Applied Energy 108 (2013) 288–297

Contents lists available at SciVerse ScienceDirect

Applied Energy

journal homepage: www.elsevier.com/locate/apenergy

Residential winter kW h responsiveness under optional time-varying pricing in British Columbia

C.K. Woo [a,b,*], R. Li [c], A. Shiu [c], I. Horowitz [a,d]

[a] Department of Economics, Hong Kong Baptist University, Hong Kong, China
[b] Energy and Environmental Economics, Inc., 101 Montgomery Street, Suite 1600, San Francisco, CA 94104, USA
[c] School of Accounting and Finance, Hong Kong Polytechnic University, Hong Kong, China
[d] Warrington College of Business, University of Florida, Gainesville, FL 32611, USA

HIGHLIGHTS

- Estimated residential kW h responsiveness under winter time-varying pricing in BC.
- Found statistically significant estimates of elasticity-of-substitution.
- Time-varying pricing sans load control causes a peak kW h reduction of 2.6–9.2%.
- Load control raises these reduction estimates to 9.2% and 30.7%.

ARTICLE INFO

Article history:
Received 12 January 2013
Received in revised form 8 March 2013
Accepted 14 March 2013
Available online 9 April 2013

Keywords:
Residential price responsiveness
Winter peak kW h reduction
Optional time-varying pricing
British Columbia

ABSTRACT

A large sample of daily electricity consumption and pricing data are available from a pilot study conducted by BC Hydro in British Columbia (Canada) of its residential customers under optional time-varying pricing and remotely-activated load-control devices for the four winter months of November 2007–February 2008. We use those data to estimate the elasticity of substitution σ, defined as the negative of the percentage change in the peak-to-off-peak kW h ratio due to a 1% change in the peak-to-off-peak price ratio. Our estimates of σ characterize residential price responsiveness with and without load control during cold-weather months. While the estimates of σ *sans* load control are highly statistically significant ($\alpha = 0.01$), they are less than 0.07. With load control in place, however, these σ estimates more than triple. Finally, we show that time-varying pricing *sans* load control causes a peak kW h reduction of 2.6% at the 2:1 peak-to-off-peak price ratio to 9.2% at the 12:1 peak-to-off-peak price ratio. Load control raises these reduction estimates to 9.2% and 30.7%.

1. Introduction

Three transformative events have taken place in the electricity industry. The first event is restructuring designed to introduce wholesale-market competition in Australia, New Zealand, parts of North and South America, and Europe [1,2]. The second event is the large-scale development of wind generation, thanks to (a) advances in our ability to economically harvest the inexhaustible, if somewhat erratic, wind that nature bestows upon us [3,4], and (b) support from government policies to do so [5,6]. The third event is the development of smart grids that enhance (a) market competition and liquidity, (b) system asset utilization, flexibility, intelligence, resilience and reliability, and (c) the integration of renewable energy resources into the electricity grid [7–9].

Insofar as wholesale-market competition is concerned, an empirical fact is that electricity spot-market prices are inherently volatile, with occasional sharp spikes, thanks to: daily fuel-cost variations, especially for the natural gas now widely used in combined-cycle gas turbines and combustion turbines; weather-dependent seasonal demands with intra-day and inter-day fluctuations that must be met in real time by generation and transmission already in place; limited economic viability of energy storage systems; changes in available capacity caused by planned and forced outages of electrical facilities; precipitation and river flow for a system with significant hydro resources; carbon-price fluctuations that affect the thermal generation that uses fossil fuels; transmission constraints that cause transmission congestion and generation redispatch; and lumpy capacity additions that can only occur with long lead times [10–13].

The electricity price volatility and its accompanying spikes are in turn exacerbated by the second event of large-scale development of wind generation [14]. Since wind generation has zero fuel

* Corresponding author at: Department of Economics, Hong Kong Baptist University, Hong Kong, China. Tel.: +852 3411 2177; fax: + 852 3411 5580.
E-mail address: ck@ethree.com (C.K. Woo).

0306-2619/$ - see front matter © 2013 Elsevier Ltd. All rights reserved.
http://dx.doi.org/10.1016/j.apenergy.2013.03.042

cost, it is economically dispatched to displace high-fuel-cost marginal generation [15,16], unless curtailed to resolve grid congestion and instability [17,18]. Wind-generation output, however, is random and intermittent, thus presenting integration challenges that can be mitigated by a smart grid armed with demand response (DR) resources [19–25].

Related to the third event of smart-grid development is the advanced metering infrastructure that allows a load-serving entity to implement time-varying electricity pricing to convey spot-price signals for effective DR management of system peaks, and economic efficiency [26–37]. That entity can be a local distribution company such as PG&E and SCE in California (U.S.) or an integrated utility such as BC Hydro in British Columbia (Canada). Reinforcing this view is the empirical evidence of statistically-significant peak kW reductions by households in response to time-of-use (TOU) pricing and critical-peak pricing (CPP) [38–43]. For example, TOU pricing is estimated to reduce residential winter evening peak kW by 5–10% in the Pacific Northwest area of the U.S. [44,45] and 10–15% in New Zealand [46]. The winter estimates for CPP are about 4–6% for residents in Washington, DC [47].

Most evidence to date, however, comes from summer-peaking utilities with relatively high electric rates. As reported in a 2010 survey of 15 experiments [42], TOU pricing induces (a) summer afternoon peak kW reductions of 3–6%, and (b) summer peak kW reductions of 13–20% due to CPP alone, and 36–44% when assisted by an enabling technology such as smart thermostats.

Partially filling this gap in empirical evidence is a recent paper [48] on the winter evening peak kW response of participants in BC Hydro's residential TOU/CPP pilot study in British Columbia, a winter-peaking Canadian province with low electric rates compared to other regions of North America.[1] Based on a large sample of hourly data for 1717 customers on 83 working weekdays from November 2007 through February 2008, the parameter estimates of 24 hourly kW regressions show that optional TOU pricing can reduce the evening peak kW by 4–11% [48]. Moreover, the incremental impact of CPP (beyond the TOU effect) is a 9–12% reduction in the peak kW. When aided by remotely-activated load control of space and water heating, CPP can achieve in excess of a 35% total reduction in the peak kW.

While transparent and informative, the analysis in [48] does not provide price elasticity estimates for predicting customer demand behavior under TOU/CPP designs that were not considered in the pilot study. The present paper fills in this gap by using daily kW h data from the pilot study, by TOU period, to estimate the residential responsiveness to optional time-varying pricing. We focus on kW h responsiveness by TOU period because the lack of hourly price variations precludes our estimation of a system of 24 hourly demand equations, as done in [49,50].

Based on three alternative estimation methods, our estimates answer the following questions that are the focus of our research:

- What are the estimates of the elasticity of substitution (σ = negative of the percentage change in the peak-to-off-peak kW h ratio due to a 1% change in the peak-to-off-peak price ratio), for BC Hydro's residential customers, under voluntary time-varying pricing? We find statistically-significant estimates ($\alpha = 0.01$) of 0.054–0.069,[2] which are at the low end of the ranges reported in [38–40,42].
- How does remotely-activated load control affect the estimates of σ? We find that load control increase the σ estimates by 0.15–0.18. To the best of our knowledge, this is the first evidence on the effect of a DR-enabling technology on a customer's winter σ estimates.
- What is the peak kW h reduction due to time-varying pricing? Without load control, the estimated reduction is about 2.6% at the low-end 2:1 peak-to-off-peak price ratio, which rises at a decreasing rate to about 9.3% at the high-end 12:1 price ratio. With load control, the estimated reduction is 9.2% at the 2:1 price ratio and 30.7% at the 12:1 price ratio. While corroborating the mostly summer evidence reported in a 2012 survey [43], these estimated reductions sharply confirm the effect of a DR-enabling technology on a customer's winter peak kW h responsiveness under optional time-varying pricing.

