Appendix E: Load Impact and Conservation Effect Analytical Model

Load Impact and Conservation Effect Analytical Model

Ontario Smart Price Pilot

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Abstract

This paper summarizes the analysis performed to assess the effects of dynamic pricing in the Ontario Smart Price Pilot on participant electricity consumption over the experimental period of August 1, 2006 to February 28, 2007. The pilot was for residential customers. Participants were placed on time-of-use prices (TOU) and divided into three sub-sets: TOU only, TOU plus critical peak prices, and TOU plus critical peak rebates. The analysis assessed demand response defined as load shifting away from critical peak hours during critical peak events, demand response defined as load shifting away from all peak hours, and conservation defined as reduction in total usage of electricity for the calendar period. To analyze demand response and conservation, a nonparametric conditional mean estimation framework was used. The framework used customer-level fixed effects and day-of-sample fixed effects. The model estimation results indicate statistically significant reductions in peak usage during critical peak hours in the summer for customers on critical peak pricing plans, in peak usage during all peak hours in the summer, and in total electricity consumption over the seven months of the pilot.

1. Introduction

The Ontario Smart Price Pilot involved 501 residential customers of Hydro Ottawa in Ottawa, Ontario for an experimental period of August 1, 2006 to February 28, 2007. The purposes of the pilot included determining the effects of dynamic pricing on participant electricity consumption over the experimental period of August 1, 2006 to February 28, 2007. The load impact and conservation econometric analysis was performed to assess the following:

1. Demand response via load *shifting* away from *critical peak hours* during critical peak events,
2. Demand response via load *shifting* away from all *peak* hours, and
3. Conservation via *reducing* total usage of electricity for the duration of the pilot, regardless of which hours the electricity was used.

These effects are determined by comparing the electricity consumption behavior of customers receiving the experimental prices (TOU, CPP, and CPR) and the behavior of customers remaining on their existing prices (increasing block tiered prices). These customer groups are the Treatment and Control groups, respectively.

The analytical model used is a nonparametric conditional mean estimation framework. This framework is the most general model one can estimate to recover the impact of a critical peak event, the independent variable in the model. Unlike other pilot results, with this framework, it is hard to think of any omitted variable that is not controlled for that could be causing the results. Additional information is provided under Methodology. Details of the analysis are given in the respective sections below, Demand Response Impacts and Conservation Effects.

During July 2006, a random sample of Hydro Ottawa customers was selected and randomly assigned to three treatment options: TOU, CPP, and CPR prices. The selected customers were then solicited to participate in the experiment. Customers who volunteered to participate were then enrolled, resulting in three groups of approximately 125 customers each for TOU, CPP, and CPR prices. Such customers received monthly energy statements showing their bill amounts for the TOU, CPP, and CPR prices for the electricity commodity (i.e., excluding distribution, transmission, and other charges).

To create the Control group, 125 customers were selected in a stratified random sample from approximately 4,500 customers with smart meters. The stratification ensured that customers with low, medium, and high consumption would be included. The 4,500 customer sample pool from which the control customers were selected included approximately 3,200 customers who had not been solicited to participate and 1,300 customers who had received the pilot solicitation but did not respond for a variety of reasons, including lack of awareness (did not open the solicitation letter), apathy, and conscious decision not to participate.

Table 1 summarizes the results of the analysis. In understanding the results, it is helpful to remember: 1) regarding critical peak usage, that TOU customers were not notified of critical peak events, and 2) regarding peak period usage, that CPP and CPR customers had both critical peak prices/rebates as well as TOU prices. Also note that many of the results are not very precisely estimated; the most robust results are those for reduction in usage during the critical peak hours on critical peak days. Additional analysis details are provided in the subsequent discussion.

Table 1: Demand Response and Conservation Effects

	Change Resulting from Participating in Ontario Smart Pricing Pilot		
Pilot Pricing Group	Critical Peak Usage*	Peak Period Usage*	Total Electric Usage
Time of Use (TOU)	-5.7%	**	-6.0%
Critical Peak Pricing (CPP)	-25.4%	-8.1%	-4.7%***
Critical Peak Rebate (CPR)	-17.5%	-5.2%	-7.4%

* - These results are for summer only (August 1-November 30). Results for the winter period for these variables were not statistically significant.

