are used for the estimation of price elasticity in this paper. In particular, a separate model is estimated for each half-hourly period, as we assume electricity demand is time-separable over half-hourly periods. The intertemporal separability of demand has also been applied by Aubin, Fougère, Husson, and Ivaldi (1995) and

Fay, D., Ringwood, J. V., Condon, M., and Kelly, M. (2003).

The remainder of the paper is organized as follows. In Section 2, we conduct a literature review covering published results from different countries to identify the best methodology available. In Section 3, we perform an empirical evaluation of the historic South Australian price elasticity, focussing on the relationship between price and demand quantiles at each half-hour of the day and different seasons. The analysis is based on the demand models established in Hyndman and Fan (2008) on forecasting the long-term peak electricity demand for South Australia. Finally, some conclusions and discussions are provided in Section 4.

2 Literature review

In past years, a number of studies of price elasticity in the electric industry have been published. Most of the early papers deal with flat electricity rates in the context of vertically integrated mechanisms.

Several surveys summarizing price elasticity studies based on a fixed pricing scheme are discussed in Lafferty, Hunger, Ballard, Mahrenholz, Mead, and Bandera (2001). Bohi (1981) gave a survey of early price elasticity studies, and categorized the related works by the type of data (aggregated, disaggregated, by industry, and whether marginal or average prices were used) and the model used. Bohi and Zimmerman (1984) concluded that the short-run price elasticity for the residential sector is -0.2 and the long-run price elasticity is -0.7. They further concluded that the wide variance of the elasticity estimates from the available studies make it difficult to report the price elasticity for either the commercial or the industrial sector. Espey and Espey (2004) provided a quantitative summary of previous studies on residential electricity demand, and they used a Meta-analysis to determine whether there are factors that systematically affect the estimated elasticity. Their research went beyond the casual categorization of electricity demand estimates and formally modeled the likely effects of different data and methods on empirical results.

Filippini (1999) estimated the residential demand for electricity using aggregate data at a city level for 40 Swiss cities over the period 1987 to 1990. A log-linear stochastic equation was employed to estimate electricity consumption. The price elasticity was estimated to be -0.30, which shows a moderate responsiveness of electricity consumption to changes in prices. He then suggested that there is little room for discouraging residential electricity consumption using general electricity price index increases, but that an alternative pricing policy, time-of-use pricing, can be an effective instrument for achieving electricity conservation.

Beenstock, Goldin and Natbot (1999) used quarterly data for Israel to compare and contrast three dynamic econometric methodologies for estimating the demand for electricity by households and industrial companies. The methodologies are the Dynamic Regression Model and two approaches to co-integration (OLS and Maximum Likelihood).

National Institute of Economic and Industry Research (NIER) (2007) undertook a review of the long-run price elasticity of electricity demand for the Australian National Electricity Market, and recommended the values of -0.25, -0.35 and -0.38 for residential, commercial and industrial customers, respectively.

Due to the deregulation of the power industry, electric utilities restructured their operation from vertically integrated mechanisms to open market systems. Consequently, many retail rate programs have been implemented to promote a greater demand response to price, and thus a more efficient electricity market. These programs rely on innovative pricing plans and terms of service for providing retail customers with an improved set of incentives in the electric marketplace. Specifically, some of the typical dynamic pricing schemes include the following (U.S. Department of Energy, 2006):

- Time-of-use (TOU) pricing: a rate with different unit prices for usage during different blocks of time, usually defined for a 24 hour day. TOU rates reflect the average cost of generating and delivering power during those time periods.
- Real-time pricing (RTP): a rate in which the price of electricity typically fluctuates hourly, reflecting changes in the wholesale electricity price.

Customers are typically notified of RTP prices on a day-ahead or hour-ahead basis.

- Critical peak pricing (CPP): CPP rates are a hybrid of the TOU and RTP designs. The basic rate structure is TOU. However, provision is made for replacing the normal peak price with a much higher CPP event price under specified trigger conditions (e.g., when system reliability is compromised or supply prices are very high).

With these new pricing plans being put into practice, price elasticity, as the key piece of information in price-based demand response programs, has received more attention in the recent literature.

Hawdon (1992) evaluated 11 studies based on 7 experimental programs where distribution companies temporarily used time of use prices in the residential sector. He found that there was a lack of consistency across studies. The studies varied considerably in their time period, tariffs, sample sizes, and peak period length making their results difficult to compare. King and Shatrawka (1994) found that dynamic pricing in England produced more significant inter-day than intra-day load shifting. They found that between 33 and 50 percent of participating customers responded to time-varying prices. Filippini (1995) estimated the price and expenditure elasticities of peak and off-peak electricity consumption using a micro data set on 220 households living in 19 Swiss cities. The household version of the Almost Ideal Demand System model (AIDS) was used as a framework. He found that peak consumption was more responsive to peak pricing than overall consumption was to an averaged price index. This was attributed to the incentive to substitute between peak and off peak consumption under differentiated tariffs.

Patrick and Wolak (1997) estimated the customer-level demand for electricity by industrial and commercial customers purchasing electricity according to half-hourly energy prices from the England and Wales electricity market. They found that price elasticities varied considerably across industries, as did the pattern of within-day substitution in electricity consumption. Price elasticities were reported only for the most price elastic industry --- the water supply industry; these price elasticities ranged from -0.142 to -0.27.

King and Chatterjee (2003) reviewed price elasticity estimates from 35 studies of residential and small commercial customers published between 1980 and 2003. They report an average own-price elasticity of -0.3 among this group of studies, with most studies ranging between -0.1 and -0.4.

Reiss and White (2005) developed a model for evaluating the effects of alternative tariff designs on electricity use. The model concurrently addresses several interrelated difficulties posed by nonlinear pricing, heterogeneity in consumer price sensitivity, and consumption aggregation over appliances and time. They estimated the model using extensive data for a representative sample of 1300 Californian households, and found the mean annual electricity price elasticity for Californian households to be -0.39. The result is considered to be reliable because it takes full account of the non-linear structure of electricity tariffs.

Faruqui and George (2005) investigated a recent residential CPP pilot experiment in California; they estimated a statewide average substitution elasticity of 0.09 on critical peak days occurring between July and September, and reported that the average statewide reduction in peak period energy use on critical peak days was about 13%. They indicated that residential and small-to-medium commercial and industrial customers conclusively reduced peak-period energy use in response to time-varying prices. The price responsiveness varied with the rate type, climate zone, season, air conditioning ownership, and other customer characteristics.