The paper proceeds as follows. Section 2 describes the pilot study, thus defining the scope of our regression analysis. Section 3 presents our empirical approach. Section 4 reports the results, and Section 5 concludes.

2. BC Hydro's TOU/CPP pilot study

The daily kW h data by TOU on 83 working weekdays in November 2007–February 2008 are derived from 1717 single-family homes in three areas of British Columbia (Canada): the Lower Mainland region (major city: Vancouver); the city of Fort St. John in the Northern Interior; and the city of Campbell River on Vancouver Island. These customers participated in the second year of BC Hydro's pilot study that entailed one flat rate schedule (RS) 1101 and eight TOU rate schedules.[3] Shown in Fig. 1, each TOU tariff's peak hours can be: (1) 4–9 pm; (2) 4–8 pm; or (3) 8–11 am and 4–8 pm. The evening peak hours aim to cover BC Hydro's system peak hour of 5–6 pm on a cold winter weekday. The morning peak hours aim to cover the local peak hour of 9–10 am on a cold winter weekday on Vancouver Island.

The TOU rate schedules have high peak and off-peak rates when compared to the non-TOU flat rate. For example, RS1142 and RS1143 have peak rates that far exceed their off-peak rate of 6.15 ¢/kW h, which is only slightly lower than the flat rate of 6.33 ¢/kW h. To encourage customer participation, the pilot study offered each TOU customer an upfront payment equal to the estimated bill increase from the TOU rates. Each TOU customer's payment was the difference between (a) the customer's pre-pilot weather-adjusted peak and off-peak kW h estimates at TOU rates, and (b) the customer's pre-pilot weather-adjusted kW h consumption at the non-TOU flat rate.[4]

RS1141B and RS1144A contain a CPP rate of 50 ¢/kW h, which is triggered with advanced notice by 5 pm the day before a CPP event. The complete list of CPP event days is: 11 December 2007 (Tuesday), 18 December 2007 (Tuesday), 09 January 2008 (Wednesday), 18 Jan-

[1] While 90% of BC Hydro's electricity generation comes from energy-limited hydro resources, peak-demand reduction has a capacity value of approximately C$150/kW-year in BC Hydro's consideration of (a) retiring the aging 900-MW Burrard Thermal Generation Station in Vancouver, and (b) procurement of new supplies to meet its system-peak growth.

[2] A σ estimate is said to be statistically significant at $\alpha = 0.01$ when its p-value is below 0.01, thereby rejecting the null hypothesis of $\sigma = 0$ based on a two-tail t-test.

[3] Based on single-family residents identified from its billing data file, BC Hydro recruited 2070 participants via direct mail in early 2006, 699 of whom were allocated to the control group and the rest to the treatment group. The allocation was balanced, without systematic differences in customer attributes between the two groups. After the pilot's first winter of November 2006–February 2007, the participants were asked to re-enroll, contributing to 1632 of the 1717 participants shown in Fig. 2. The remaining 85 participants were newly recruited to permit estimation of the peak-load effect of shortening the 4–9 pm peak period by 1 h, to 4–8 pm.

[4] While the participation payment was made before the customer's actual consumption under time-varying pricing, it could shrink the σ estimates for two reasons. First, the payment might have encouraged customers with poor load-shifting capability to join the pilot study. Second, it might have exacerbated the free-rider problem in which residents with relatively low peak consumption could enjoy TOU/CPP bill savings without changing their demand behaviors [26,27,31,52]. Notwithstanding these caveats, our σ estimates demonstrate statistically-significant ($\alpha = 0.01$) effectiveness of optional time-varying pricing in reducing residential peak kW h.

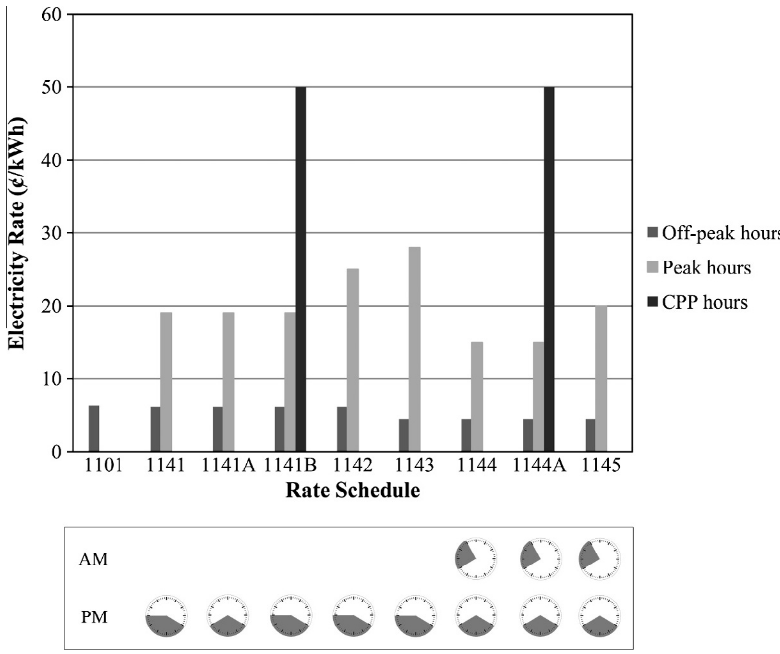

Fig. 1. Electricity rate schedules of BC Hydro's pilot study: (a) Rate Schedule 1101 has a flat rate of 6.3¢/kWh; and (b) remaining rate schedules are TOU tariffs with peak hours shown as shaded areas in the clocks.

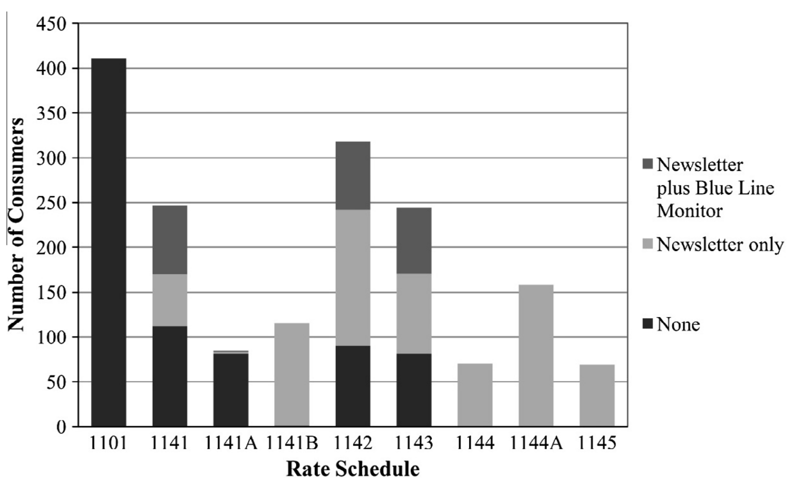

Fig. 2. Number of customers by rate schedule and communication method.

uary 2008 (Friday), 23 January 2008 (Wednesday), 04 February 2008 (Monday), 16 February 2008 (Saturday), and 28 February 2008 (Thursday). For these eight CPP days, the peak-to-off-peak price ratio could be as high as 11:1 (i.e., 50 ¢/kW h÷4.5 ¢/kW h = 11.1).

Fig. 2 reports the number of customers by rate schedule and communication method. It shows that 713 customers received a monthly newsletter and 228 customers a monthly newsletter plus the Blue Line Monitor that provides real-time feedback on electricity consumption. Based on a 2011 survey [51], information feedback tends to reduce residential consumption.