** - Result not statistically significant.

*** - Result not statistically significant at the 90% level, but nearly so (approximately 88% probability).

While the three treatment groups have been referred to as TOU, CPP, and CPR in this paper, it is important to clarify that the participants subject to CPP and CPR also paid the same TOU prices as the TOU-only group during all non-critical peak event hours. Accordingly, the three price plans for the treatment groups are technically characterized as TOU, CPP(+TOU), and CPR(+TOU).

2. Methodology

The demand response impact and conservation effect analysis used a nonparametric conditional mean estimation framework. The framework uses customer-level fixed effects and day-of-sample fixed effects. The demand response impacts were determined using hourly data for the pilot period of August 2006 through February 2007, while the conservation effect was determined using bi-monthly billing consumption data for the treatment and control customers for the 12 months preceding the pilot in combination with the hourly data during the pilot.

The fixed effects approach uses a separate intercept term for each customer to control for effects that are unique to that customer and constant over the time period being examined. The unique effects of the stable, but unmeasured characteristics of each customer are their "fixed effects" from which this method takes its name. The fixed effects nature of the model means the model does not need to include unchanging customer characteristics such as square footage, number of floors, equipment, etc. Controlling for fixed effects controls the amount of variance (noise) the model is faced with, since each customer has a different base load, a different response to weather, and a different pattern of consumption that changes over time. We are also using time effects, which means that the model controls for all differences in consumption across days in the sample due to temperature, sunshine and any other factors common to all customers for the same day. {{I don't think any of these studies use day-of-sample fixed effects too.}} This approach also provides for a much closer fit to the data than most models, as individual responsiveness is incorporated. This approach has worked well in estimating the impacts of mass-market programs such as the California Statewide Pricing Pilot, the Idaho Power critical peak pricing pilot, and the Sacramento Municipal Utilities District air conditioning direct load control program. Such an approach is also consistent with the recommendations of the California Evaluation Framework prepared for the California Public Utilities Commission.[1]

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[1] - The Framework, a 500-page compendium, was prepared in June 2004 by the team of TecMarket Works, Megdal Associates, Architectural Energy Corporation, RLW Analytics, Resource Insight, B&B

The Framework describes the various regression models available for the type of data in the pilot and highlights the benefit of a more general approach:

> Most regression models are estimated as ordinary least squares (OLS), generalized least squares (GLS), or other forms of maximum likelihood estimation. These methods generally produce similar results under similar circumstances. Generalized least squares, as its name implies, is a more generalized statistical equation. If the error term is normally distributed, both OLS and GLS may be identical to the maximum likelihood estimate (MLE). There are differences in these estimation methods, however, that lead to the decision of which model specification is more appropriate for different circumstances. The more generalized the method, the more it can often be used to correct for different issues. At the same time, it can become more computationally difficult.[2]

The analysis of the pilot could be estimated by GLS but that would not be as robust as the technique used for this pilot. To use technical statistical jargon, we are using OLS with standard errors that are robust to heteroscedasticity and autocorrelation of an unknown form. If we modeled the structure of correlation and used a GLS estimator, we may be able to improve the apparent efficiency of the estimates, but we would be subject to the criticism that our results may be driven by the method we used to correct for autocorrelation and heteroscedasticity, a complaint that cannot be lodged against the results presented here.

Demand Response

To estimate the analysis results for demand response, we use the model

$$y_{(i,t)} = \alpha_i + \lambda_t + \text{Treat}_i\text{*TOU}_t\text{* }\beta 1 + \text{Treat}_i\text{*CPP}_t\text{* }\beta 2 + \text{Treat}_i\text{*CPR}_t\text{* }\beta 3 + \varepsilon_{(i,t)} \qquad [1]$$

where:

Resources, Ken Keating Associates, Ed Vine Associates, American Council for an Energy Efficient Economy, Ralph Prahl Associates, and Innovologie.