Taylor, Schwarz and Cochell (2005) estimated average hourly own-price and substitution elasticities for RTP programs in the U.K. for large commecial and industrial customers, and found substantial variation in own-price elasticity values over the course of the day and among customers. They observed larger load reductions during higher priced hours, as industrial customers gained experience with hourly pricing. As compared to a TOU rate, net benefits were $14,000 per customer per month, approximately 4% of the average customer's bill, and much greater than metering costs. This study also concluded that many large commercial and industrial customers exhibit complementary electricity usage across blocks of afternoon hours. That is, high prices in one hour result in a reduced usage in both that hour and adjacent hours. This is consistent with industrial batch process loads that, once started, must continue for a specified period.

In summary, the majority of the results are for the residential sector, and the results from different papers and sources are not very consistent. The numbers that come up most often are -0.2 to -0.4 for the short run elasticity, and -0.5 to -0.7 for the long run. Table 1 summarizes the results from different studies. Since energy customers can find substitutions for their energy consuming appliances when more time is given, price elasticity for the long run is stronger than that for the short run, which allows little time for substitution There was no obvious evidence indicating significant differences among price elasticities for the commercial, residential and industrial sectors.

Table 1 Summary of the literature on price elasticity for electricity demand

Researcher	Year	Region	Sector	Elasticity	Comments
Bohi & Zimmerman	1984	U.S (various utilities)	Residential, industrial and commercial	Residential sector Short-run: -0.2 Long-run: -0.7	Difficult to report the price elasticity for either the commercial or industrial sectors.
Filippini	1999	Swiss (40 cities)	Aggregation	-0.3	Suggested TOU pricing for achieving electricity conservation, instead of general electricity price index increases.
Beenstock et al.	1999	Israel	Residential and industrial	Residential -0.21 to -0.58 Industrial -0.002 to -0.44	Compared dynamic regression models with OLS and maximum likelihood methods for estimating the demand.
NIEIR	2007	Australia	Residential, industrial and commercial	Residential: 0.25 industrial: 0.38 commercial: 0.35	The long-run price elasticity of electricity demand for each State of the Australia was also estimated.
King & Shatrawka	1994	England	Residential and industrial	Substitution elasticity Inter-day: 0.1 to 0.2 Intra-day: 0.01	Between 33 percent and 50 percent of participating customers responded to time-varying prices.

				to 0.02	
Patrick & Wolak	1997	England and Wales	Industrial and commercial	Water supply industry: -0.142 to -0.27	Price elasticities varied across industries; the most price elastic industry was the water supply industry.
King & Chatterjee	2003	California	Residential and commercial	-0.1 to -0.4.	An average own-price elasticity of 0.3 was reported.
Reiss	2005	California	Residential	-0.39	Developed a model for evaluating the effects of alternative tariff designs on electricity use.
Faruqui & George	2005	California	Residential, industrial and commercial	Substitution elasticity: 0.09	Residential, commercial and industrial customers conclusively reduced peak-period energy use in response to time-varying prices.
Taylor et al.	2005	U.K.	Industrial	-0.05 to -0.26	Investigated RTP programs in the U.K.; larger load reductions were observed during higher priced hours, as industrial customers gained experience with hourly pricing.

The vast majority of the literature on price elasticity in electricity markets attempts to measure the change in demand for electricity due to a change in price (price elasticity) precisely, using rigorous econometric analysis. A major issue with econometric methods are the high data requirements (information on household-specific appliance holdings and residence features). In addition, the nonlinear structure of tariff schedules and aggregation of metered consumption behaviour over time and appliances also introduce complex simultaneity problems between marginal prices and consumption (Reiss and White, 2005).

Generally, these differences in techniques lead to criticisms and counter-criticisms over the techniques used. The selection of models depends mainly on the availability of data and the objectives of the research. In this paper, we aim to provide information for Australian electricity regulators about the medium to long-run responsiveness of electricity consumers to price changes in South Australia. In particular, we try to determine whether there is any variation in price sensitivity with the time of day or quantile. The demographic & economic data provided by the Australian Energy Market Operator (AEMO) are yearly, which means constant electricity prices apply throughout the year. Considering the objective of this research and data constraints, we use annual log-linear econometric models of the electricity demand to estimate the historic South Australian price elasticity, focussing on the relationship between price and demand quantiles at each half-hour of the day.

3 Price elasticity in South Australia

3.1 Historical data of South Australia

The AEMO provided half-hourly South Australian electricity demand values and half-hourly temperature data for Kent Town and Adelaide Airport. The data were from 1 July 1997 to 30 June 2008.

The demand data are South Australian native demand (effectively the total of all scheduled generation in South Australia plus net imports into South Australia), plus non-scheduled generation, plus any known demand-side management activity. This is thought to be the best representation of demand that is available on a half-hourly basis.

Each day is divided into 48 periods, which correspond to NEM settlement periods. Period 1 is midnight to 0:30am Eastern Standard Time (note that South Australian time is 30 minutes behind, so that period 1 corresponds to 11.30pm to 12 midnight in South Australia). Figures 1 shows time plots of the half-hourly demand data from 1 July 1997 to 30 June 2008.

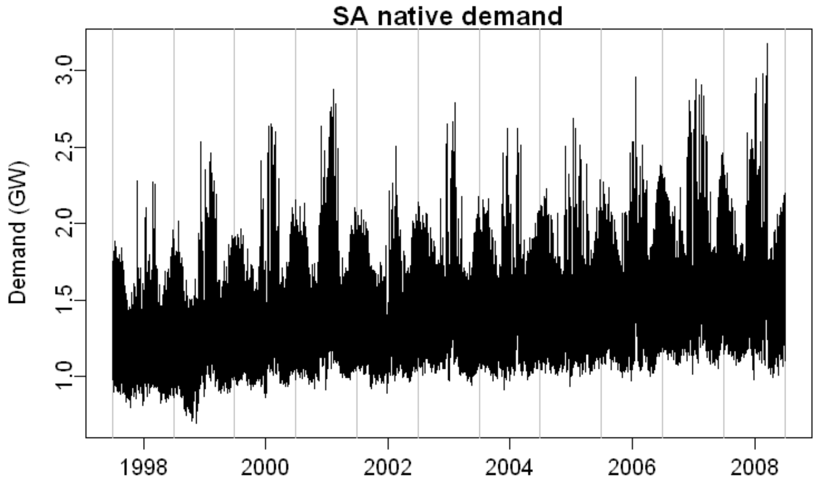

Fig 1 Half-hourly demand data for South Australia from 1 July 1997 to 30 June 2008

The demand values include relatively large mining loads, which are shown in Figure 2. This load has increased from an average of around 50 MW at the start of the period to more than double this at the end of the period, and is likely to grow strongly in the future. Although this load can vary considerably over time (e.g., plant outages at the sites that have sometimes persisted for several months), it is generally not temperature sensitive. On the other hand, electricity prices may play a (small) role in the decision to invest in the industry in a long term context (e.g., the owners might not re-invest in expansion, or might even shut down the factories if it potentially became unprofitable due to very high electricity prices). However, the underlying major mining loads, are generally not sensitive to the electricity price at current levels. Therefore, we subtract this mining load from the overall electricity demand in the following investigation.