Forty-four Campbell River customers voluntarily participated in the load-control option that uses remotely-activated load-control devices to automatically reduce space and water-heating load during CPP events. These devices were: (a) digital control to cycle the load of baseboard heater and water heater; and (b) a programmable, communicating thermostat to control central heating and forced-air furnaces. These customers could override the device's activation and hence they had full discretion as to how they might respond to BC Hydro's CPP signals. The control devices functioned well on the CPP days, except for 09 January 2008 (Wednesday) when the remote-activation signal failed. This signal-failure event provides a unique opportunity to verify the impact of load control on a customer's price responsiveness.

The data file generated by the customer sample summarized in Figs. 1 and 2 permits us to compare customer consumption patterns, thereby delineating the impacts of TOU pricing, CPP rate, load control, and communication method. Since the communication method's effect has been found to be statistically insignificant ($\alpha = 0.05$) [48], our analysis herein focuses on the effect of optional time-varying pricing on residential kW h, and how this effect may vary by the peak-to-off-peak price ratio and load control.

The descriptive statistics in Table 1A shows that 85% of the customers from the Lower Mainland and Fort St. John sample reside in Lower Mainland, 5% have primary and 34% secondary electric heating,[5] and have pre-pilot monthly consumption of 970 kW h. These

[5] A customer has primary electric heating if the customer uses baseboard or heat pump as the main space heater. A customer has secondary electric heating if the customer uses a portable electric heater to supplement a natural-gas furnace or wood stove for space heating.

Table 1A
Descriptive statistics for customer-days: Lower Mainland and Fort St. John.

Variable	Description	Number of observations	Mean	Standard deviation	Minimum	Maximum
V_k	=1 if Lower Mainland, else 0	87,650	0.8519	0.3552	0.0000	1.0000
H_{1k}	=1 if primary electric heat, else 0	87,650	0.0552	0.2283	0.0000	1.0000
H_{2k}	=1 if secondary electric heat, else 0	87,650	0.3419	0.4743	0.0000	1.0000
Q_{kt}	Pre-pilot monthly kW h	87,361	969.6	618.8	4.6667	6615.5
W_{kt}	Daily sum of heating degree hours	87,650	383.9	175.1	161.1	1235.4
X_{1kt}	Daily peak kW h consumption	87,650	8.41	5.84	0.0800	70.22
X_{2kt}	Daily off-peak kW h consumption	87,650	23.18	17.59	0.3300	225.7
P_{1kt}	Daily peak price ($/kW h)	87,650	0.2200	0.0643	0.0633	0.5000
P_{2kt}	Daily off-peak price ($/kW h)	87,650	0.0579	0.0070	0.0450	0.0633

Table 1B
Descriptive statistics for customer-days: Campbell River.

Variable	Description	Number of observations	Mean	Standard deviation	Minimum	Maximum
H_{1k}	=1 if primary electric heat, else 0	30,555	0.4003	0.4900	0.0000	1.0000
H_{2k}	=1 if secondary electric heat, else 0	30,555	0.2148	0.4107	0.0000	1.0000
Q_{kt}	Pre-pilot monthly kW h	29,884	1724.5	953.6	66.3	10844.9
W_{kt}	Daily sum of heating degree hours	30,555	324.9	65.4018	149.4	462.6
X_{1kt}	Daily peak kW h consumption	30,555	18.72	12.10	0.5490	95.79
X_{2kt}	Daily off-peak kW h consumption	30,555	37.99	24.89	1.63	224.33
P_{1kt}	Daily peak price ($/kW h)	30,555	0.1530	0.0793	0.0633	0.5000
P_{2kt}	Daily off-peak price ($/kW h)	30,555	0.0489	0.0075	0.0450	0.0633

customers face daily fluctuating cold weather, with average daily peak consumption of 8.41 kW h and off-peak consumption of 23 kW h.

The descriptive statistics in Table 1B shows that 40% of the Campbell River sample customers have primary and 21% secondary electric heating, with pre-pilot monthly consumption of 1724 kW h. These customers also face daily fluctuating cold weather, with average daily peak consumption of about 19 kW h and off-peak consumption of 38 kW h.

3. Empirical approach

To present our empirical approach, this section first states the economic model underlying our regression specifications and hypotheses. It then discusses our estimation strategy to ensure that our findings are not highly sensitive to the choice of estimation method. It ends with a suggestion for computing the peak kW h reduction due to an increase in the peak-to-off-peak price ratio.

3.1. The constant-elasticity-of-substitution electricity expenditure function

Consider a customer's constant-elasticity-of-substitution (CES) electricity expenditure function, which is commonly used to analyze residential electricity demand by TOU [38–40,42,53–55]:

$$C(P_1, P_2, \boldsymbol{E}) = [aP_1^{\rho} + (1-a)P_2^{\rho}]^{1/\rho} F(\boldsymbol{E}), \tag{1}$$

where P_1 = peak price; P_2 = off-peak price; and $F(\boldsymbol{E})$ = a scalar function of electricity services $\boldsymbol{E}$ (e.g., cooking, lighting and heating). Invoking Shephard's Lemma yields the least-cost peak and off-peak electricity demands [56]:

$$\partial C(\bullet)/\partial P_1 = X_1 = aP_1^{\rho-1} G^{(1/\rho)-1} F(\boldsymbol{E}), \tag{2}$$

and

$$\partial C(\bullet)/\partial P_2 = X_2 = (1-aP_2^{\rho-1} G^{(1/\rho)-1} F(\boldsymbol{E}), \tag{3}$$

where $G = [aP_1^{\rho} + (1-a)P_2^{\rho}]$. It is easy to verify $C(P_1, P_2, \boldsymbol{E}) = P_1X_1 + P_2X_2$, which is the customer's electricity expenditure.

Although $F(\boldsymbol{E})$ is unobservable, we can use the TOU price and kW h data to estimate the following log-ratio equation:

$$\ln(X_1/X_2) = \beta_0 + \beta \ln(P_1/P_2), \tag{4}$$

where $\beta_0 = \ln[a(1-a)]$ and $\beta = \rho - 1$. Since $\sigma \equiv \partial\ln(X_1/X_2)/\partial\ln(P_2/P_1)$, we have $\sigma = -\beta$.

Eq. (4) is the basis for our regression specification for explaining the variations in $\ln(X_{1kt}/X_{2kt})$, customer k's peak-to-off-peak kW h ratio on day t. Since $\ln(X_{1kt}/X_{2kt})$ varies across customers and days, we assume the intercept β_0 to be a linear function of controls for day of the week and month of the year, locale, customer size, peak-period length, and the weather. To account for the effect of load control on σ, we assume that β depends on whether a customer is in fact subject to load control.

3.2. Lower Mainland and Fort St. John

Based on Eq. (4) and the discussion thereof, we use Eq. (5) below as our regression model with an intercept γ and a random-error ε_{kt} for Lower Mainland and Fort St. John[6]:

$$\begin{aligned}\ln(X_{1kt}/X_{2kt}) = \gamma &+ \sum_m \mu_m M_{mt} + \sum_d \delta_d D_{dt} + \lambda V_k + \theta \ln(Q_{kt}) \\ &+ \phi R_k + \omega \ln(W_{kt}) + \omega_1 \ln(W_{kt}) H_{1k} + \omega_2 \\ &\times \ln(W_{kt}) H_{2k} + \beta \ln(P_{1kt}/P_{2kt}) + \varepsilon_{kt}.\end{aligned} \tag{5}$$

The independent variables are defined as follows:

- Three month-of-the-year binary indicators: M_{mt} is equal to unity if day t is in month m and is zero otherwise, for m = 11 for November, 12 for December and 1 for January. These indicators aim to capture the residual month-of-the-year effect unaccounted for by the other variables.

[6] The random-error term ε_{kt} has a zero mean and a finite variance. It reflects the difference between the actual $\ln(X_{1kt}/X_{2kt})$ and its predicted value portrayed by the regression. Since its distribution is not known *a priori*, Section 3.4 below discusses three estimation methods to obtain the coefficient estimates of Eq. (5).