2 - TecMarket Works, "The California Evaluation Framework," June 2004, p. 108.

$y_{(i,t)}$ is the natural logarithm of consumption for customer *i* during the peak hours on day *t*,

α_i is the customer-level fixed effects,

λ_t is the day of sample fixed effect,

$Treat_i$ is the dummy variable whether a customer is treatment or control,

TOU_t or CPP_t or CPR_t is the dummy variable indicating whether a day is a critical peak day or not,

β1, 2, 3 is the change in consumption due to the pricing plan for TOU, CPP, and CPR customers, respectively, and

$\varepsilon_{(i,t)}$ is the error term for customer *i* during the peak hours on day *t*.

The estimate of β controls for persistent differences in consumption across customers (the α_i) and persistent differences in consumption across days for all customers (the λ_t). In this way, it isolates the impact of the desired effect only to the treatment group. The day-of-sample fixed effects account for weather, and other common factors impacting all Hydro Ottawa customers during a given day. Thus, claims cannot be made that the load impacts are because it is a hot day or a selected sample was selected, because we control for both of these factors. The statistical error term (the $\varepsilon_{(i,t)}$) is the unexplained variance in hourly electricity consumption for customer *i* during the peak hours on day *t*. The simplicity of the model is its strength: it is the most general model one can estimate to recover the impact of a critical peak day.

<u>Conservation</u>

To estimate the analysis results for conservation, the same approach is used. For this analysis, we use the model

$$y_{(i,t)} = \alpha_i + \delta_t + Treat_i{*}TOU_t{*}\ \beta1 + Treat_i{*}CPP_t{*}\ \beta2 + Treat_i{*}CPR_t{*}\ \beta3 + \varepsilon_{(i,t)} \qquad [2]$$

where:

$y_{(i,t)}$ is the natural logarithm of consumption for customer *i* during the bimonthly billing period for period *t*,

α_i is the customer-level fixed effects,

δ_t is the year of sample fixed effect,

$Treat_i$ is the dummy variable whether a customer is treatment or control,

TOU_t or CPP_t or CPR_t is the dummy variable indicating whether a period is for the previous year or not,

β is change in consumption due to the pricing plan, and

$\varepsilon_{(i,t)}$ is the error term for customer *i* during the bimonthly billing period for period *t*.

The period-of-sample fixed effects account for weather, and other common factors impacting all Hydro Ottawa customers during a given bimonthly period. Thus, claims cannot be made that the conservation effects are because it is a hot day or a selected sample was selected, because we control for both of these factors. The statistic error term (the $\varepsilon_{(i,t)}$) is the unexplained variance in bimonthly energy consumption for customer *i* during the period *t*.

3. Demand Response Impacts

The analysis of demand response characterizes the effects of dynamic pricing on critical peak and peak electricity usage over the experimental period of August 1, 2006 to February 28, 2007. This analysis uses the estimates developed from the models above. Two sets of results were calculated for critical peak reductions: one where all critical peak days are assigned a value of “1” for the dummy variable and a second where critical peak days are assigned a fractional value for the dummy variable, based on the portion of peak hours covered by the critical peak hours. Thus, the interpretation of the coefficients for the second specification assumes the critical peak event was for the entire peak period, whereas the coefficients for the first specification just assume a critical event occurred during the specified critical peak hours. Another set of results was calculated to estimate peak load reductions all weekdays. For these results, the dummy variable was assigned a value of "1" for all weekdays (except holidays), not just critical peak days.

Table 2 uses a CPP day dummy for CPP_t and shows statistically significant – at the 90% confidence level – reductions in peak period consumption of 11.9% and 8.5% for CPP, and CPR customers, respectively. The results for the other pricing periods – mid-peak and off-peak – are not statistically significant.

