The Impact of Dynamic Pricing on Residential and Small Commercial and Industrial Usage: New Experimental Evidence from Connecticut

Ahmad Faruqui, Sanem Sergici**, and Lamine Akaba****

ABSTRACT

Among U.S. households, a quarter have smart meters but only one percent are on any form of dynamic pricing. Commissions and utilities continue to study the potential benefits of dynamic pricing through experimentation but most of it involves the residential sector. We add to that body of knowledge by presenting the results of a pilot in Connecticut which included small commercial and industrial (C&I) customers in addition to residential customers. The pilot featured a time-of-use rate, two dynamic pricing rates and four enabling technologies. Customers were randomly selected and allocated to these rates, to ensure representativeness of the final results. The experiment included a total of around 2,200 customers and ran during the summer of 2009. Using a constant elasticity of substitution model, we find that customers do respond to dynamic pricing, a finding that matches that from most other experiments. We also find that response to critical-peak pricing rates is higher than response to peak-time rebates, unlike some other experiments where similar results were found. Like many other pilots, we find that there is virtually no response to TOU rates with an eight hour peak period. And like the few pilots that have compared small C&I customer response to residential response, we find that small C&I customers are less price responsive than residential customers. We also find that some enabling technologies boost price responsiveness but that the Energy Orb does not.

Keywords: Dynamic Pricing, Impact Evaluation, Time-of-Use Rates, Critical-Peak Pricing, Peak Time Rebates, Enabling Technologies, Residential Customers, Small Commercial and Industrial (C&I) Customers, Elasticity of Substitution

http://dx.doi.org/10.5547/01956574.35.1.8

1. INTRODUCTION

1.1 Overview of the Issues

Electricity cannot be stored economically in large quantities, and has to be consumed instantly on demand. The load duration curve for most utility systems is very peaky, with some eight to eighteen percent of annual peak load being concentrated in the top one percent of the hours

* Corresponding author. *The Brattle Group*, 201 Mission Street, Suite 2800, San Francisco, CA 94105, USA. E-mail: Ahmad.Faruqui@Brattle.com.

** *The Brattle Group*, 44 Brattle Street, Cambridge, MA 02138, USA.

*** *The Brattle Group*, 201 Mission Street, Suite 2800, San Francisco, CA 94105, USA.

of the year. These two factors, taken in conjunction with the time-variation in marginal energy and capacity costs that characterizes different generation technologies, mean that the optimal way for pricing electricity is to institute time-varying rates.[1] Not only would this increase economic efficiency, it would also eliminate inter-customer cross-subsidies that are embedded in flat rates.[2] Of course, dynamic pricing can only be carried out once smart meters are in place. As of this writing, about a quarter of U.S. households are on smart meters and the number is projected to rise by the end of the decade to nearly a hundred percent. However, only one percent of the households are on any type of time-varying rate and only one percent of that one percent are on any form of dynamic pricing rate (Federal Energy Regulatory Commission (2012)). Commissions and utilities continue to study the potential rollout of dynamic pricing. Well-designed experiments in which customers are randomly placed on different rates provide an important avenue for gaining insights into the likely impact of those rates.[3]

1.2 A New Experiment in the New England Region

The extant literature discusses experiments with dynamic pricing that have been carried out in Australia, Europe, North America and New Zealand during the past decade. However, most of them have been located in regions with hot and humid summers such as the District of Columbia, Florida, Illinois, Maryland, Michigan and Oklahoma.[4]

It is uncertain whether the results observed in these pilots would apply to regions with milder climates, such as New England, where the saturation of central air conditioning (CAC) systems is under 30 percent. An earlier experiment, carried out in California in the 2003–04 time frame, found that customer response in the mildest climate zone (the coastal regions and mountains) was less than half the size of response in the strongest climate zone (the central valley) (Charles River Associates (2005)).[5]

This paper presents an impact evaluation of a dynamic pricing pilot that was carried out in New England by the Connecticut Light & Power Company (CL&P). Called the Plan-It Wise Energy Pilot (PWEP), it was designed to test if time-varying pricing could lower future power costs by curtailing peak demands during critical periods or by shifting them to other periods.

Although other dynamic pricing pilots had published their findings prior to the execution of the PWEP, they had been carried out in different geographies and it was not clear whether the results from these pilots would be transferable to New England, given differences in socio-demographic and climatic conditions (Faruqui and Sergici (2009) and Faruqui and Sergici (2011)). The

1. For a survey, see Crew, Fernando and Kleindorfer (1995). A case for dynamic (as opposed to static) time-varying rates was provided by Vickrey (1971). Chao (1983) introduced uncertainty into the analysis. Littlechild (2003) considered the consequences of passing through wholesale costs to retail customers. Borenstein (2005) compared the efficiency gains of dynamic and static time-varying rates.

2. Faruqui (2010) discusses the ethics of cross-subsidies.

3. A framework for carrying out a cost-benefit analysis is illustrated with four hypothetical case studies in Faruqui et al. (2011). Additional details on how to assess the benefits of dynamic pricing can be found in Faruqui and Wood (2008).

4. Wolak (2011) discusses the D.C. pilot, Allcott (2011) discusses the Illinois pilot, Faruqui and Sergici (2011) discuss the Maryland pilot, Faruqui, Sergici and Akaba (2012) discuss the Michigan pilot, and Faruqui, Hanser, Hledik and Palmer (2010), Newsham and Bowker (2010) and Rowlands and Furst (2011) discuss various pilots that have been carried out in Ontario, Canada. For a bibliography on dynamic pricing and time-of-use rates, please see Enright and Faruqui (2013).

5. The impact in the mildest zone was estimated at 8 percent versus 17 percent in the strongest climate zone. http://sites.energetics.com/madri/toolbox/pdfs/pricing/cra_2005_impact_eval_ca_pricing_pilot.pdf. Additional results from this pilot can be found in Herter (2007) and Herter, McAuliffe and Rosenfield (2007).

PWEP was intended to provide results that would support the execution of a cost-benefit analysis of advanced metering infrastructure (AMI).

Unlike other pilots, which only included residential customers, the PWEP also included small C&I customers. Around 2,200 customers were included in the experiment, equally divided between the residential and small C&I classes. The pilot featured three rate designs: critical-peak pricing (CPP), peak-time rebates (PTR) and standard time-of-use (TOU) rates. Low and high values of each rate design were included in PWEP to allow precise estimation of price elasticities. Each variant was designed to be revenue neutral for the class as a whole relative to the existing tariffs. The time-varying rates were also tested with and without enabling technologies. Four types of technologies were considered in the PWEP: In-Home Displays which show how much electricity is being used at different times of day and the associated cost, the Energy Orb which changes color as prices change, a Smart Thermostat that raises the temperature setting as prices rise and a switch to cycle the compressor unit of central air conditioning systems during critical peak hours.