- Four day-of-the-week binary indicators: D_{dt} is equal to unity if day t falls on weekday d and is zero otherwise, for $d = 1$ for Monday through $d = 4$ for Thursday. These indicators aim to capture the residual day-of-the-week effect unaccounted for by the other variables.
- A customer-location indicator: V_k is equal to unity if customer k resides in Lower Mainland (major city: Vancouver), and is zero otherwise. This indicator is included to capture any residual location effect that is unaccounted for by the other variables.
- Customer size is measured by $\ln(Q_{kt})$, the natural logarithm of customer k's pre-pilot consumption for the same month that contains day t.[7] For example, if t is in November 2007, Q_{kt} is the pre-pilot study consumption a year earlier, in November 2006. The fact that larger customers tend to have a greater number of electrical appliances and flatter load profiles than do their smaller counterparts translates into hypothesis H_1: $\theta < 0$.
- A shortened-peak-period indicator: R_k is equal to unity if customer k is on the rate schedule RS1141A, which has a 4–8 pm peak period, and is zero otherwise. Inasmuch as the 4–8 pm period covers one less hour than does the 4–9 pm period, we would expect lower peak kW h consumption from customer k on schedule RS1141A on any given day t. This expectation translates into hypothesis H_2: $\phi < 0$.
- Weather is measured by $\ln(W_{kt})$, the natural logarithm of daily heating-degree hours, which is the daily sum of max(18 °C – hourly temperature, 0). Because cold weather tends to encourage a customer to spend more time at home, which results in a lower peak-to-off-peak consumption ratio, we arrive at hypothesis H_3: $\omega < 0$. As the weather effect depends upon a customer's space-heater ownership, we also include as independent variables the cross-product terms $\ln(W_{kt})H_{1k}$ and $\ln(W_{kt})H_{2k}$, where H_{1k} is equal to unity if customer k's primary heating is electric, and is zero otherwise; and H_{2k} is equal to unity if customer k's secondary heating is electric, and is zero otherwise.[8] Because falling temperatures are likely to cause customers to increase their heating loads for all hours, and since a customer's heating load is limited by the heater's capacity, the increase in heating load tends to flatten the customer's load profile, thus causing the consumption ratio to decline. Hence, we arrive at hypotheses H_4 and H_5: $\omega_1 < 0$ and $\omega_2 < 0$, respectively.
- Customer k's daily natural logarithm of the peak-to-off-peak price ratio is $\ln(P_{1kt}/P_{2kt})$, whose coefficient is $\beta = -\sigma$. If the customer responds to time-varying pricing, an increase in the price ratio likely causes the consumption ratio to decline. Hence, we have H_6: $\beta < 0$.

3.3. Campbell River

Retaining our original notation for ease of interpretation, we modify Eq. (5) to analyze the Campbell River data:

$$\begin{aligned}\ln(X_{1kt}/X_{2kt}) = {} & \gamma + \sum_m \mu_m M_{mt} + \sum_d \delta_d D_{dt} + \theta \ln(Q_{kt}) \\ & + \omega \ln(W_{kt}) + \omega_1 \ln(W_{kt}) H_{1k} + \omega_2 \ln(W_{kt}) H_{2k} \\ & + \beta \ln(P_{1kt}/P_{2kt}) + \beta_1 \ln(P_{1kt}/P_{2kt}) A_{kt} + \beta_2 \\ & \times \ln(P_{1kt}/P_{2kt}) F_{kt} + \varepsilon_{kt}. \end{aligned} \quad (6)$$

Eq. (6) differs from Eq. (5) as follows:

- It does not have V_k as an explanatory variable because all customers are in Campbell River.
- It does not have R_k as an explanatory variable, because there is only one peak-period definition for Campbell River customers.
- It introduces $\ln(P_{1kt}/P_{2kt})A_{kt}$ as an additional explanatory variable to capture the impact of load control on σ. To see this point, consider the binary indicator A_{kt}, which is equal to unity if customer k is a load-control customer and t is a CPP event day, and is zero otherwise. A customer without load control has an elasticity of substitution of $\sigma = -\beta$. For a customer with load control, however, the elasticity is $-(\beta + \beta_1)$. Thus, the differential impact of load control is β_1, for which we have hypothesis H_7: $\beta_1 < 0$ when load control magnifies the size of σ.
- It introduces $\ln(P_{1kt}/P_{2kt})F_{kt}$ as an additional explanatory variable to capture the impact of load-control failure on the elasticity of substitution. Comparable to the role of A_{kt}, the binary indicator F_{kt} is equal to unity if customer k is a load-control customer and t is a CPP event day (Wednesday, 09 January 2008) with signal failure, and is zero otherwise. Since the elasticity for a customer with load control is $-(\beta + \beta_1)$, when load control fails the customer's elasticity becomes $-(\beta + \beta_1 + \beta_2)$. Since load-control failure is similar to no load control, we expect a zero combined impact of failed load control, which translates into hypothesis H_8: $\beta_1 + \beta_2 = 0$.

3.4. Estimation strategy

We use three alternative methods to ensure that the regression coefficient estimates are not highly sensitive to the choice of estimation method. The first method is ordinary least squares (OLS), which serves to produce our initial results. When ε_{kt} is normally and independently distributed, the OLS coefficient estimates are unbiased minimum-variance estimators of the population parameters.

The second method is robust regression [57].[9] We use this method to allow for the possibility that the OLS normality assumptions about the random-error term are invalid, and in particular to minimize the impact of any outliers that may cause estimation bias.[10] Such outliers can exist because the distribution of ε_{kt} may be asymmetric and can have large values.

Our third method is panel-data analysis [59, Chapter 14] because our estimation sample is generated by 1717 customers observed over 83 working days. To implement this method, we estimate (a) a fixed-effects model that uses customer-specific intercepts to control for customer heterogeneity; and (b) a random-effects model that uses customer-specific random factors to control for customer heterogeneity. Since (a) is rejected by the data at $\alpha = 0.05$, we shall only report the results for (b) below.

3.5. Peak kW h reduction

Based on [60], here we propose how to use Eq. (5) [or (6)] to compute the percent reduction in peak kW h by peak-to-off-peak price ratio. Suppressing the subscripts for notational simplicity, consider $\ln(X_1/X_2) = Z$, the non-random portion of the regression line. Simple algebraic manipulation yields the peak kW h share:

$$S = X_1/X = e^Z/(1 + e^Z), \quad (7)$$

where $X = (X_1 + X_2)$ = daily total consumption.

Now, the peak kW h is $X_1 = SX$, implying $\ln(X_1) = \ln(S) + \ln(X)$. Hence, the percent change in peak kW h is:

[7] We use pre-pilot consumption to measure customer size because the information is readily available from BC Hydro's billing data, and it is accurate since it is based on actual customer bills. Although the demographic data such as house and family size were available for most customers thanks to a customer survey, including those data in the regression causes a severe reduction in sample size due to missing or inaccurate values.

[8] Both heating indicators are readily available from BC Hydro's billing data and thus have very few missing values.

[9] This is done using method M in PROC ROBUSTREG in SAS [58].

[10] An outlier is an observation whose OLS studentized residual has a size over 3.0. Removing the outliers would reduce the estimation sample by 0.02%.