Table 2: CPP Treatment Effect on Peak Period Consumption
Summer Period (08/01/2006-10/31/2006)

	Natural Log of Peak Consumption in KWh		Natural Log of Mid-Peak Consumption in KWh		Natural Log of Off-Peak Consumption in KWh	
Treatment Group	Coefficient Estimate	Standard Error	Coefficient Estimate	Standard Error	Coefficient Estimate	Standard Error
TOU	-0.0240	0.0447	0.0064	0.0328	-0.0236	0.0306
CPP	**-0.1190**	0.0468	-0.0101	0.0356	-0.0003	0.0280
CPR	**-0.0849**	0.0450	0.0008	0.0327	-0.0040	0.0290

In Table 3, the dummy variable CPP_t is set as the fraction of the entire peak period of the day that the critical peak period covers (only three or four hours of the six-hour peak period for each critical peak day were critical peak hours). Table 3 shows statistically significant reductions in peak period consumption of 25.4%, and 17.5% for CPP and CPR customers, respectively under the assumption that the CPP event occurred for the entire peak period rather than simply fraction of the peak period as was in fact that case for all CPP events.

Table 3: CPP Treatment Effect on Critical Peak Hours Consumption Summer Period (08/01/2006-10/31/2006)						
	Natural Log of Peak Consumption in KWh		Natural Log of Mid-Peak Consumption in KWh		Natural Log of Off-Peak Consumption in KWh	
Treatment Group	Coefficient Estimate	Standard Error	Coefficient Estimate	Standard Error	Coefficient Estimate	Standard Error
TOU	-0.0568	0.0839	0.0054	0.0617	-0.0495	0.0569
CPP	**-0.2542**	0.0875	-0.0345	0.0673	-0.0047	0.0520
CPR	**-0.1745**	0.0842	-0.0058	0.0621	-0.0167	0.0538

Tables 4 and 5 use data for the winter period to estimate the same models as above. In this case, only four results are significant – and all are counterintuitive, i.e., opposite of the expected effect of higher or lower electricity prices.

Table 4: CPP Treatment Effect on Peak Period Consumption Winter Period (11/01/2006-02/28/2007)						
	Natural Log of Peak Consumption in KWh		Natural Log of Mid-Peak Consumption in KWh		Natural Log of Off-Peak Consumption in KWh	
Treatment Group	Coefficient Estimate	Standard Error	Coefficient Estimate	Standard Error	Coefficient Estimate	Standard Error
TOU	**0.0610**	0.03322	**0.0449**	0.0341	-0.0103	0.0316
CPP	-0.0335	0.0331	-0.0090	0.0333	-0.0390	0.0321
CPR	-0.0083	0.0318	0.0005	0.0323	-0.0352	0.0321

Table 5: CPP Treatment Effect on Critical Peak Hours Consumption Winter Period (11/01/2006-02/28/2007)						
	Natural Log of Peak Consumption in KWh		Natural Log of Mid-Peak Consumption in KWh		Natural Log of Off-Peak Consumption in KWh	
Treatment Group	Coefficient Estimate	Standard Error	Coefficient Estimate	Standard Error	Coefficient Estimate	Standard Error
TOU	**0.1145**	0.0682	0.0881	0.0708	-0.0246	0.0653
CPP	-0.0725	0.0680	-0.0285	0.0690	**-0.0855**	0.0662
CPR	-0.0259	0.0655	-0.0035	0.0674	-0.0774	0.0660

Table 6 provides an estimate of load shifting away from the on-peak period for CPP days over the entire pilot period from August 1, 2006 to February 28, 2007. These results show statistically significant reductions in peak period consumption of 8.1% and 5.2% for CPP and CPR customers during CPP days, respectively. The results for the TOU customers are not statistically significant.

Table 6: Load Shifting on All Critical Peak Days for Full Pilot Period (8/01/2006-2/28/2007)		
	Natural Log of Peak Load Consumption in KWh	
Variable Name	Coefficient Estimate	Standard Error
TOU*CP(t)	0.0108	0.0267
CPP*CP(t)	**-0.0812**	0.0279
CPR*CP(t)	**-0.0518**	0.0278

Table 7 shows the model estimates of load shifting away from the on-peak period for each of the seven critical peak days, individually.