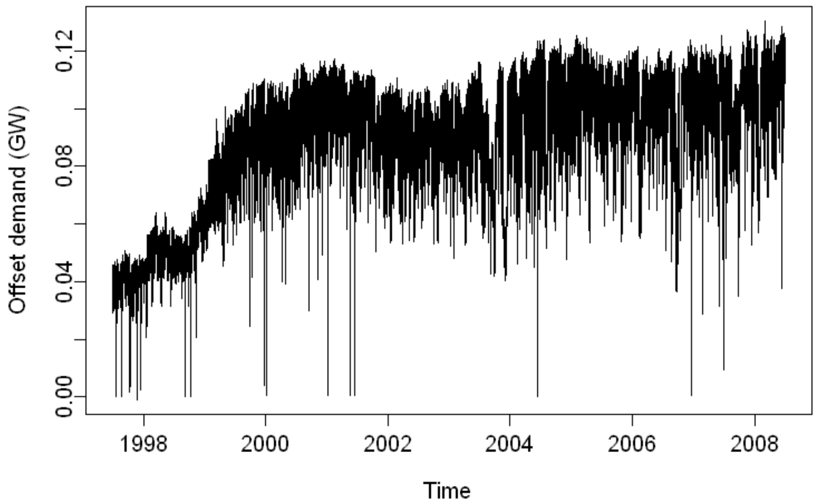

Fig 2 Half-hourly demand data for major mining demand. 1 July 1997--30 June 2008

AEMO also provided half-hourly temperature data for two locations (Kent Town and Adelaide Airport), from 1 July 1997 to 30 June 2008. The relationship between demand (excluding major mining loads) and the average temperature of the two locations is shown in Figure 3, in which the non-linear relationship between demand and temperature, with a heating and a cooling effect, is evident.

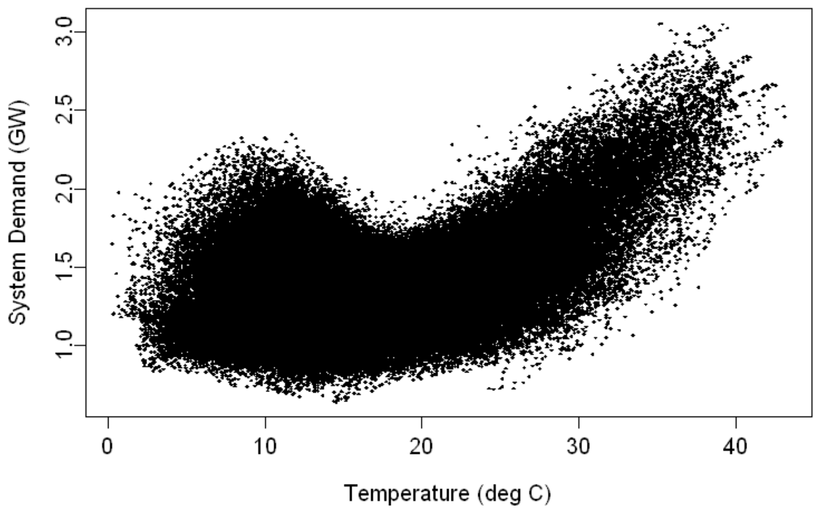

Fig 3 Half-hourly SA electricity demand (excluding major mining demand), plotted against temperature (degrees Celsius)

Demographic and economic data from AEMO from 1996/1997 to 2007/2008 are given in Table 2, including annual population, Gross State Production (GSP) and average electricity price.

Table 2 Annual demographic and economic data

	Population	GSP ($m)	Price (cents/kWh)
1996-97	1478603	53088.89	12.794
1997-98	1486511	55423.62	12.724
1998-99	1494726	57160.11	12.662
1999-00	1502937	58277.18	12.404
2000-01	1509199	60398.02	13.190
2001-02	1517675	62991.11	13.788
2002-03	1527469	63863.59	14.484
2003-04	1537257	66613.38	14.613
2004-05	1547824	67384.21	14.299
2005-06	1562113	69011.64	13.677
2006-07	1578213	69540.00	12.881
2007-08	1594987	71470.68	12.880

3.2 Electricity demand model

The work in this paper aims to estimate the annual price elasticity for flat rate schedules in South Australia. Previously, a semi-parametric additive model was proposed to estimate the relationship between demand and its drivers: temperature, calendar effects, demographic variables and economic variables. This model is described in detail by Hyndman and Fan (2008).

As is indicated above, the major mining loads are subtracted and the remaining demand is modelled using temperature, calendar and economic effects. The model for each half-hour period can be written as

$$\log(y_{t,p} - o_{t,p}) = h_p(t) + f_p(\mathbf{w}_{1,t}, \mathbf{w}_{2,t}) + \sum_{j=1}^{J} c_j z_{j,t} + n_t, \tag{1}$$

where $y_{t,p}$ denotes the demand at time t (measured at half-hourly intervals) during period p ($p = 1,\ldots,48$);

$o_{t,p}$ denotes the major mining demand for time t during period p, This demand is generally determined by the production schedule and is not sensitive to the electricity price at current levels. It has therefore been substracted from the entire demand;

$h_p(t)$ models all calendar effects, including annual, weekly and daily seasonal patterns as well as public holidays;

$f_p(\mathbf{w}_{1,t}, \mathbf{w}_{2,t})$ models all temperature effects, where $\mathbf{w}_{1,t}$ is a vector of recent temperatures at Kent Town and $\mathbf{w}_{2,t}$ is a vector of recent temperatures at Adelaide airport;

$z_{j,t}$ is a demographic or economic variable of degree days at time t; its impact on demand is measured via the coefficient c_j (these terms do not depend on the period p); and

n_t denotes the model error at time t.

Here, the log half-hourly demand is modelled, rather than the raw demand. We tried a variety of transformations of demand from the Box-Cox (1964) class, and found that the logarithm resulted in the best fit to the available data. Natural logarithms have been used in all calculations. The effect of this transformation is that major mining demand has an additive effect on demand, but calendar, temperature, economic and demographic variables have multiplicative effects on demand.