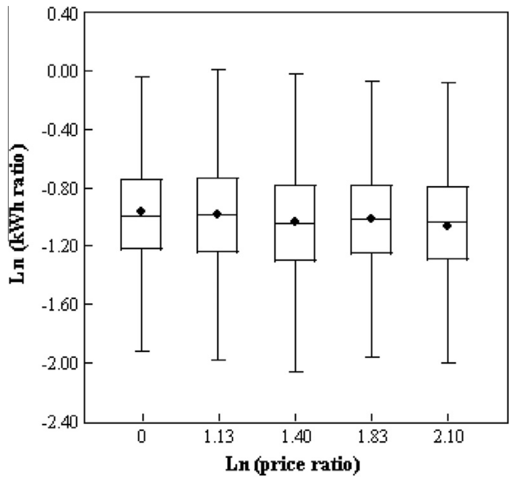

Fig. 3. Natural logarithm of kW h ratios by natural logarithm of price ratios for Lower Mainland and Fort St. John.

$$\Delta X_1/X_1) = (\Delta S/S) + (\Delta X/X)$$
$$= \text{Load-shifting effect} + \text{Total kW h effect}. \quad (8)$$

Since the load-shifting effect can be computed using Eq. (7), the missing information is the total kW h effect.

The total kW h effect can be estimated as the product of (a) the price elasticity of daily kW h, and (b) the percent change in the daily average price. For our current study, the total kW h effect is basically zero because BC Hydro has estimated (a) to be −0.1 [61] and (b) is close to zero for a "revenue–neutral" time-varying rate design [27].[11] Moreover, a research report submitted by the first author to BC Hydro indicates that the pilot study did not reveal a total kW h effect for a revenue-neutral design. Hence, our peak kW h reduction can be based solely on ($\Delta S/S$).

Since each daily value of ($\Delta S/S$) is customer-specific and depends on the price-ratio assumption, we use the estimated version of Eq. (5) [or (6)] to compute ($\Delta S/S$). The resulting estimates form the basis for empirical distributions of peak kW h reduction by price ratio, which can then be compared to the experimental results reported in [43].

4. Results

4.1. Data distributions

Fig. 3 presages our regression results for the estimates of the elasticity of substitution. In particular, the figure presents box plots for the Lower Mainland and Fort St. John of the natural logarithms of the kW h ratios, shown on the vertical axis, by the natural logarithm of the price ratio, shown on the horizontal axis. In this figure, the bottom dash denotes the minimum and the top dash denotes the maximum natural logarithm of the kW h ratio. The bottom border of each box shows the first quartile, the middle line the median, and the top border the third quartile. The middle ⧫ is the mean. This figure suggests wide data dispersion and small σ estimates.

Fig. 4 presents the box plots for Campbell River customers without load control. As is the case with Fig. 3, Fig. 4 suggests wide data dispersion and small σ estimates. The box plots in Fig. 5, however, indicate that load control likely enlarges the σ estimates.

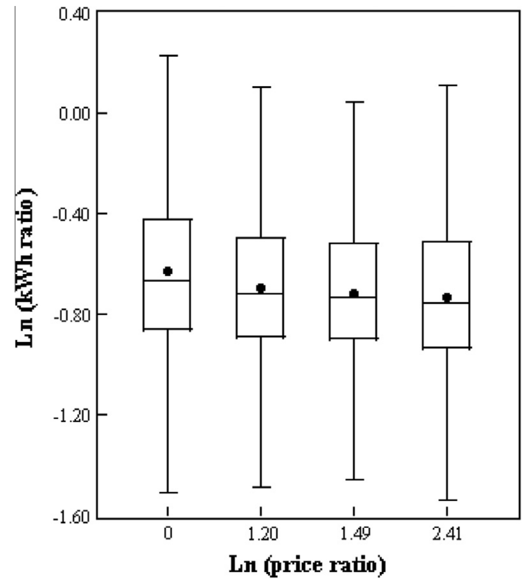

Fig. 4. Natural logarithm of kW h ratios by natural logarithm of price ratios for Campbell River (without load control).

Finally, all three figures indicate wide dispersion of the natural logarithms of the kW h ratios, supporting our use of robust regressions to remove the possibility of undue influence of outliers on the coefficient estimates.

4.2. Lower Mainland and Fort St. John

Table 2 presents the regression results based on Eq. (5). The following observations emerge from the OLS parameter estimates that appear in column 2:

- The relatively low $R^2 = 0.064$ indicates that the estimated regression explains 6.4% of the variance in the natural logarithm of the consumption ratio. Though low, it is in line with what is generally observed in the TOU demand literature. It is not unexpected when applying a parsimonious specification to a large sample of noisy customer-day observations.

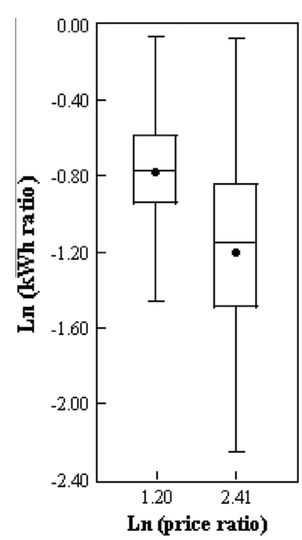

Fig. 5. Natural logarithm of kW h ratios by natural logarithm of price ratio for Campbell River (with load control).

[11] A revenue-neutral design aims to collect the same total revenue from the customers under time-varying pricing as the flat rate. The design necessarily has a peak rate above and an off-peak rate below the flat rate, yielding a sales-weighted average of the peak and off-peak rates equal to the flat rate. Hence, the expected percent change in the daily average price is close to zero under a revenue-neutral design.

- The statistically-significant ($p < 0.0001$) estimates for the month-of-the-year binary indicators indicate that the consumption ratios in November, December and January are higher than those in February.
- The statistically-significant ($p < 0.0001$) estimate for the Lower Mainland binary indicator indicates that the consumption ratios of Lower Mainland customers tend to be higher than those of Fort St. John customers.
- The statistically-significant ($p < 0.0001$) estimates for the day-of-the-week binary indicators indicate that the consumption ratios are higher on Monday through Thursday than on Friday.
- The coefficient estimate for $\ln(Q_{kt})$ is statistically significant ($p < 0.0001$) and negative, thus supporting H_1: $\theta < 0$, or a larger customer tends to have a lower consumption ratio.
- The coefficient estimate for R_k is statistically significant ($p < 0.0001$), negative and large in size. This supports H_2: $\phi < 0$, or a shortened peak period reduces the consumption ratio.
- The coefficient estimates for $\ln(W_{kt})$, $\ln(W_{kt})\,H_{1k}$ and $\ln(W_{kt})\,H_{2k}$ are statistically significant ($p < 0.0001$) and negative, thus supporting H_3: $\omega < 0$, H_4: $\omega_1 < 0$ and H_5: $\omega_2 < 0$, respectively. Hence, falling temperatures tend to reduce a customer's consumption ratio, especially when the customer has electric heating.
- The coefficient for $\ln(P_{1kt}/P_{2kt})$ is negative and statistically significant ($p < 0.0001$). While supporting H_6: $\beta < 0$, the estimate suggests a small σ estimate of 0.062, implying limited customer responsiveness to time-varying pricing.

The robust-regression results in Table 2 are similar to the OLS results, thus yielding similar interpretations.

The results for the random-effects model are also similar, with one exception: notably, the coefficient estimate for $\ln(Q_{kt})$ is statistically insignificant ($p = 0.897$) and close to zero. Though somewhat unexpected, this is understandable because the model also applies customer-specific factors to control for customer heterogeneity.

4.3. Campbell River

Table 3 presents the regression results based on Eq. (6). For the most part, the results are qualitatively similar to those in Table 2. In particular, the σ estimates for customers not subject to load control, or $-\beta$, are statistically significant ($p < 0.0001$) and equal to 0.069 for the OLS regression, 0.058 for the robust regression, and 0.054 for the random-effects model.

Table 2
Regression results based on Eq. (5) for Lower Mainland and Fort St. John with p-value in () for a two-tailed test of the null hypothesis: coefficient = 0; sample size = 87,361 customer-day observations for working weekdays in November 2007–February 2008.