The pilot ran from June 1, 2009 through September 30, 2009. Ten critical peak days were called during June, July and August. Hourly usage was recorded for both the treatment and the control customers during the pilot period to determine if the treatment group used less electricity during the more expensive periods. In addition, to assess for any pre-existing difference in the groups, hourly usage was also recorded during a pre-pilot phase. Econometrically, a difference-in-differences estimation procedure was applied to an unbalanced panel for estimating the treatment effects.

The PWEP, formulated as a scientific experiment, was designed to test five major hypotheses: (1) Do customers exhibit similar price responsiveness (as measured by elasticities of substitution) to the CPP, PTR and TOU tariffs? (2) Are the enabling technologies employed in the pilot effective in increasing customers' price responsiveness? (3) Does dynamic pricing elicit lower response in a mild climate compared to a warmer climate?[6] (4) Do customers respond to longer peak windows? And (5) Do the residential and small C&I customers respond differently to price signals?

Section 2 of this paper describes the experimental design of the PWEP. Section 3 summarizes the analytical methods and data used in the estimation of the load impacts. Section 4 reports on the empirical findings and Section 5 concludes the paper.

2. PWEP EXPERIMENTAL DESIGN

2.1 Rate Design

CL&P's standard rate is a flat, seasonal, volumetric rate that includes a fixed customer charge. During the PWEP period, the control group customers paid the standard rate which, on an all-in basis, amounts to $0.201/kWh for residential customers and $0.203/kWh for small C&I customers. These rates applied to all customers in those classes, regardless of their load profile.

The treatment customers were placed on one of the three following rate designs which included low and high rate variations. Under the *Critical Peak Pricing (CPP)* rate design, the hours between 2 pm through 6 pm on non-holiday weekdays were designated as the peak period and were priced between $0.17/kWh and $0.19/kWh for residential customers and between $0.15/kWh and

6. Our comparisons across different climates are only qualitative in nature as we do not make an effort to control for other differences in the pilot designs.

$0.19/kWh for small C&I customers. On the ten critical peak days that were called on a day-ahead basis, the peak hours would become the critical peak hours and be priced between $0.86/kWh and $1.82/kWh for residential customers and between $0.86/kWh and $1.80/kWh for small C&I customers. On non-critical weekdays and weekends, the treatment customers faced an off-peak price between $0.17/kWh and $0.19/kWh for residential customers and between $0.15/kWh and $0.18/kWh for small C&I customers, respectively. The rates were designed so that customers whose load profiles corresponded to the load profile of their class would see no change in their bills, in the absence of load shifting. Thus the off-peak price was lower than the standard tariff.

Under the *Peak Time Rebate (PTR)* rate design, the PWEP participants were still subject to the standard CL&P rates. However, on the ten critical peak days, between the hours of 2 pm and 6 pm, they had the opportunity to receive a rebate between $0.78/kWh ($0.86 all-in rate) and $1.74/kWh ($1.82 all-in rate) for residential customers and between $0.78/kWh ($0.86 all-in rate) and $1.73/kWh ($0.80 all-in rate) for small C&I customers, if they reduced their consumption below their typical usage during these hours.

Finally, under the *Time-of-Use (TOU)* rate design, the hours between 12 pm through 8 pm on non-holiday weekdays and on critical days were designated as the peak period and were priced, for both the residential customers and small C&I customers, between $0.27/kWh and $0.34/kWh. All the remaining hours were designated as the off-peak period and priced between $0.14/kWh and $0.17/kWh. Additional details on these rates are presented in the Appendix 1.

2.2 Technology

The PWEP program also tested the effectiveness of enabling technologies in facilitating demand response when offered in conjunction with dynamic rates. In order to distinguish the impacts of enabling technologies from that of prices alone, each rate design was tested with and without enabling technologies.

The PWEP involved four types of technologies: In-Home Displays, Energy Orb, Smart Thermostat and a Control Switch to cycle the CAC compressor. The In-Home Display provided real-time electricity usage and cost information. This was intended to enable customers to lower peak usage and/or shift it to off-peak hours. The Energy Orb, a small sphere, emitted different colors to notify participants of changes in electricity prices. The Smart Thermostat allowed CL&P to adjust the “normal” central air conditioner temperature setting during peak demand periods. And the Control Switch, placed on the compressor of the CAC, enabled CL&P to cycle the compressor of the central air conditioner during peak hours. Of course, the smart thermostat and the control switch required the customer to have a central air conditioner and were not applicable to those customers who did not have central air conditioners. A combination of three time-varying rate designs and four different technologies yielded a rich tableau of 44 treatment cells.

2.3 Sample Design

The PWEP featured 1,251 residential customers of which 1,114 customers were the program participants and constituted the treatment group while 137 customers constituted the control group. The pilot also featured 1,186 small C&I customers which 1,123 participants and 63 participants made up the treatment and the control groups, respectively. CL&P identified a random sample of customers that represent the residential and small C&I customer population, and recruited the participants through direct mailing and follow-up phone calls from this sample. During the recruitment process, CL&P mailed invitations to randomly selected customers inviting them to join the

Table 1: The PWEP Sample Design: Number of Customers by Program Cell and Class

Residential

	PTP HI	PTP LO	PTR HI	PTR LO	TOU HI	TOU LO	Treatment Group	Control Group	TOTAL
TOTAL	**183**	**188**	**189**	**193**	**183**	**178**	**1,114**	**137**	**1,251**
NO TECH	**98**	**104**	**100**	**108**	**90**	**98**	**598**	**0**	**598**
TECH	**85**	**84**	**89**	**85**	**93**	**80**	**516**	**0**	**516**
*ORB & IHD**	*43*	*48*	*43*	*44*	*66*	*63*	*307*	*0*	*307*
*Thermostat & Switch***	*42*	*36*	*46*	*41*	*27*	*17*	*209*	*0*	*209*

Notes:
** IHD applies to TOU rate only.*
*** Switch does not apply to TOU rate.*

C&I

	PTP HI	PTP LO	PTR HI	PTR LO	TOU HI	TOU LO	Treatment Group	Control Group	TOTAL
TOTAL	**176**	**185**	**197**	**185**	**185**	**195**	**1,123**	**63**	**1,186**
NO TECH	**93**	**97**	**102**	**98**	**93**	**100**	**583**	**0**	**583**
TECH	**83**	**88**	**95**	**87**	**92**	**95**	**540**	**0**	**540**
ORB	*56*	*52*	*57*	*57*	*92*	*95*	*409*	*0*	*409*
*Thermostat & Switch**	*27*	*36*	*38*	*30*	*0*	*0*	*131*	*0*	*131*

Notes:
** Switch does not apply to TOU rate.*

pilot in a specific treatment. The customers who received the mailings could contact CL&P's hot line by email or telephone to confirm their participation. CL&P also used outbound calls to contact customers who did not respond. Ample information was provided in the mailing to clearly describe the pilot. The mailing described the type of rate design and/or enabling technology to each invitee. The letter offered selected customers a specific treatment and did not mention any other rates. To ensure a high response rate to the sociodemographic survey instrument, residential customers were offered $25 upon enrollment. They were also offered an appreciation payment of $75 if they stayed on the treatment through the end of the pilot.