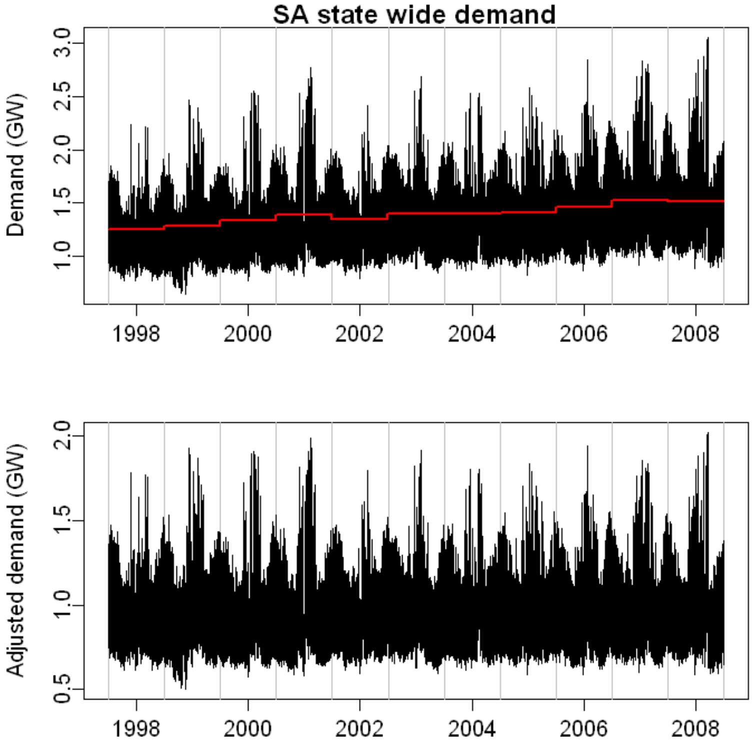

Fig 4 Top: Half-hourly demand data for South Australia from 1 July 1997 to 30 June 2008. Bottom: Adjusted half-hourly demand, where each year of demand is normalized by the average annual demand

One feature of this model is that the model has been split into two separate models, one a linear model based on annual variables (demographic and economic variables and degree days), and the other a nonparametric model based on the remaining variables, which are measured at half-hourly intervals. Thus,

$$\log(y_{t,p} - o_{t,p}) = \log(y^*_{t,p} \times \bar{y}_i) = \log(y^*_{t,p}) + \log(\bar{y}_i), \tag{2}$$

where $\bar{y}_i$ is the average non-offset demand for each year in which time t falls, and $y^*_{t,p}$ is the standardized non-offset demand for time t and period p.

The top panel of Figure 4 shows the original demand data, with the average annual demand values shown in red, and the bottom panel shows the half-hourly adjusted demand data. Then

$$\log(y^*_{t,p}) = h_p(t) + f_p(\mathbf{w}_{1,t}, \mathbf{w}_{2,t}) + e_t \tag{3}$$

and

$$\log(\bar{y}_i) = \sum_{j=1}^{J} c_j z_{j,i} + \varepsilon_i, \tag{4}$$

where the two error terms, e_t and ε_i, sum to n_t.

By doing this, the annual and half-hourly effects of the demand have been separated, and we are thus able to estimate the price elasticity using equation (4) based on the available annual demographic and economic variables.

3.3 Estimating the annual model and calculating price elasticity

In addition to population, GSP and price, climate indexes are also considered in the model. The climate indexes include summer cooling degree-days (SCDD) and winter heating degree-days (WHDD). In this paper, we define the period October–March as “summer”, and April–September as “winter”. For each day, the cooling degrees is defined as the difference between the mean temperature and 18.5° C. If this difference is negative, the cooling degrees is set to zero. These values are added up for each summer to give the cooling degree-days for the summer, that is,

$$\text{SCDD} = \sum_{\text{summer}} \max(0, t_{\text{mean}} - 18.5^\circ). \tag{5}$$

Similarly, the heating degrees is defined as the difference between 18.5° C and the mean temperature. If this difference is negative, the heating degrees is set to zero. These values are added up for each winter to give the heating degree-days for the winter,

$$\text{WHDD} = \sum_{\text{winter}} \max(0, 18.5^\circ - t_{\text{mean}}). \tag{6}$$

Another factor that may have influenced demand is the household disposable income. Generally, we would expect price elasticity to increase as the proportion of household disposable income spent on electricity increases. However, income and GSP are highly collinear, and we should avoid including both of them in the demand model. In addition, income is difficult to use in demand forecasting because it is hard to predict.

The demographic and economic data with degree days and average annual demand are plotted in Figure 5. As a lagged relationship between electricity price changes and consumers responses usually exists, the lagged price — the average price in the previous financial year for modelling the demand in the next year — is used. Table 3 gives the correlations among the driving variables, together with the annual demand.

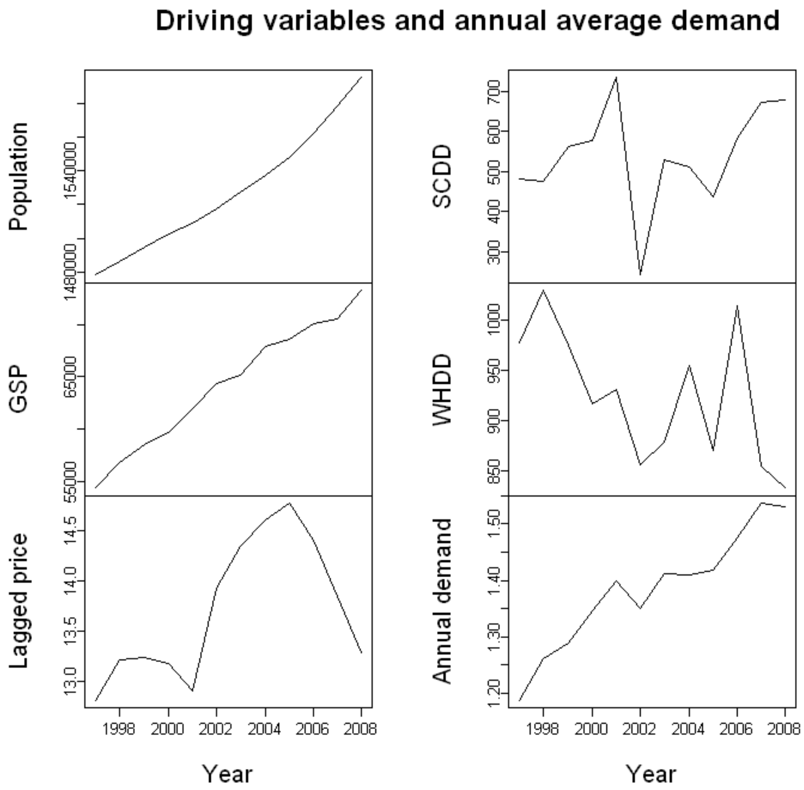

Fig 5 Time plots of the driver variables and annual average demand

Table 3 Correlations among drivers and annual average demand

	Population	*GSP*	*Lagged price*	*SCDD*	*SHDD*	**Annual demand**
Population	1.00	0.97	0.49	0.35	-0.56	0.95
GSP		1.00	0.63	0.24	-0.56	0.95
Lagged price			1.00	-0.33	-0.21	0.47
SCDD				1.00	0.00	0.46
SHDD					1.00	-0.57
Annual demand	0.95	0.95	0.47	0.46	-0.57	1.00

According to Figure 5 and Table 3, it can be seen that the average annual electricity demand has a much closer relationship with GSP and degree-days than with electricity prices. Since the demand should have a reverse relationship with price, the positive correlation between demand and lagged price in Table 3 indicates that demand is dominated by GSP and degree-days, instead of price. As population and GSP are highly collinear, only one of them should be included in the model.