Variable: Coefficient	Estimation method		
	OLS	Robust regression	Random effects
R^2	0.0638	0.0570	0.0583
Intercept: γ	−0.4214 (<.0001)	−0.4125 (<.0001)	−0.7608 (<.0001)
M_{11t} = 1 if t in November; 0, otherwise: μ_{11}	0.0545 (<.0001)	0.0528 (<.0001)	0.0529 (<.0001)
M_{12t} = 1 if t in December; 0, otherwise: μ_{12}	0.0656 (<.0001)	0.0689 (<.0001)	0.0575 (<.0001)
M_{1t} = 1 if t in January; 0, otherwise: μ_1	0.0458 (<.0001)	0.0463 (<.0001)	0.0381 (<.0001)
D_{1t} = 1 if t on Monday; 0, otherwise: δ_1	0.0514 (<.0001)	0.0519 (<.0001)	0.0514 (<.0001)
D_{2t} = 1if t on Tuesday; 0, otherwise: δ_2	0.0593 (<.0001)	0.0575 (<.0001)	0.0599 (<.0001)
D_{3t} = 1if t on Wednesday; 0, otherwise: δ_3	0.0493 (<.0001)	0.0485 (<.0001)	0.0492 (<.0001)
D_{4t} = 1if t on Thursday; 0, otherwise: δ_4	0.0342 (<.0001)	0.0351 (<.0001)	0.0339 (<.0001)
V_k = 1if customer k in Lower Mainland; 0, otherwise: λ	0.0695 (<.0001)	0.0734 (<.0001)	0.0779 (0.0002)
$\ln(Q_{kt})$ = ln(customer kW h size): θ	−0.0526 (<.0001)	−0.0550 (<.0001)	−0.0008 (0.8967)
R_k = 1if customer k on RS1141A; 0, otherwise: ϕ	−0.2997 (<.0001)	−0.2991 (<.0001)	−0.3060 (<.0001)
$\ln(W_{kt})$ = ln(daily sum of heating degree hours): ω	−0.0422 (<.0001)	−0.0432 (<.0001)	−0.0414 (<.0001)
$\ln(W_{kt})\,H_{1k} = \ln(W_{kt}) \times$ primary electric heating indicator: ω_1	−0.0239 (<.0001)	−0.0204 (<.0001)	−0.0253 (<.0001)
$\ln(W_{kt})\,H_{2k} = \ln(W_{kt}) \times$ secondary electric heating indicator: ω_2	−0.0065 (<.0001)	−0.0065 (<.0001)	−0.0094 (0.0001)
$\ln(P_{1kt}/P_{2kt})$ = ln(peak-to-off-peak price ratio): β	−0.0616 (<.0001)	−0.0536 (<.0001)	−0.0692 (<.0001)

Table 3
Regression results based on Eq. (6) for Campbell River with p-value in () for a two-tail test of the null hypothesis: coefficient = 0; sample size = 29,884 customer-day observations for working weekdays in November 2007–February 2008.

Variable: Coefficient	Estimation method		
	OLS	Robust regression	Random effects
R^2	0.0554	0.0515	0.0537
Intercept: γ	−0.0724 (0.2759)	−0.0140 (0.7976)	−0.2823 (0.0013)
M_{11t} = 1if t in November; 0, otherwise: μ_{11}	0.0511 (<.0001)	0.0505 (<.0001)	0.0525 (<.0001)
M_{12t} = 1if t in December; 0, otherwise: μ_{12}	0.0600 (<.0001)	0.0609 (<.0001)	0.0549 (<.0001)
M_{1t} = 1if t in January; 0, otherwise: μ_1	0.0319 (<.0001)	0.0349 (<.0001)	0.0270 (v.0001)
D_{1t} = 1if t on Monday; 0, otherwise: δ_1	0.0151 (0.0285)	0.0172 (0.0025)	0.0161 (0.0020)
D_{2t} = 1if t on Tuesday; 0, otherwise: δ_2	0.0095 (0.1707)	0.0122 (0.0338)	0.0093 (0.0751)
D_{3t} = 1if t on Wednesday; 0, otherwise: δ_3	0.0196 (0.0044)	0.0178 (0.0017)	0.0199 (0.0001)
D_{4t} = 1if t on Thursday; 0, otherwise: δ_4	0.0173 (0.0091)	0.0166 (0.0023)	0.0180 (0.0003)
$\ln(Q_{kt})$ = ln(customer kW h size): θ	−0.0525 (<.0001)	−0.0648 (<.0001)	−0.0240 (0.0203)
$\ln(W_{kt})$ = ln(daily sum of heating degree hours): ω	−0.0270 (0.0087)	−0.0250 (0.0032)	−0.0284 (0.0006)
$\ln(W_{kt})\,H_{1k} = \ln(W_{kt}) \times$ primary electric heating indicator: ω_1	−0.0174 (<.0001)	−0.0163 (<.0001)	−0.0191 (0.0001)
$\ln(W_{kt})\,H_{2k} = \ln(W_{kt}) \times$ secondary electric heating indicator: ω_2	−0.0148 (<.0001)	−0.0058 (<.0001)	−0.0162 (0.0060)
$\ln(P_{1kt}/P_{2kt})$ = ln(peak-to-off-peak price ratio): β	−0.0685 (<.0001)	−0.0583 (<.0001)	−0.0536 (<.0001)
$\ln(P_{1kt}/P_{2kt})\,A_{kt} = \ln(P_{1kt}/P_{2kt}) \times$ Load control indicator: β_1	−0.1767 (<.0001)	−0.1503 (<.0001)	−0.1639 (<.0001)
$\ln(P_{1kt}/P_{2kt})\,F_{kt} = \ln(P_{1kt}/P_{2kt}) \times$ Load control failure indicator: β_2	0.1262 (<.0001)	0.1488 (<.0001)	0.1255 (<.0001)

The coefficient estimates of β_1 adhering to $\ln(P_{1kt}/P_{2kt})A_{kt}$ are statistically significant ($p < 0.0001$) and equal to -0.177 for the OLS regression, -0.150 for the robust regression, and -0.164 for the random-effects model. These estimates support H_7: $\beta_1 < 0$, implying that load control magnifies the size of σ.

The coefficient estimates of β_2 adhering to $\ln(P_{1kt}/P_{2kt})\ F_{kt}$ are statistically significant ($p < 0.0001$) and equal to 0.126 for the OLS regression, 0.149 for the robust regression and 0.126 for the random-effects model. These coefficient estimates suggest that load-control failure shrinks a load-control customer's estimated σ. As a final check, we cannot reject H_8: $\beta_1 + \beta_2 = 0$ ($\alpha = 0.05$) for the robust regression, thus implying a zero combined impact of failed load control.

4.4. Peak kW h reduction

In light of the wide data dispersions in Fig. 3, we use the robust regression's coefficient estimates in Table 2 to compute the percent peak kW h reductions by price ratio for the customers in Lower Mainland and Fort St. John. Moreover, the robust regression's σ estimates are the smallest in size, implying that the resulting peak kW h reductions are conservative estimates. Finally, using the OLS or random-effects regressions leads to similar outcomes because of the similarity among the three sets of coefficient estimates.

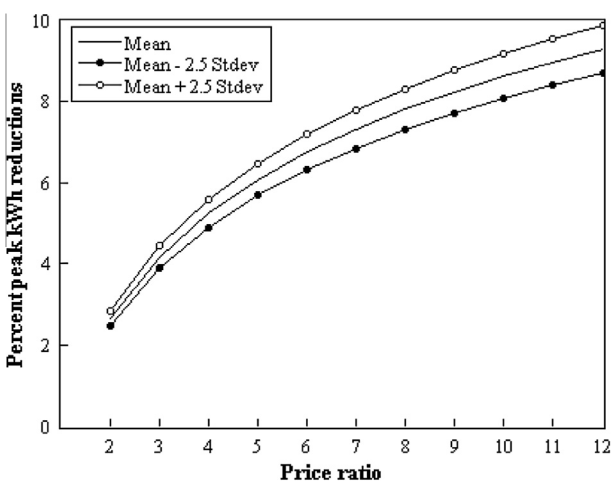

Fig. 6. Percent peak kW h reductions by price ratio for Lower Mainland and Fort St. John.