Table 7: Load Shifting on Individual Critical Peak Days for Full Pilot Period (8/01/2006-2/28/2007)			
	Natural Log of Peak Load Consumption in KWh		
Critical Peak Day	Coefficient Estimate	Standard Error	T statistic
1	**-0.2769**	0.0859	-3.22
2	**-0.1011**	0.0728	-1.39
3	-0.0281	0.0596	-0.47
4	-0.0307	0.0680	-0.45
5	**0.0724**	0.0431	1.68
6	0.0451	0.0454	0.99
7	0.004	0.0465	0.09

Table 8 shows the model estimates of load shifting away from the on-peak period for all non-holiday weekdays over the entire pilot period from August 1, 2006 to February 28, 2007. Only the result for CPP is significant – and counterintuitive.

Table 8: Load Shifting on All Non-Holiday Weekdays for Full Pilot Period (8/01/2006-2/28/2007)		
	Natural Log of Peak Load Consumption in KWh	
Variable Name	Coefficient Estimate	Standard Error
TOU*Experiment(t)	0.0030	0.0766
CPP*Experiment(t)	**0.1075**	0.0715
CPR*Experiment(t)	0.0730	0.0714

4. Conservation Effect

In addition to estimating load shifting away from the critical peak hours, the load impact analysis estimated the conservation effect associated with the program. “Conservation” is defined as a reduction in total electricity consumption, regardless of when the electricity is used.

While a main purpose of time-of-use and critical peak pricing is to reduce peak demand via the shifting of consumption, these programs typically result in a small reduction in total electricity consumption (or a “conservation effect”) as well. There are three reasons a reduction often occurs. First, higher peak or critical peak prices induce load reductions during peak hours, not all of which is shifted to other times. Some reductions are uses that are shifted to other time periods, such as laundry for a residence or a production process for a business. In these cases, the usage is “recovered” at other times. Other reductions, such as lower lighting, are not recovered, as there is no reason for it. Second, dynamic pricing programs cause participants to have a higher awareness of how they use electricity, which, in turn, results in lower consumption. Third, these programs usually increase the amount of usage information, or feedback, received by the customer, also lowering consumption.

As described above, the basic methodology for assessing the conservation effect was the same as that used for load shifting. Again, a nonparametric conditional mean estimation framework was used. The framework used customer-level fixed effects, time effects, and a “2006” fixed effect, where “2006” denotes the customer’s usage in the year-earlier period in either 2005 or 2006. Specifically, usage from August 2006 through December 2006 is compared with usage from August 2005 through December 2005, and usage from January through February 2007 is compared with usage from January through February 2006.

The key difference from the load shifting analysis is that the conservation analysis utilized previous period billing data for pilot customers. The reason is that too little of the necessary data was available from smart meters, because the conservation analysis requires comparing the usage of the control and treatment groups before and after being placed on the pilot prices. Specifically, the analysis compares the usage of the two groups (technically four, since the treatment customers were on three different price plans) before the pilot, then after going on the pilot. By comparing the differences between the groups for the pre-experimental period with the experimental period, the conservation effect is revealed.

Table 9 provides an estimate of the total reduction in electricity consumption caused by a customer's being on the pricing pilot. These results show conservation of 6.0%, 4.7%, and 7.4% for TOU, CPP, and CPR customers, respectively; the average is 6.0%. All of the results are fairly precisely estimated.

Table 9: Conservation Effect (Total Usage Reduction)
Full Pilot Period (8/01/2006-2/28/2007)

	Natural Log of Peak Load Consumption in KWh		
Treatment Group	Coefficient Estimate	Standard Error	T statistic
TOU	**-0.0598**	0.0382	-1.57
CPP	-0.0472*	0.0386	-1.22
CPR	**-0.0742**	0.0388	-1.91

* - Probability level approximately 88%.