According to Figure 5, it can also be inferred that consumption and price have non-stationary trends. Consequently, the estimated parameters may vary over time, resulting in model mis-specification and potentially biased results. In this paper, we adopt the assumption that the parameters of the demand function are stable over time based on findings in Kumar and Smyth (2005). Kumar and Smyth found that the parameters for residential electricity demand for Australia are stable over time, using the Pesaran and Pesaran (1997) and Hansen (1992) tests for parameter stability.

A highly significant model term does not necessarily translate into good forecasts. We need to find the best combination of input variables for producing accurate demand forecasts. We consider models of the form of equation (4) in selecting the various demographic and economic variables. Because there is so little annual data available, we could not use out-of-sample tests for variable selection in model (4). Instead, we used the corrected Akaike's Information Criterion (Harrell, 2001, p.202) to select the best model. The corrected AIC can be expressed as

$$AIC_c = -2L + 2p\left(1 + \frac{p+1}{n-p-1}\right), \tag{7}$$

where L is the log-likelihood of the model, p is the number of parameters in the model and n is the number of observations used in fitting the model. Therefore it is a penalized likelihood method. Based on the AIC, the best annual demand model is found to include the GSP, the lagged average price and (cooling and heating) degree days, with the following coefficients (the percentage changes of demand with regard to the increments of GSP, price and degree days are calculated based on the demand equation as given in (4)):

- The coefficient of GSP is 1.432×10^{-5}. That is, annual demand increases by $e^{0.01432}-1=1.44\%$ for every additional \$1 billion of GSP.
- The coefficient of the price variable is -0.03442. That is, annual demand decreases by $1-e^{-0.03442}=3.38\%$ for every additional cent/kWH that the price increases.
- The coefficient of cooling degree-days is 1.37×10^{-4}. That is, annual demand increases by $e^{0.0137}-1=1.38\%$ for every additional 100 cooling degree-days.
- The coefficient of heating degree-days is 2.155×10^{-4}. That is, annual demand increases by $e^{0.02155}-1=2.18\%$ for every additional 100 heating degree-days.

As stated before, the own-price elasticity of electricity demand is calculated as

$$\varepsilon = \frac{\%\Delta\text{demand}}{\%\Delta\text{price}} = \frac{\Delta q/q}{\Delta p/p}, \qquad (8)$$

where ε is the price elasticity, p is the electricity price, and q is the demand.

Note that the numerator and denominator are expressed as a percentage of the change. This elasticity coefficient indicates the relative change in the demand for electricity that would result from a change in the electricity price. Then, the price elasticity based on model (4) is

$$\varepsilon = (e^{c_P}-1)z_{P,i}, \qquad (9)$$

where c_P is the coefficient of price, and $z_{P,i}$ is the price in year i. Equation (9) indicates that price elasticity is correlated with price levels, and that there is a unique price elasticity coefficient for a given equilibrium point (q_0, p_0). By using equation (9), the overall price elasticity is calculated as ranging from -0.363 to

-0.428, and the value estimated at the sample median is -0.386.

Besides the original model (4), we also consider the following log-linear demand model in this paper:

$$\log(\bar{y}_i) = \sum_{j=1}^{J} c_j \log(z_{j,i}) + \varepsilon_i, \tag{10}$$

where we model both the log demand and the log input variables. This model provides an estimate of the price elasticity, which is constant with respect to price:

$$\varepsilon = \frac{d \ln q}{d \ln p} = c_P. \tag{11}$$

The estimated coefficient is $\varepsilon = -0.4165$.

3.4 Price elasticity at different time periods and demand levels

To further investigate customers' price responses at different time periods and different demand levels, the above demand models were applied to estimate the relationships between price and different demand levels at each half-hour period. In particular, we model the annual average demands at different half-hour periods against the annual demographical and economic variables, including electrical price.

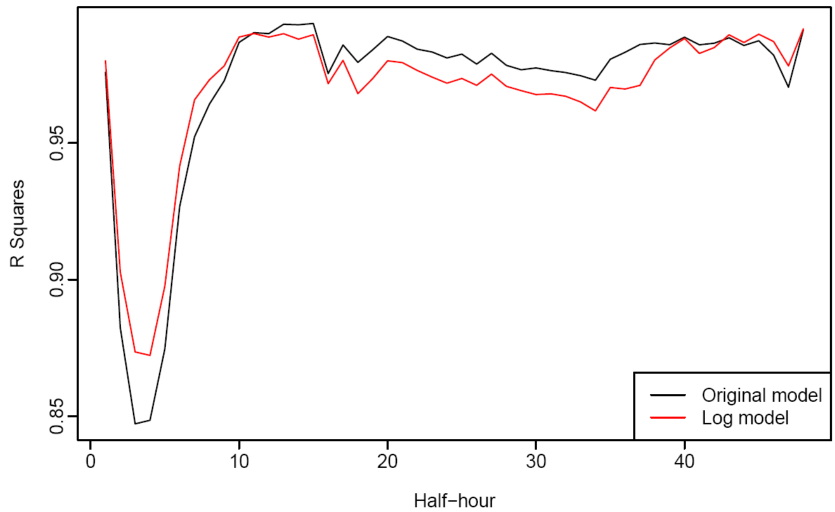

Fig 6 The R^2 values for each half-hourly model, showing the amount of the variation in the demand data that is explained by each model

The R^2 values are calculated to evaluate the fitting performances of the two demand models for each half-hourly period in Figure 6, showing the amount of variation in the demand data that is explained by each model. It can be seen that both models explain the demand well, and that the R^2 values are higher during working hours because temperature is a stronger driver during such periods.

The two models are then used to estimate the consumers' price responses at different time periods and at different demand quantiles. Specifically, the estimations are performed for 48 half-hour periods and demand quantiles of 10%, 20%, … , 95% and 98%. Thus, $48 \times 11 = 491$ coefficients of lagged price are obtained.

Figure 7 shows the coefficients of the lagged price at each half-hour period, estimated using model (4) for different quantiles. Figure 8 gives the coefficients of the log lagged price in model (10) (these coefficients are actually price elasticity coefficients). The top panel of Figure 9 provides the price elasticity at each half-hourly period for median demand (50% quantile), which is given in the bottom panel.