CL&P constructed the control group from its load research sample. It is important to note that the control group customers were not aware of their involvement in the PWEP. These customers were intended to serve as a proxy for the behavior of the treatment group customers and to help define conditions in the "but-for" world.

Table 1 shows the distribution of the treatment and the control customers into different program cells as of August 2009.

In order to verify that the treatment and control group customers were comparable, and mitigate self- selection bias, we compared the pre-treatment period usages and socio-demographic and appliance characteristics between the two groups.

Based on Table 2, the control group was found to be slightly larger than the treatment group in terms of mean and median average daily load in the pre-treatment period. The differences in the sizes were accounted for by the inclusion of fixed effect terms and the difference-in-differences terms in the regression analysis. In order to assess whether the difference in the sizes is indicative of other differences between treatment and control group customers, we also compared the survey responses of the control and treatment customers. We found that they were comparable in many aspects including CAC saturation, education, attitudes towards greenness, and total in-

Table 2: Load Distribution Comparison-Control vs. Treatment

Percentiles Summary of Average Daily Load, Residential Control versus Treatment

Control

	Percentiles	*Smallest*		
1%	5.3	3.8		
5%	6.0	5.3		
10%	7.9	5.3	*Obs*	137
25%	14.3	5.4	*Sum of Wgt.*	137
50%	20.8		*Mean*	24.8
		Largest	*Std. Dev.*	15.6
75%	31.8	67.4		
90%	46.7	68.3	*Variance*	243.7
95%	59.1	73.4	*Skewness*	1.3
99%	73.4	80.5	*Kurtosis*	4.6

Treatment

	Percentiles	*Smallest*		
1%	1.7	0.0		
5%	4.2	0.2		
10%	6.1	0.2	*Obs*	1,114
25%	10.3	0.3	*Sum of Wgt.*	1,114
50%	17.8		*Mean*	21.0
		Largest	*Std. Dev.*	14.7
75%	27.1	85.2		
90%	39.8	90.2	*Variance*	216.4
95%	48.6	98.2	*Skewness*	1.6
99%	75.5	115.5	*Kurtosis*	7.0

come.[7] These two pieces of information, when viewed together, assure us that the treatment and control group customers were comparable in the pre-treatment period.

We believe that this sample design, which features separate but random recruitment of customers into specific treatment groups and into the control group allows robust conclusions to be derived that have both internal and external validity. An alternative design, which is being widely recommended in the DOE-funded customer behavior pilots, recruits customers randomly into a pool of experimental participants. Most of them are later allocated randomly to specific treatment groups while some are denied treatment all together and allocated to the control group. This "recruit and deny" design may be judged to be superior to the PWEP design in terms of internal validity since it ensures that the treatment and control groups customers are matched not only in terms of observable characteristics but also the unobservable characteristics. However, it may have less external validity since is unclear how representative this design is of the population at large for the simple reason that some people may not elect to join the pilot in the first place, knowing neither whether they would be given or denied a treatment and knowing neither what treatment they would be given, should they be given one.

7. On the advice of a referee, to eliminate any lingering concerns about our results being contaminated with self-selection bias, we have included the results in Appendix 2.

2.4 Customer Communication

CL&P called ten critical peak days between the months of June and August. The pilot participants were notified of the critical peak days on a day-ahead basis through one or more of the following options: telephone messages, e-mail communication, and SMS text messages. In addition, customers with the Energy Orb also received information through that channel.

3. DATA AND METHODOLOGY

3.1 Data

CL&P metered the *hourly usage* of the treatment and control group customers both before and during the pilot period. The data compilation yielded two datasets from May to August: A residential data set involving 1,251 customers and a small C&I data set consisting of 1,186 customers.

Price series that entered into the estimation process were first converted to all-in prices in order to reflect the sum total of transmission, distribution, generation, and other customer charges. We used the following procedures to integrate different price structures in our dataset. First, the *standard all-in rates* were matched to the control group customers in the pre-treatment as well as the treatment periods. They were also matched to the treatment customers in the pre-treatment period since the pilot rates were not yet in effect. Second, the *CPP all-in rates* were converted into all-in rates and matched to the CPP customers making sure that off-peak, peak, and critical peak prices corresponded to the hours in the definition of the CPP program. Next, the *PTR all-in rates* were converted into all-in rates and matched to the PTR customers during the critical peak hours. It is important to note that we summed up the rebate component with the all-in standard rate to obtain the all-in PTR rate. We conjecture that an additional kWh of consumption means foregoing the rebate amount and, therefore, constitutes an opportunity cost for the customer. Finally, the *TOU all-in rates* were converted into all-in rates and matched to the TOU customers making sure that the off-peak and peak prices correspond to the hours in the definition of the TOU program.

We also used two hourly weather variables, dry bulb temperature and dew point temperature, to create a temperature-humidity index (THI) variable. THI is a standard index to measure the discomfort level and widely used in the industry mostly in the context of load forecasting and weather normalization.

The hourly load, price, and weather data for each of the customers in the sample formed an unbalanced panel as well as the basis for estimating the demand models.

3.2 Demand Model

We first specified electricity demand models that represent the electricity consumption behavior of the CL&P customers. Second, we used panel data econometrics to estimate and parameterize the models. Finally, we simulated the impact of the treatments that were deployed in the pilot as well as intermediate treatments that could be deployed in the post-pilot phase.

We used the demand models to estimate the demand response impacts of each PWEP pricing option, as opposed to alternative methods such as the analysis of variance and covariance because they allow for the estimation of demand curves and price elasticities. This capability is vital to being able to estimate the impact of prices other than those used in the pilot.