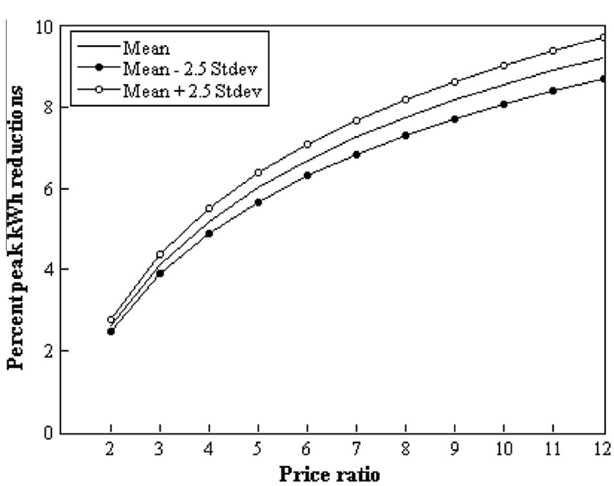

Fig. 7. Percent peak kW h reductions by price ratio for Campbell River (without load control).

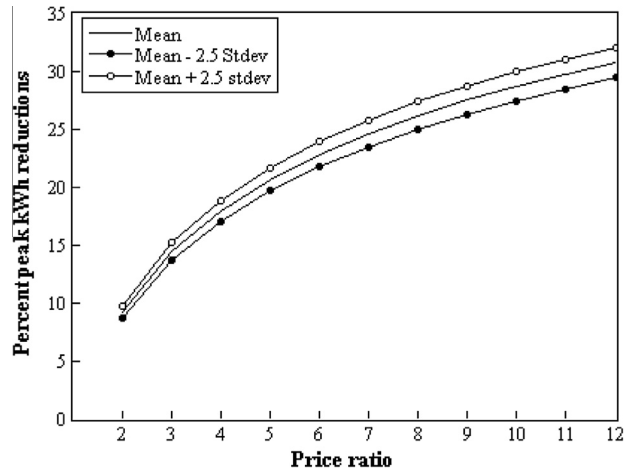

Fig. 8. Percent peak kW h reductions by price ratio for Campbell River (with load control).

The computation entails the following steps:

- *Step* 1: Apply the robust regression's coefficient estimates in Table 2 to compute S, the peak kW h share for each customer-day at the 1:1 price ratio.
- *Step* 2: Compute S', the peak kW h share for each customer-day at an alternative price ratio that ranges from 2:1 to 12:1.
- *Step* 3: Use the results from Steps 1 and 2 to compute $\Delta S/S = 1 - (S'/S)$, the customer-day-specific percent change in the peak kW h share.
- *Step* 4: Repeat Steps 1–3 for all customer-days.
- *Step* 5: Compute descriptive statistics for the results from Step 4.
- *Step* 6: Plot the mean and its lower and upper bounds (=mean ± 2.5 standard deviations). These bounds approximate the 1- and 99-percentile of the estimated peak reductions.

Fig. 6 portrays the percent peak kW h reductions by price ratio for Lower Mainland and Fort St. John. The reduction is about 2.6% at the 2:1 peak-to-off-peak price ratio and it increases at a decreasing rate to 9.2% at the 12:1 peak-to-off-peak price ratio, thus corroborating the findings in [51].

Using the robust regression's coefficient estimates in Table 3, we repeat the percent peak reduction computation for Campbell River. Fig. 7 shows that absent load control, the reductions in Campbell River are similar to those in Lower Mainland and Fort St. John. With load control in place, however, Fig. 8 shows that the reduction estimates are 9.2% at the 2:1 peak-to-off-peak price ratio and 30.7% at the 12:1 peak-to-off-peak price ratio.

5. Conclusion

The technology for smart grids and advanced metering infrastructure affords households the opportunity to manage their electricity consumption and bills under time-varying pricing and is doubtless the wave of the future. Consumption adjustments by households presumably lead to peak-demand reductions, offering system benefits of investment deferral, reliability improvement, flexible operation, and renewable resource integration. But will households take advantage of this opportunity?

Using a large and unique data base from BC Hydro, we have shown that indeed they will. We have also shown that a remotely-activated load-control device is particularly effective in inducing demand reductions in response to peak price increases. Moreover, these reductions are robust to three alternative estimation procedures – OLS, robust regression, and random-effects. Thus, our results not only validate the efficacy of time-varying prices for a winter-peaking utility, but they also provide concrete evidence of the potential import of remotely-activated load-control devices in helping both the utility and its customers to better manage their resources.

We would be remiss if we failed to acknowledge that based on BC Hydro's pricing pilot, one would have a difficult time arguing that enhanced communication has a discernible effect on customer consumption behavior. What seems to be a lack of response is nonetheless understandable in a set of participating customers that were enthusiastic volunteers already trying hard to conserve energy and shift load. Going forward, however, we encourage further research on the role of customer education and information feedback in determining customer kW h responsiveness to time-varying pricing.

Acknowledgements

This paper is partially funded by the Hong Kong Baptist University and Hong Kong Polytechnic University. It is partly based on the time-varying pricing research supported by BC Hydro. The views expressed in this paper are solely the authors'. Without implications, all errors are ours.