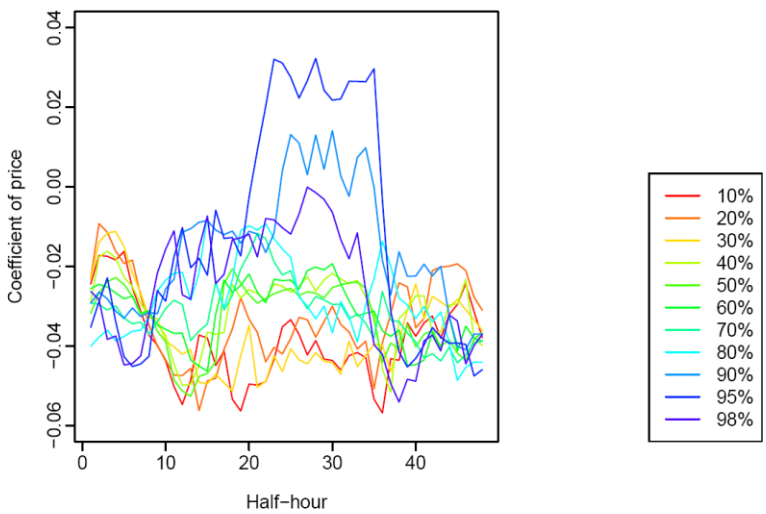

Fig 7 Coefficients of lagged price at each half-hourly period, estimated using original model (4) for different quantiles

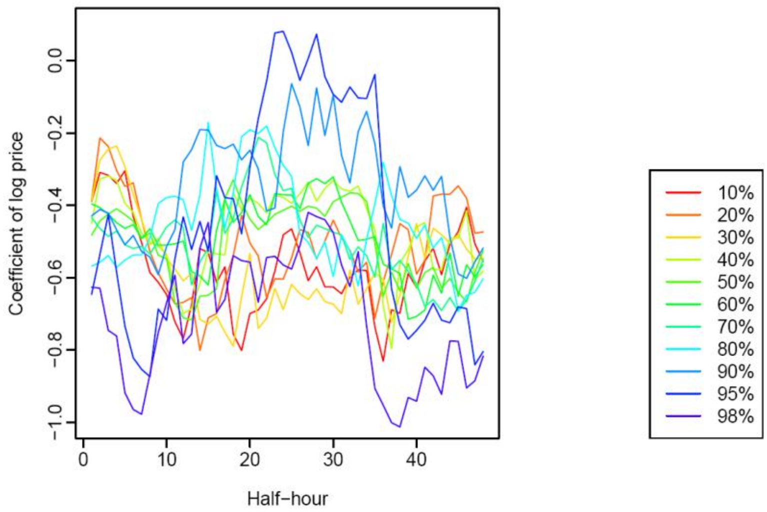

Fig 8 Coefficients of the log lagged price at each half-hourly period, estimated using log model (10) for different quantiles

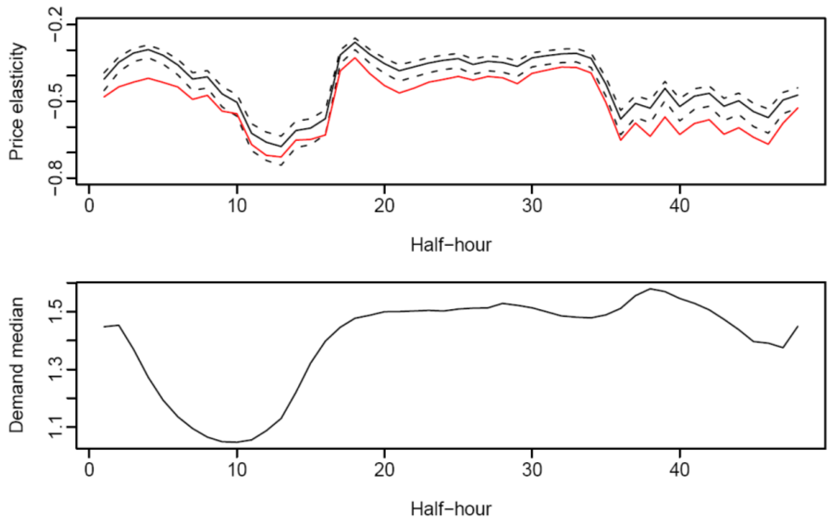

Fig 9 Coefficients of lagged price at each half-hourly period, for the demand median. In the top panel, the black lines indicate the price elasticity estimated using model (4), the solid line gives the elasticity estimated at the price median and the two dashed lines show the elasticity range; the red line indicate the price elasticity estimated using model (10)

From these three figures, the following observations can be made. First, the results from the two models are consistent and in the expected range. Second, the price responses below the 80% demand quantile are generally stable and vary similarly throughout the day; i.e., the strongest price responses seem to appear in the early morning and the afternoon, and customers' price sensitivity is weak around midnight. Third, the price responses above the 80% demand quantile exhibit different variation: they become considerably weaker from noon to late afternoon. However, the coefficients at the 98% quantile, as seen in Figure 9, show an increase in price responsiveness late in the afternoon. In fact, the price elasticity of around -1.0, as shown in Figure 9 for the 98% quantile line, appears to be one of the highest elasticities identified anywhere, and this occurs at about 5:30pm.

Finally, according to Figure 9, a strong price response is coincident with the peak demand median in the late afternoon, indicating the price elasticity over half-hourly periods is largely affected by the shift in the consumption. On the other hand, the price elasticity is also large during the early morning when the demand is low, implying inconsistent correlation between price coefficients and demands at such periods.

3.5 Price elasticity at different seasons

At different seasons of the year, consumers may use different household energy appliances; for instance, they may use air conditioners in summer and electric or gas heaters in winter. Meanwhile, the peak and off-peak periods may also vary; the summer peak usually happens around 4 o'clock in the afternoon when the temperature is high, while the winter peak tends to appear at about 7 o'clock in the evening, when the temperature is low and electric heating appliances are used. These differences could result in the price responses varying between seasons. Therefore, the relationships between demand and price are estimated separately for summer and winter. Cooling degrees for summer and heating degrees for winter are used in the model separately.

The price elasticity is compared for the median demand of summer, winter and the entire year in Figure 10. Specifically, the top panel provides price elasticity estimated using model (4); the solid line indicates the elasticity estimated at the price median and the dashed lines give the range. The middle panel gives the price elasticity estimated using model (10); and the bottom panel shows the median demand at each half-hourly period.

Figure 11 shows R^2 values for each half-hourly model. We can see that all of the models explain the demand in an acceptable range, and that the R^2 values are higher during working hours because temperature is a stronger driver during such periods.