We employed a widely used model, the constant elasticity of substitution (CES) model, to estimate customer demand curves for electricity by time period and also used the CES model to derive the peak to off-peak substitution and daily price elasticities. The model merits some discussion. Data in electricity pricing studies that involve individual customers, whether experimental or otherwise, is limited to repeated observations of electricity consumption and prices by period. Thus, if the analyst wishes to estimate demand functions that are consistent with the theory of utility maximization, he or she is forced to assume a two-stage budgeting process on the consumer's part. Often, this means invoking the assumption of homothetic separability in consumer preferences, which posits inter alia that the ratio of peak to off-peak consumption does not depend on the amount being spent on electricity. The CES model allows the elasticity of substitution to take on any value and it has been found to be well-suited to the TOU pricing studies involving electricity.

For a two-period rate structure, the CES model consists of two equations. The first equation models the ratio of the log of peak to off-peak quantities as a function of the ratio of the log of peak to off-peak prices and other terms, and the second equation models the average daily electricity consumption as a function of the daily price of electricity. The two equations constitute a system for predicting electricity consumption by time period where the first equation essentially predicts the changes in the load shape caused by changing peak to off-peak price ratios and the second equation predicts the changes in the level of daily electricity consumption caused by changing the average daily electricity price.

3.3 Econometric Estimation

We used a "fixed-effects" estimation routine to estimate the CES demand system. Fixed effects estimation uses a data transformation method that removes any unobserved time-invariant effect that has a potential impact on the dependent variable. By estimating a fixed effects model, we effectively controlled for all customer specific characteristics that don't vary over time and isolate their impact on the dependent variable. Fixed-effects estimation routine controls for the unobserved time-invariant variables that are likely to impact the dependent variable.[8] However, there are also several observed variables that may affect the level of the dependent variable and, therefore, needed to be explicitly controlled for in the model. We discuss these variables and more generally the econometric specifications of the substitution and the daily demand equations below:

***Substitution Demand Equation*.** This equation captures the ability of customers to substitute relatively inexpensive off-peak consumption for relative expensive peak consumption. It is true that the decision to substitute between peak and off-peak periods is mainly affected by the relative prices between these two periods. However, the relative weather conditions between the periods should also be factored in the analysis because weather has a strong influence on load. Keeping everything else constant, the average peak load is greater than the average off-peak load on a hot summer day, because the average peak temperature is higher than the average off-peak temperature, which leads to more cooling during the peak period. In the New England region, humidity augments the effect of temperature. In order to capture the impact of temperature and humidity on the electricity load, we created a variable called the "temperature-humidity index (THI)" (sometimes called the discomfort index). The variable is a weighted average of the dry bulb temperature (air temperature shielded

8. We have also clustered the standard errors at the individual customer level.

from moisture) and the dew point temperature (a measure of relative humidity) and is computed as follows:

$$\text{THI} = 0.55 \times \text{Drybulb Temperature} + 0.20 \times \text{Dewpoint Temperature} + 17.5$$

The substitution equation takes the following functional form:

$$\begin{aligned}
\ln\left(\frac{Peak_kWh}{OffPeak_kWh}\right)_{it} &= \alpha_0 + \alpha_1 THI_DIFF_t + \sum_{k=1}^{3}\delta_k(THI_DIFF_t xD_Month_k) \\
&+ \alpha_3 \ln\left(\frac{Peak_Price}{OffPeak_Price}\right)_{it} xTHI_DIFF_t + \alpha_4 \ln\left(\frac{Peak_Price}{OffPeak_Price}\right)_{it} xTHI_DIFFxPTR_i \\
&+ \alpha_5 \ln\left(\frac{Peak_Price}{OffPeak_Price}\right)_{it} xTHI_DIFFxORB_i + \alpha_6 \ln\left(\frac{Peak_Price}{OffPeak_Price}\right)_{it} xTHI_DIFFxET_i \\
&+ \alpha_7 D_TreatPeriod_t + \alpha_8 D_TreatPeriod_t xTreatCustomer_i + \sum_{k=1}^{3}\beta_k D_Month_k \\
&+ \alpha_{10} D_WEEKEND_t + v_i + u_{it}
\end{aligned}$$

where:

$\ln\left(\frac{Peak\_kWh}{OffPeak\_kWh}\right)_{it}$: Logarithm of the ratio of peak to off-peak load for a given day.

THI_DIFF_t : The difference between average peak and average off-peak THI.

$THI\_DIFF_t xD\_Month_k$: Interaction of THI_DIFF variable with monthly dummies.

$\ln\left(\frac{Peak\_Price}{OffPeak\_Price}\right)_{it} xTHI\_DIFF_t$: Interaction of $\ln\left(\frac{Peak\_kWh}{OffPeak\_kWh}\right)_{it}$ and THI_DIFF.

$\ln\left(\frac{Peak\_Price}{OffPeak\_Price}\right)_{it} xTHI\_DIFFxPTR_t$: Interaction of $\ln\left(\frac{Peak\_kWh}{OffPeak\_kWh}\right)_{it}$, THI_DIFF and PTR. (applies to CPP/PTR regressions; the term is omitted for the TOU regression).
PTR: is equal to 1 for a PTR customer, 0 otherwise.

$\ln\left(\frac{Peak\_kWh}{OffPeak\_kWh}\right)_{it}$: Interaction of $\ln\left(\frac{Peak\_kWh}{OffPeak\_kWh}\right)_{it}$, THI_DIFF and *ORB*
ORB: is equal to 1 if the customer has an Energy Orb but no A/C Switch or thermostat.

$\ln\left(\frac{Peak\_kWh}{OffPeak\_kWh}\right)_{it}$: Interaction of $\ln\left(\frac{Peak\_kWh}{OffPeak\_kWh}\right)_{it}$, THI_DIFF and ET.
ET: is equal to 1 if the customer has a thermostat or an A/C Switch.

$D\_TreatPeriod_t$	: Dummy variable is equal to 1 when the period is June 2009 through August 31, 2009.
$D\_TreatCustomer_i$	: is equal to 1 for the treatment customers.
$D\_TreatPeriod_t xTreatCustomer_i$	: Interaction $D\_TreatPeriod_t$ of with $D\_TreatCustomer_i$
D_Month_k	: Dummy variable that is equal to 1 when the month is k.
$D\_WEEKEND_t$	: Dummy variable that is equal to 1 on weekends.
v_i	: Time invariant fixed effects for customers.
u_{it}	: Normally distributed error term.