References

[1] Sioshansi FP, Pfaffenberger W, editors. Electricity market reform: an international perspective. San Diego, California: Elsevier; 2006.
[2] Woo CK, Chow LCH, Lior N, editors. Electricity market reform and deregulation. Energy 2006;31(6–7).
[3] Lu X, McElroy MB, Kiviluoma J. Global potential for wind-generated electricity. Proc Natl Acad Sci 2009;106(27):10933–8.
[4] McElroy MB, Lu X, Nielson CP, Wang YX. Potential for wind-generated electricity in China. Science 2009;325:1378–80.
[5] Alagappan L, Orans R, Woo CK. What drives renewable energy development? Energy Policy 2011;39:5099–104.
[6] Reuter WH, Szolgayová J, Fuss S, Obersteiner M. Renewable energy investment: policy and market impacts. Appl Energy 2012;97:249–54.
[7] Li F, Qiao W, Sun H, Wan H, Wang J, Xia Y, et al. Smart transmission grid: vision and framework. IEEE Trans Smart Grid 2010;1(2):168–77.
[8] Wang J, Conejo AJ, Wang C, Yan J. Smart grids, renewable energy integration, and climate change mitigation – future electric energy systems. Appl Energy 2012;96:1–3.
[9] Blumsack S, Fernandez A. Ready or not, here comes the smart grid! Energy 2012;37(1):61–8.
[10] Weron R. Modeling and forecasting electricity loads and prices. New York, New York: John Wiley; 2006.
[11] Tishler A, Milstein I, Woo CK. Capacity commitment and price volatility in a competitive electricity market. Energy Econ 2008;30(4):1625–47.
[12] Milstein I, Tishler A. The inevitability of capacity underinvestment in competitive electricity markets. Energy Econ 2012;34:62–77.
[13] Schweppe FC, Caramanis MC, Tabors RD, Bohn RE. Spot pricing of electricity. Boston, Massachusetts: Kluwer; 1988.
[14] Woo CK, Horowitz I, Moore J, Pacheco A. The impact of wind generation on the electricity spot-market price level and variance: the Texas experience. Energy Policy 2011;39(7):3939–44.
[15] Sensfuß F, Ragwitz M, Genoese M. The merit-order effect: a detailed analysis of the price effect of renewable electricity generation on spot market prices in Germany. Energy Policy 2008;36(8):3086–94.
[16] EWEA. Wind energy and electricity prices. European Wind Energy Association; 2010. <http://www.ewea.org/fileadmin/ewea_documents/documents/publications/reports/MeritOrder.pdf>.
[17] Kumar A, Srivastava SC, Singh SN. Congestion management in competitive power market: a bibliographical survey. Electr Power Syst Res 2005;76(1–3):153–64.
[18] Woo CK, Zarnikau J, Moore J, Horowitz I. Wind generation and zonal-market price divergence: evidence from Texas. Energy Policy 2011;39:3928–38.
[19] Chao HP. Efficient pricing and investment in electricity markets with intermittent resources. Energy Policy 2011;39(7):3945–53.
[20] Woo CK, Greening L, Lund H, editors. Demand response resources. Energy; 2010. p. 35.
[21] Vojdani A. Smart integration. IEEE Power Energy Mag 2008;6(6):71–9.
[22] Rahimi F, Ipakchi A. Demand response as a market resource under the smart grid paradigm. IEEE Trans Smart Grid 2010;1(1):82–8.
[23] Moura PS, de Almeida AT. The role of demand-side management in the grid integration of wind power. Appl Energy 2010;87(8):2581–8.
[24] Finn P, Fitzpatrick C, Connolly D, Leahy M, Relihan L. Facilitation of renewable electricity using price based appliance control in Ireland's electricity market. Energy 2011;36(5):2952–60.
[25] Cappers P, Mills A, Goldman C, Wiser R, Eto JH. An assessment of the role mass market demand response could play in contributing to the management of variable generation integration issues. Energy Policy 2012;48:420–9.
[26] Horowitz I, Woo CK. Designing Pareto-superior demand-response rate options. Energy 2006;31(6–7):1040–51.
[27] Woo CK, Kollman E, Orans R, Price S, Horii B. Now that California has AMI, what can the state do with it? Energy Policy 2008;36(4):1366–74.
[28] Faria P, Vale Z. Demand response in electrical energy supply: an optimal real time pricing approach. Energy 2011;36:5374–84.
[29] Moghaddam MP, Abdollahi A, Rashidinejad M. Flexible demand response programs modeling in competitive electricity markets. Appl Energy 2011;88:3257–69.
[30] Aalami HA, Moghaddam MP, Yousefi GR. Demand response modeling considering interruptible/curtailable loads and capacity market programs. Appl Energy 2010;87:243–50.
[31] Ericson Torgeir. Households' self-selection of dynamic electricity tariffs. Appl Energy 2011;88:2541–7.
[32] Ghadikolaei HM, Tajik E, Aghaei J, Charwand M. Integrated day-ahead and hour-ahead operation model of discos in retail electricity markets considering DGs and CO_2 emission penalty cost. Appl Energy 2012;95:174–85.
[33] Valenzuela J, Thimmapuram PR, Kim J. Modeling and simulation of consumer response to dynamic pricing with enabled technologies. Appl Energy 2012;96:122–32.
[34] Venkatesan N, Solanki J, Solanki SK. Residential demand response model and impact on voltage profile and losses of an electric distribution network. Appl Energy 2012;96:84–91.
[35] Rastegar M, Fotuhi-Firuzabad M, Aminifar F. Load commitment in a smart home. Appl Energy 2012;96:45–54.
[36] Di Giorgio A, Pimpinella L. An event driven smart home controller enabling consumer economic saving and automated demand side management. Appl Energy 2012;96:92–103.
[37] Bradley P, Leach M, Torriti J. A review of the costs and benefits of demand response for electricity in the UK. Energy Policy 2013;52:312–27.
[38] Faruqui A, Malko JR. The residential demand for electricity by time-of-use: a survey of twelve experiments with peak load pricing. Energy 1983;8:781–96.
[39] Aigner DJ. The residential electricity time-of-use pricing experiments: what have we learned? In: Hausman JA, Wise DA, editors. Social experimentation. Chicago, Illinois: University of Chicago Press; 1985. p. 11–53.
[40] DOE. Benefits of demand response in electricity markets and recommendations for achieving them. Department of Energy, Washington, DC; 2006. <http://www.oe.energy.gov/DocumentsandMedia/congress_1252d.pdf>.
[41] Newsham GR, Bowker BG. The effect of utility time-varying pricing and load control strategies on residential summer peak electricity use: a review. Energy Policy 2010;38:3289–96.
[42] Faruqui A, Segici S. Household response to dynamic pricing of electricity: a survey of 15 experiments. J Regul Econ 2010;38:193–225.
[43] Faruqui A, Palmer J. The discovery of price responsiveness – a survey of experiments involving dynamic pricing of electricity. Brattle Group; 2012. <http://papers.ssrn.com/sol3/papers.cfm?abstract_id=2020587>.
[44] Faruqui AF, George SS. Demise of PSE's TOU program imparts lessons. Electr Light Power 2003;81(1):14–5.
[45] Hammerstrom DJ. Pacific northwest gridwise testbed demonstration projects, Part I. Olympia Peninsula project. Pacific Northwest National Laboratory; 2007. <http://sites.energetics.com/madri/toolbox/pdfs/pricing/pnnl_2007_pacific_nw_gridwise_olympic_peninsula.pdf>.
[46] Thorsnes P, Williams J, Lawson R. Consumer responses to time varying prices for electricity. Energy Policy 2012;49:552–61.
[47] Wolak FA. An experimental comparison of critical peak and hourly pricing: the PowerCentsDC program. Stanford University; 2010. <http://sedc-coalition.eu/wp-content/uploads/2011/06/Wolak-10-03-15-PowerCentsDC-Paper.pdf>.
[48] Woo CK, Horowitz I, Sulyma IM. Relative kW response to residential time-varying pricing in British Columbia. Working paper available from the first author.
[49] Taylor TN, Schwarz PM, Cochell JE. 24/7 Hourly response to electricity real-time pricing with up to eight summers of experience. J Regul Econ 2005;27(3):235–62.
[50] Zarnikau J, Hallett I. Aggregate industrial energy consumer response to wholesale prices in the restructured Texas electricity market. Energy Econ 2008;30:1798–808.
[51] Faruqui A, Sergici S, Sharif A. The impact of informational feedback on energy consumption – a survey of the experimental evidence. Energy 2010;35:1598–608.
[52] Hartway R, Price S, Woo CK. Smart meter, customer choice and profitable time-of-use rate option. Energy 1999;24:895–903.
[53] Caves DW, Christensen L. Econometric analysis of residential time-of-use rates electricity pricing experiments. J Econometr 1980;14:287–306.

[54] Caves DW, Christensen L, Herriges JA. Consistency of residential customer response in time-of-use electricity experiments. J Econometr 1984;26:179–203.
[55] Parks RW, Weitzel D. Measuring the consumer welfare effects of time-differentiated electricity prices. J Econometr 1984;26:35–64.
[56] Varian HR. Microeconomic analysis. New York, New York: Norton; 1984.
[57] Huber PJ. Robust regression: asymptotics, conjectures, and Monte Carlo. Ann Stat 1973;1:799–821.
[58] SAS, SAS/STAT 9.1 User's guide. SAS Institute Inc., Gary, North Carolina; 2004.
[59] Greene WH. Econometric analysis. Upper Saddle River, New Jersey: Prentice Hall; 2000.
[60] Park RE, Acton JP. Large business customer response to time-of-day electricity rates. J Econometr 1984;26:229–52.
[61] BC Hydro. 2008 Long term acquisition plan [Appendix E]. <http://www.bchydro.com/etc/medialib/internet/documents/info/pdf/2008_ltap_appendix_e.Par.0001.File.2008_ltap_appendix_e.pdf>.