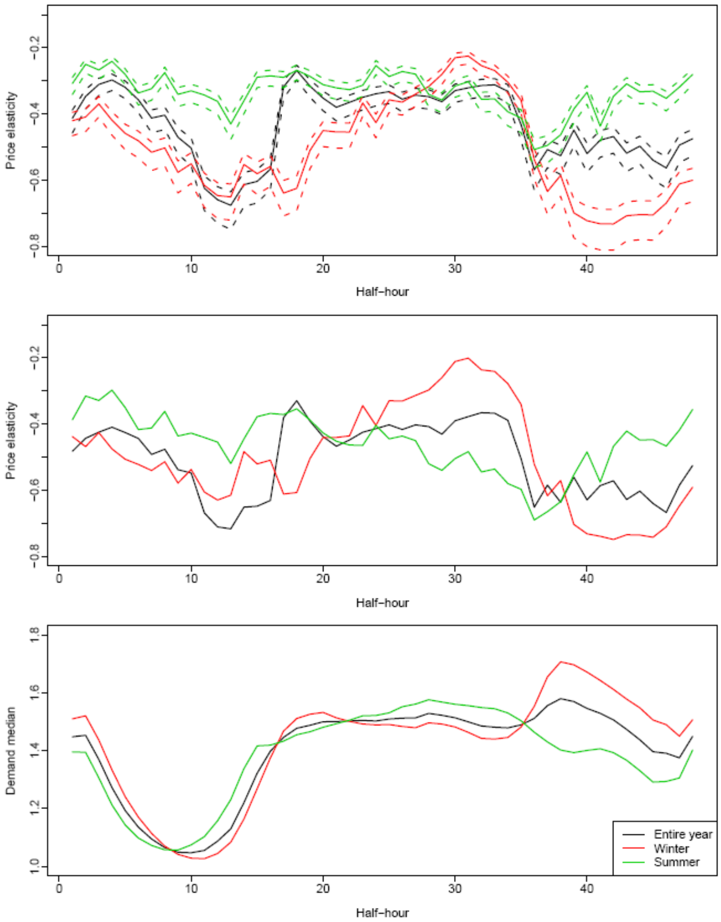

Fig 10 Price elasticity coefficients for each half-hourly period, for the median demand of the entire year, winter and summer. The top panel provides the price elasticity estimated using model (4), with the solid line indicating the elasticity estimated at the price median and the dashed lines showing the range; the middle panel gives the price elasticity estimated using model (10); and the bottom panel shows the median demand at each half-hourly period

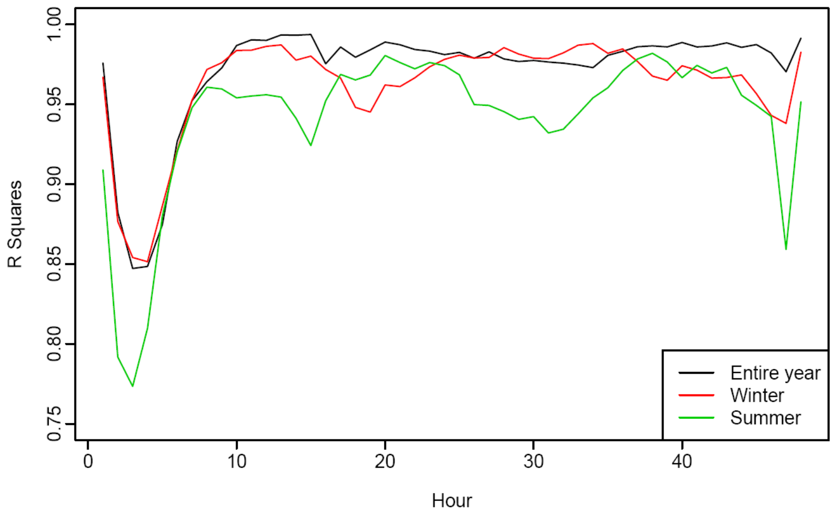

Fig 11 The R^2 values of half-hourly models for the entire year, winter and summer

According to Figure 10, it appears that consumers' price responses are stronger in winter than in summer over most periods of the day. This may be because consumers have more choices in winter for resisting coldness; for instance, they can use a gas heater or wear more clothes. On the other hand, we also observe that the elasticity is higher in summer than in winter during the mid- and late-afternoon periods (i.e., from around noon to 6 pm); this is particularly noticeable in the central panel of Figure 10. This observation indicates significant price responses at the critical times of day during summer. Again, the price elasticity coefficients reach their largest absolute values approximately at the peak period, i.e., around 4 o'clock in the afternoon for summer and 7 o'clock in the evening for winter.

3.6 Price elasticity at different demand quantiles

The price elasticity coefficients are also calculated for different demand deciles, without considering the time of day. Since the results from models (4) and (10) are generally similar, we perform the estimation using model (4). Figure 12 provides a plot of elasticity coefficients estimated at 11 demand quantiles for the entire year, winter and summer. Figure 13 shows R^2 values models estimated at different demand quantiles. It can be seen that all of the models explain the demand well.

According to these results, it can be seen that customers' sensitivities to price are weakest at the highest demand quantile. Moreover, for demand quantiles below 80%, the price elasticities are higher in winter than in summer. However, this relationship is reversed above the 80% demand quantiles, which may indicate that customers have comparatively weak sensitivities to price during both the hottest and coldest days.

The findings from Figure 12 actually indicate an approximate non-linear relationship between electricity demand and price; i.e., the price elasticities vary with both the time of day and the time of year.

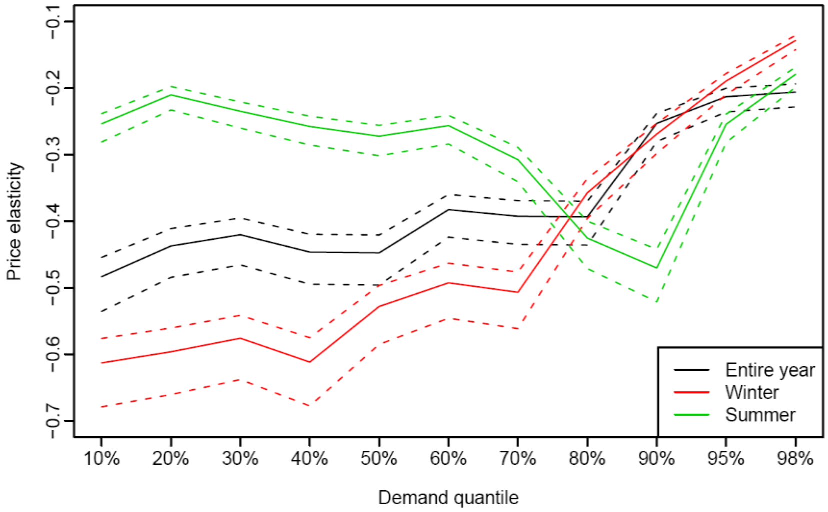

Fig 12 Price elasticity estimated at different demand quantiles for the entire year, winter and summer, showing the range estimated as the sample space