It is important to note that the substitution equation was estimated using data on both the treatment and the control customers before and during the pilot period. This type of database allows one to isolate the true impact of the experiment by controlling for any potential biases due to: (i) differences between control and treatment customers in the pre-treatment period; (ii) any changes in the consumption behavior of the treatment customers between the pre-treatment and the treatment periods that are not related to the treatment *per se* (Faruqui, Hledik and Sergici (2009)). These potential confounding factors are controlled for by introducing dummy variables pertaining to the customer type and the analysis period.

This equation was estimated to determine the substitution elasticity of the pilot customers. The *substitution elasticity* indicates the percent change in the ratio of peak to off-peak consumption due to a one percent change in the ratio of peak to off-peak prices.

A priori, we hypothesize that the substitution elasticity will increase in absolute terms with weather. To capture this behavior, we interacted the price ratio and the weather term in the model.[9] We also found that the substitution elasticities differ for customers with and without the enabling technologies. We introduced the interaction terms between the price ratios and dummy variables for the enabling technologies to capture the incremental impact of these technologies on the price responsiveness of the customers. Finally, we found that the substitution elasticities differ for the TOU, the CPP and the PTR customers. We introduced an interaction term between the price ratio and PTR customer dummy variable to identify the incremental effect of PTR, above and beyond that of CPP. We estimated a separate model for the TOU customers as the peak period is eight hours long compared to four hours long for the CPP and PTR customers. Also, the dummy variable "ORB" refers to the IHD technology in the TOU regressions as the IHD technology is only applicable to the TOU customers. The estimation results for the substitution demand model are provided in Table 3.

Daily Demand Equation. The daily demand equation captures the change in the average daily consumption due to the changes in the average daily price. We use the following specification:

9. Ideally, we would fully specify the model to include the variables in linear and non-linear forms to capture the direct effect of the price ratio term and the interaction effect of the price ratio term with weather. However, the correlation matrix revealed that most pairs of variables were highly correlated and it became empirically infeasible to estimate the fully specified model. For reference purposes, on the advice of a referee, we have included the model results with both linear and non-linear terms in Appendix 3.

Table 3: Substitution Demand Equations, by Class and Rate Design

Substitution Equation
Dependent Variable: ln (peak_kwh/offpeak_kwh)

	RESIDENTIAL		SMALL C&I	
VARIABLES	**TOU & Control RESID**	**CPP/PTR & Control RESID**	**TOU & Control C&I**	**CPP/PTR & Control C&I**
thi_diff	−0.002	0.001	0.006**	0.004**
	(0.199)	(0.353)	(0.000)	(0.001)
thi_diffxjune	0.002	0.000	−0.005	0.003
	(0.357)	(0.877)	(0.155)	(0.052)
thi_diffxjuly	0.011**	0.009**	−0.005	0.004*
	(0.000)	(0.000)	(0.215)	(0.022)
thi_diffxaug	0.017**	0.009**	0.006	0.011**
	(0.000)	(0.000)	(0.072)	(0.000)
TreatCustomerxTreatPeriod	−0.077**	−0.067**	−0.051*	0.031
	(0.000)	(0.000)	(0.042)	(0.215)
ln_price_ratioxthi_diff	−0.010*	−0.017**	0.006	−0.003*
	(0.016)	(0.000)	(0.259)	(0.032)
ln_price_ratioxthi_diff_PTR		0.006*		0.003*
		(0.024)		(0.048)
ln_price_ratioxthi_diff_ORB	0.005	0.006	0.009	0.002
	(0.376)	(0.057)	(0.177)	(0.387)
ln_price_ratioxthi_diff_TECH	−0.006	−0.010**	0.000	−0.005*
	(0.466)	(0.009)	(.)	(0.044)
june	0.050**	0.079**	0.069**	−0.003
	(0.006)	(0.000)	(0.004)	(0.911)
july	0.022	0.062**	0.084**	0.014
	(0.289)	(0.001)	(0.000)	(0.599)
aug	0.023	0.016	0.037	−0.030
	(0.261)	(0.399)	(0.112)	(0.266)
weekend	0.073**	0.085**	−0.259**	−0.326**
	(0.000)	(0.000)	(0.000)	(0.000)
Constant	0.099**	−0.009	0.293**	0.280**
	(0.000)	(0.328)	(0.000)	(0.000)
Observations	59669	102384	52692	96555
R-squared	0.012	0.013	0.071	0.097
Number of customer	498	890	440	799

Robust p-values in parentheses
** $p<0.01$, * $p<0.05$
Note: The reported R-squareds do not include the explanatory power of the customer fixed effects. When the explanatory power of the fixed effects is included, the adjusted R-squareds are around 0.2 for residential regressions and 0.6 for commercial regressions.
TreatCustomer variable drops from the regression due to fixed effects estimation. TreatmentPeriod variable also drops due to collinearity.

$$
\begin{aligned}
\ln(kWh)_{it} = {} & \alpha_0 + \alpha_1 \ln(THI)_t + \sum_{k=1}^{3} \delta_k (\ln(THI)_t xD\_Month_k) + \alpha_3 \ln(Price)_{it} x\ln(THI)_t \\
& + \alpha_4 \ln(Price)_{it} x\ln(THI)_t xPTR_i + \alpha_5 \ln(Price)_{it} x\ln(THI)_t xORB_i + \alpha_6 \ln(Price)_{it} x\ln(THI)_t xET_i \\
& + \alpha_7 D\_TreatPeriod_t + \alpha_8 D\_TreatPeriod_t xTreatCustomer_i + \sum_{k=1}^{3} \beta_k D\_Month_k \\
& + \alpha_{10} D\_WEEKEND_t + v_i + u_{it}
\end{aligned}
$$

where:

$\ln(kWh)_{it}$	: Logarithm of the daily average of the hourly load.
$\ln(THI)_{it}$	: Logarithm of the daily average of the hourly THI.
$\ln(THI)_t xD\_Month_k$	: Interaction of ln(*THI*) variable with monthly dummies.
$\ln(Price)_{it} x\ln(THI_t$	: Interaction of ln(*price*) with ln(*THI*).
$\ln(Price)_{it} x\ln(THI)xPTR_t$	: Interaction of ln(*price*) with ln(*THI*) and PTR (Applies to CPP/PTR regressions; the term is omitted for TOU). PTR: is equal to 1 for a PTR customer.
$\ln(Price)_{it} x\ln(THI)xORB_t$	: Interaction of ln(price) with ln(THI) and ORB. ORB: is equal to 1 if the customer has an Energy Orb but no A/C Switch and no thermostat.
$\ln(Price)_{it} x\ln(THI)xET_t$	: Interaction of ln(*price*) with ln(*THI*) and ET. ET: is equal to 1 if the customer has a thermostat or an A/C Switch.
$D\_TreatPeriod_t$	: Dummy variable is equal to 1 when the period is June 2009 through August 31, 2009.
$D\_TreatCustomer_i$	: is equal to 1 for the Treatment customers.
$D\_TreatPeriod_t xTreatCustomer_i$	: Interaction of $D\_TreatPeriod_t$ with $D\_TreatCustomer_i$
D_Month_k	: Dummy variable that is equal to 1 when the month is k.
$D\_WEEKEND_t$	: Dummy variable that is equal to 1 on weekends.
v_t	: Time invariant fixed effects for customers.
u_{it}	: Normally distributed error term.

The daily equation is estimated to determine the daily price elasticity of the CL&P customers. Daily price elasticity indicates the percent change in the daily average consumption due to a one percent change in the daily average price. Similar to the substitution elasticities, the daily price elasticities are interacted with the weather term. The estimation results for the daily demand equation are presented in Table 4.

4. RESULTS

4.1 Elasticities

After estimating the parameters of the substitution and the daily equations, we next calculated the substitution and the daily price elasticities. As mentioned earlier, the CL&P price elasticities are weather dependent, *i.e.*, they take on different values for different weather conditions. The impact of the weather on the substitution elasticity and the daily elasticity is captured through the THI_DIFF variable and the ln (THI) variable, respectively. In order to quantify the load impacts

Table 4: Daily Demand Equations, by Class and Rate Design

Daily Equation **Dependent Variable:** ln (average_daily_consumption)				
	RESIDENTIAL		**SMALL C&I**	
VARIABLES	**TOU & Control RESID**	**CPP/PTR & Control RESID**	**TOU & Control C&I**	**CPP/PTR & Control C&I**
ln_thi	−0.208	0.001	−0.012	0.478**
	(0.178)	(0.983)	(0.991)	(0.000)
ln_thixjune	1.168**	1.060**	0.229*	0.427**
	(0.000)	(0.000)	(0.021)	(0.000)
ln_thixjuly	2.587**	2.758**	0.874**	1.098**
	(0.000)	(0.000)	(0.000)	(0.000)
ln_thixaug	3.102**	3.022**	1.019**	1.005**
	(0.000)	(0.000)	(0.000)	(0.000)
TreatCustomerxTreatPeriod	−0.043	−0.016	0.046	0.042
	(0.194)	(0.562)	(0.393)	(0.209)
ln_pricexln_thi	−0.107	−0.006*	−0.359	0.004
	(0.214)	(0.016)	(0.580)	(0.437)
ln_pricexln_thi_PTR		0.007		−0.003
		(0.098)		(0.656)
ln_pricexln_thi_ORB			−0.040	0.005
			(0.734)	(0.504)
ln_pricexln_thi_TECH				0.013
				(0.082)
june	−4.789**	−4.347**	−0.992*	−1.805**
	(0.000)	(0.000)	(0.017)	(0.000)
july	−10.697**	−11.422**	−3.643**	−4.588**
	(0.000)	(0.000)	(0.000)	(0.000)
aug	−12.801**	−12.472**	−4.233**	−4.166**
	(0.000)	(0.000)	(0.000)	(0.000)
weekend	0.032**	0.022**	−0.478**	−0.491**
	(0.000)	(0.000)	(0.000)	(0.000)
Constant	−0.440	−0.580**	−2.099**	−1.443**
	(0.064)	(0.002)	(0.000)	(0.000)
Observations	60564	108145	53112	97421
R-squared	0.161	0.173	0.183	0.199
Number of customer	498	890	443	806

Robust p-values in parentheses
** $p<0.01$, * $p<0.05$
Note: The reported R-squared values do not include the explanatory power of the customer fixed effects. When the explanatory power of the fixed effects is included, the adjusted R-squared values are around 0.8 for residential regressions and 0.9 for commercial regressions.
The TreatCustomer variable drops from the regression due to fixed effects estimation. The TreatmentPeriod variable also drops due to collinearity.

from the PWEP, we determined the "average CPP event day weather" to be used in the calculation of the price elasticities. We identified the average CPP event day weather by finding the average values of the THI_DIFF and the THI variables. We calculated the averages for the six event days in June-July and also separately for the four event days in August. As the event days called during June and July had very mild temperatures and were not representatives of the critical peak event days, we used the event days in August to calculate the average event day weather variable.[10,11] Resulting values of the weather variables are provided in the Appendix 1.

Substitution Elasticity. The substitution elasticities can be derived from the following equations:

$$Subst\_Elasticity_{price\_CPP/TOU} = \alpha_3 {*} THI\_DIFF_t \text{ (Price,Weather)} \tag{1}$$

$$Subst\_Elasticity_{price\_PTR} = (\alpha_3 + \alpha_4) {*} THI\_DIFF_t \text{ (Price,Weather)}$$

$$Subst\_Elasticity_{price + ORB\_CPP/TOU} = (\alpha_3 + \alpha_5) {*} THI\_DIFF_t \text{ (Price,Weather, and ORB)} \tag{2}$$

$$Subst\_Elasticity_{price + ORB\_PTR} = (\alpha_3 + \alpha_4 + \alpha_5) {*} THI\_DIFF_t \text{ (Price,Weather, and ORB)}$$

$$Subst\_Elasticity_{price + ET\_CPP/TOU} = (\alpha_3 + \alpha_6) {*} THI\_DIFF_t \text{ (Price,Weather, and ET)} \tag{3}$$

$$Subst\_Elasticity_{price + ET\_PTR} = (\alpha_3 + \alpha_4 + \alpha_6) {*} THI\_DIFF_t \text{ (Price,Weather, and ET)}$$

These equations make it possible to determine a substitution elasticity conditional on a specific weather condition and the existence of an enabling technology.

Daily Elasticity. The daily price elasticities from the estimated model can be derived using the following equations:

$$Daily\_Elasticity_{price\_CPP/TOU} = \alpha_3 {*} \ln(THI)_{it} \text{ (Price,Weather)} \tag{4}$$

$$Daily\_Elasticity_{price\_PTR} = (\alpha_3 + \alpha_4) {*} \ln(THI)_{it} \text{ (Price,Weather)} \tag{5}$$

It is also possible to estimate a daily price elasticity conditional on a specific weather condition using this equation.

4.2 Empirical Findings

Table 5 reports the estimated substitution and daily price elasticities for the PWEP residential customers. Overall, we found that the elasticities of substitution, while smaller than those observed in warmer climates, are statistically significant. Unlike the substitution elasticities, the daily price elasticities were statistically insignificant except for the CPP and the PTR residential customers.