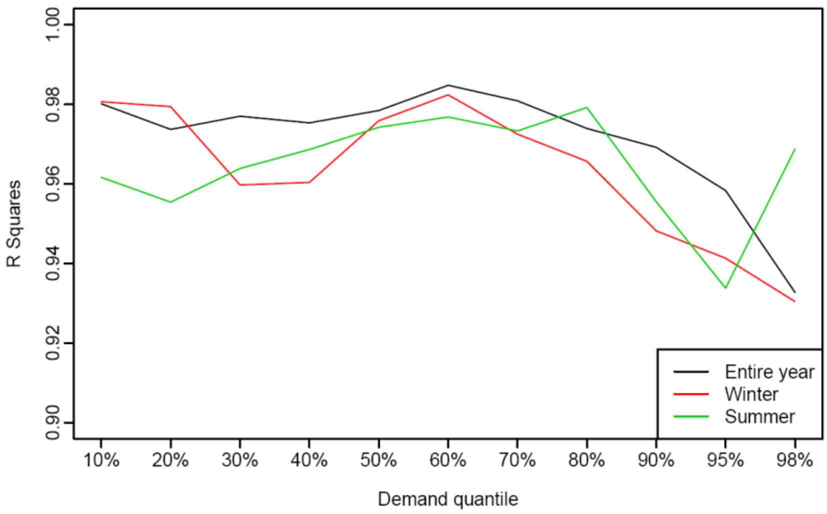

Fig 13 The R^2 values of models at different demand quantiles for the entire year, winter and summer

4 Conclusion and discussion

4.1 Summary of results

The results obtained in this report can be compared and summarized as follows.

In Section 3.3, the price elasticity is estimated based on annual median demand. The elasticity measures are therefore indicative of the price effect on annual sales levels. Specifically, model (4) gives a price elasticity in the range of -0.363 to -0.428, and model (10) gives a price elasticity of -0.4165.

In Section 3.4, the data are split by the demand decile and time of day to give $48 \times 11 = 491$ estimates. The results are indicative of a price effect on demand at different levels of demand and at different times of the day. The results are summarized in the following two tables, respectively. Note that the value for each time is an estimate averaged over an hour.

Table 4 Summary of the coefficients of the lagged price at each half-hourly period, estimated for different quantiles using model (4)

	10%	**50%**	**90%**	**95%**	**98%**
Midnight	-0.405	-0.445	-0.430	-0.525	-0.420
Noon	-0.455	-0.335	-0.110	0.395	-0.150
4pm	-0.545	-0.310	-0.004	0.350	-0.195
7pm	-0.500	-0.490	-0.250	-0.560	-0.655

Table 5 Summary of the coefficients of the lagged price at each half-hourly period, estimated for different quantiles using model (10)

	10%	**50%**	**90%**	**95%**	**98%**
Midnight	-0.475	-0.505	-0.475	-0.725	-0.725
Noon	-0.475	-0.405	-0.130	0.050	-0.575
4pm	-0.590	-0.370	-0.270	-0.085	-0.575
7pm	-0.645	-0.600	-0.335	-0.750	-0.970

In Section 3.5, the demand data are split by the time of day and season, and so give an indication of the differences in elasticity across the year. The results are summarized in the following two tables, respectively. As in the previous section, the value for each time is an estimate averaged over an hour.

Table 6 Summary of the price elasticity at each half-hourly period, for the entire year, winter and summer, using model (4)

	Entire year	Winter	Summer
Midnight	−0.445	−0.510	−0.295
Noon	−0.335	−0.395	−0.270
4pm	−0.310	−0.260	−0.355
7pm	−0.490	−0.645	−0.435

Table 7 Summary of the price elasticity at each half-hourly period, for the entire year, winter and summer, using model (10)

	Entire year	Winter	Summer
Midnight	−0.505	−0.515	−0.375
Noon	−0.405	−0.365	−0.425
4pm	−0.370	−0.240	−0.540
7pm	−0.600	−0.635	−0.595

In Section 3.6, the demand data are split by decile and season, and so give an indication of how the price response varies with the level of demand in different seasons. The results are summarized in Table 8.

Table 8 Summary of the price elasticity for different demand quantiles, for the entire year, winter and summer, using model (4)

	Entire year	Winter	Summer
10%	-0.48	-0.61	-0.25
50%	-0.45	-0.53	-0.27
90%	-0.25	-0.27	-0.47
95%	-0.21	-0.19	-0.25
98%	-0.21	-0.13	-0.18

4.2 What have we learned?

Some inferences we have learned from this work can be summarized as follows.

- Until recently, most industrial, commercial, and residential customers in South Australia have been insulated from the volatile electricity spot market price, and pay a flat rate for the electricity they consume. Therefore, their demands have mainly been affected by the cycle of their own activities, and the state-wide electricity demands are largely driven by the economy, demography and weather.
- The overall price elasticity in South Australia, estimated using historical data, ranges from -0.363 to -0.428, showing a moderate responsiveness of electricity consumption to changes in prices.
- For the demand median, the strongest price responsiveness appears approximately at the peak period; i.e., around 4 o'clock in the afternoon for summer and 7 o'clock in the evening for winter. The price elasticity varies throughout the day, which suggests that flexible pricing schemes like TOU pricing could be an effective measure for abating the demand in peak periods, and balanceing the ratio of peak to off-peak usage.
- Consumers' price responses are stronger in winter than in summer for

demand quantiles below the 80% level, indicating that consumers may have more choices for resisting coldness in winter. However, in extreme weather conditions in both summer and winter, customers' sensitivities to price become comparatively weak, despite the high demand levels in such periods.

- An approximately non-linear relationship between electricity demand and price can be observed, i.e., the price elasticities vary with both the time of day and time of year. Therefore, applying annual demand models for each half-hourly period appears to be a likely way of improving future demand forecasting models.

Generally speaking, there are various difficulties in calculating the price elasticity. First, the estimation will be biased if the substitution of other inputs for the use of electricity occurs. This is ignored by the model used to make the price elasticity estimation. Such information is usually hard to acquire, and the inclusion of more data will result in a more complex model, with associated difficulties. Second, the price elasticity may vary widely across different sectors (residential, industrial and commercial) and regions, and accurate estimation requires a knowledge of the mix of sectors and the disaggregation of the data. Furthermore, the application of the nonlinear structure of tariff schedules makes the price elasticity more difficult to quantify.

There are several further investigations that we think are worthwhile doing, for example, disaggregating the data among residential, industrial and business sectors, and then estimating the price responses for each of these different sectors. As the electricity price sometimes changes within the year, it may also be helpful to use data of a higher resolution (e.g., quarterly data), so that the relationship between demand and its driving variables can be modelled in a more detailed manner.

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