We also found that the customers do not show the same price responsiveness to the equivalently designed PTR and CPP rates. This finding contradicts the result of the BGE pilot in Maryland which, during its first year of operation in 2008, tested both the CPP and PTR rates. However, it is in line with the results of the PowerCents DC pilot carried out by Pepco in the District of Columbia which ran during the summers of 2008–2009 (Faruqui and Sergici (2011) and Wolak (2011)).

10. These days nevertheless were included in the regression models since additional variability in the exogenous variables leads to greater precision in the parameter estimates.

11. For the purpose of calculating elasticities and impact estimations, we determined the weighted average weather terms using Bradley and White Plains average August event-day weather information. We used the distribution of the treatment customers to the weather stations as weights in the calculation.

Table 5: Residential Elasticity Estimates

Elasticity Type	TOU	CPP	PTR
	Substitution Elasticity Estimates		
Price Only	–0.047	–0.081	–0.052
S.E.	*0.019*	*0.010*	*0.009*
Price + ORB	–0.047	–0.081	–0.052
S.E.	*0.022*	*0.013*	*0.012*
Price + TECH	–0.047	–0.128	–0.100
S.E.	*0.034*	*0.017*	*0.017*
	Daily Elasticity Estimates		
Price Only	–0.453	–0.026	–0.026
S.E.	*0.364*	*0.010*	*0.014*
Price + ORB	–0.453	–0.026	–0.026
S.E.	*0.364*	*0.010*	*0.014*
Price + TECH	–0.453	–0.026	–0.026
S.E.	*0.364*	*0.010*	*0.014*

Note: Numbers in grey represent insignificant elasticities. They were treated as zero in the impact calculations.

Based on the results presented in Table 5, the CPP customers were more price responsive than the PTR and TOU customers. The CPP substitution elasticity was estimated as –0.081 (using August event-day weather). This is very similar to the average substitution elasticity of –0.076 reported in the California Statewide Pricing Pilot (SPP). It is lower than the value of –0.096 reported in the BGE pilot.[12] Similarly, the PTR customers were more price responsive than the TOU customers. The incremental effect from ORB was not statistically significant for any of the TOU, the CPP or the PTR programs. This finding contrasts with the result observed in the Maryland pilot where the ORB provided a boost. However, the incremental effect from the TECH was statistically significant for the CPP and the PTR programs, but not for the TOU program. Finally, the CPP and the PTR customers exhibited some daily price responsiveness, whereas the TOU customers did not. The CPP daily elasticity was estimated as –0.026, about half the value observed in the California experiment. Table 6 reports the estimated substitution and daily price elasticities for the PWEP small C&I customers.

Based on the results presented in Table 6, the small C&I TOU customers, with or without enabling technology, did not respond to dynamic prices in a statistically significant way. The CPP customers responded to prices without any enabling technologies, whereas the PTR customers did not. Overall, the price responsiveness of small C&I customers was substantially lower than that of residential customers. The incremental effect from ORB was not statistically significant for any of the CPP and PTR programs. However, the CPP and PTR customers both responded to prices when prices are accompanied with enabling technologies. Finally, none of the CPP, PTR, and TOU customers exhibited daily price responsiveness.

Overall, the findings from the PWEP bear some resemblance to those from other dynamic pricing pilots: (i) customers do respond to dynamic pricing, (ii) price responsiveness increases when the prices are paired with enabling technologies, (iii) price responsiveness is higher in hotter cli-

12. See Faruqui and George (2005) for the SPP analysis and Faruqui and Sergici (2011) for the BGE analysis.

Table 6: Small C&I Elasticity Estimates

Elasticity Type	TOU	CPP	PTR
Substitution Elasticity Estimates			
Price Only	0.028	–0.016	0.002
S.E.	*0.025*	*0.007*	*0.007*
Price + ORB	0.072	–0.016	0.012
S.E.	*0.028*	*0.011*	*0.009*
Price + TECH	0.028	–0.042	–0.022
S.E.	*0.025*	*0.012*	*0.012*
Daily Elasticity Estimates			
Price Only	–1.527	0.015	0.005
S.E.	*2.755*	*0.019*	*0.022*
Price + ORB	–1.698	0.036	0.024
S.E.	*2.718*	*0.024*	*0.027*
Price + TECH	–1.527	0.071	0.060
S.E.	*2.755*	*0.027*	*0.029*

Note: Numbers in grey represent insignificant elasticities. They were treated as zero in the impact calculations.

mates, and (iv) price responsiveness of small C&I customers is lower than that of residential customers.

However, some of the results differ from those of the earlier pilots: (i) the ORB impact was not found to be significant; (ii) the PTR rates yielded a lower response compared to the CPP rates; and (iii) the TOU responsiveness was low for the residential customers and non-existent for the small C&I customers, perhaps because the peak period was eight hours long (it was only six hours long in the California SPP pilot and customers with and without enabling technology showed price responsiveness, unless they were less than 20 kW in size).

4.3 Simulating Demand Response Impacts

After estimating the substitution and daily demand equations, we determined demand response impacts for the rates tested in the PWEP. We determined the impacts through the *Pricing Impact Simulation Model (PRISM)* software. The PRISM software emerged from the California (SPP) (Faruqui and George (2005)). Originally developed for California, PRISM has been adapted to conditions in other parts of North America after making adjustments for weather, customer price responsiveness (price elasticities), rate, and load shape characteristics. We calibrated the PRISM model to the estimated elasticities, the typical CL&P residential and small C&I load profiles, and all-in rates the control and the PWEP customers pay during the pilot period and create the CL&P-PRISM model. Using the CL&P-PRISM model, we calculate the demand response impacts for the rates that were tested in the PWEP program. CL&P-PRISM also allows calculating the impacts from other rates that are not tested in the PWEP.

The PRISM model generates several metrics including percent change in peak and off-peak consumption on critical and non-critical days and percent change in total monthly consumption.

4.4 Customer Impacts

Table 7 presents the residential PWEP customer impacts. The TOU customers reduced their critical peak period usage by 1.6 to 3.1 percent while the PTR customers reduced their critical

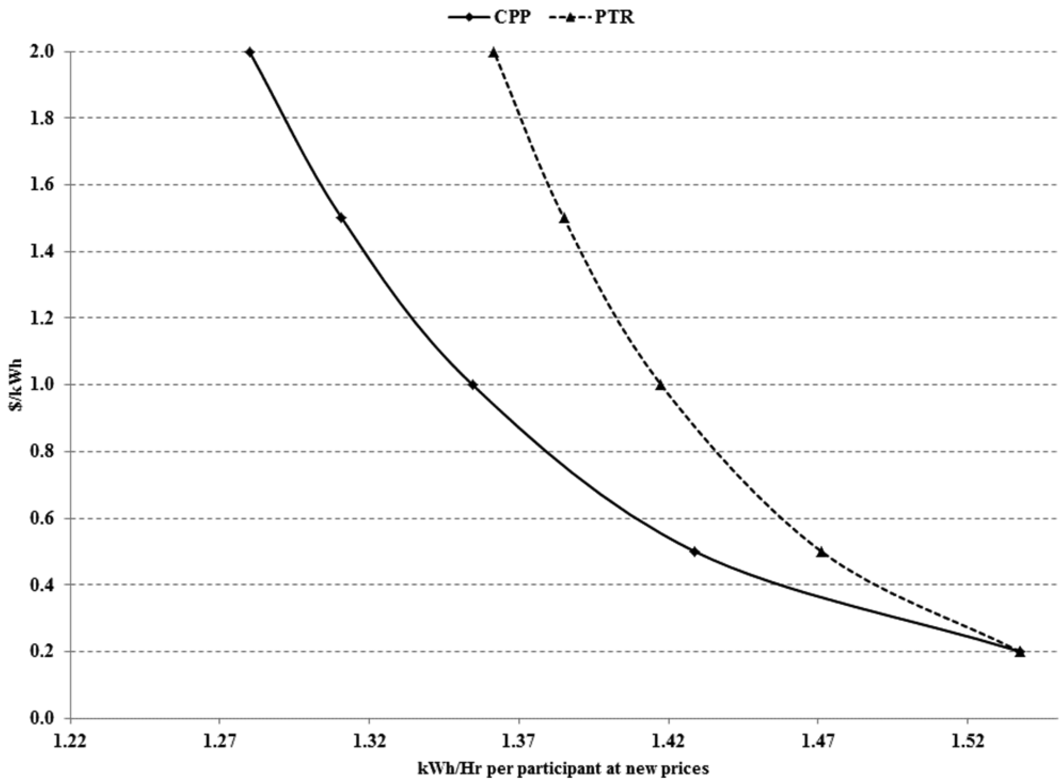
Table 7: Demand Impact Results—Residential

	RESIDENTIAL—AVERAGE CUSTOMER					
	CPP_HI	**CPP_HI_ORB**	**CPP_HI_TECH**	**CPP_LO**	**CPP_LO_ORB**	**CPP_LO_TECH**
Critical Days-Peak (% of original consumption)	**–16.1%**	**–16.1%**	**–23.3%**	**–10.2%**	**–10.2%**	**–15.1%**
Critical Days-Off-Peak (% of original consumption)	1.9%	1.9%	4.3%	1.5%	1.5%	3.2%
Non-Critical Days-Peak (% of original consumption)	0.5%	0.5%	0.5%	0.2%	0.2%	0.2%
Non-Critical Days-Off-Peak (% of original consumption)	0.5%	0.5%	0.5%	0.2%	0.2%	0.2%
Total Change in Consumption (%/month)	**0.2%**	**0.2%**	**0.3%**	**0.1%**	**0.1%**	**0.1%**

	RESIDENTIAL—AVERAGE CUSTOMER					
	PTR_HI	**PTR_HI_ORB**	**PTR_HI_TECH**	**PTR_LO**	**PTR_LO_ORB**	**PTR_LO_TECH**
Critical Days-Peak (% of original consumption)	**–10.9%**	**–10.9%**	**–17.8%**	**–7.0%**	**–7.0%**	**–11.8%**
Critical Days-Off-Peak (% of original consumption)	–0.1%	–0.1%	2.3%	0.3%	0.3%	2.0%
Non-Critical Days-Peak (% of original consumption)	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
Non-Critical Days-Off-Peak (% of original consumption)	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
Total Change in Consumption (%/month)	**–0.3%**	**–0.3%**	**–0.2%**	**–0.2%**	**–0.2%**	**–0.1%**

	RESIDENTIAL—AVERAGE CUSTOMER					
	TOU_HI	**TOU_HI_ORB**	**TOU_HI_TECH**	**TOU_LO**	**TOU_LO_ORB**	**TOU_LO_TECH**
Peak (% of original consumption)	**–3.1%**	**–3.1%**	**–3.1%**	**–1.6%**	**–1.6%**	**–1.6%**
Off-Peak (% of original consumption)	1.1%	1.1%	1.1%	0.6%	0.6%	0.6%
Total Change in Consumption (%/month)	–0.1%	–0.1%	–0.1%	–0.1%	–0.1%	–0.1%

Figure 1: Residential Demand Curves for CPP and PTR Customers



peak period usage by 7.0 to 17.8 percent. The CPP customers achieved the largest peak reduction of all three rate types, which ranged from 10.2 to 23.3 percent. As a result of the program, the total monthly consumption increased by about 0.2 percent for the CPP program and decreased by about 0.2 percent for the PTR and the TOU programs.[13] Figure 1 lays out the implied demand curves for PWEP residential customers on the CPP and PTR rates; the relative shapes of these curves are consistent with the finding that the customers were more price responsive to the CPP rates than they were to the PTR rates.

We also found that within the subset of the PWEP residential customers who did respond to the income question, the elasticities of substitution for low income customers were essentially the same as those for the average customer with known income data. It is important to note that this result only holds for customers who responded to the survey, as only 552 out of 1,251 customers responded to the income question on the survey. Using the second definition of low income, hardship status as certified by the state, the results were slightly different. In this case, results indicated that hardship customers responded slightly less than the average treatment customer to the PTP rate,

13. It might seem counter intuitive that the total monthly consumption increases as a result of CPP pricing. The reason is that higher CPP rates were effective only on a small number of hours; therefore the demand reductions took place on a small number of hours. On the other hand, all other hours were priced lower than the standard rate; therefore there was a load increase on a large number of hours. As a result, the total usage reduction was more than offset by total usage increase on a monthly basis.

although they did still respond. The incremental effect of the PTR rate was similar for hardship and non-hardship customers. We estimate that where average customers responded to the high PTP rate with a 20 percent peak reduction, hardship customers responded with a roughly 13 percent reduction, or about two-thirds as much (Faruqui, Sergici, and Palmer (2010)) .

As mentioned earlier, the small C&I customers were less price responsive compared to the residential customers. The TOU customers did not respond to the TOU programs in a statistically significant fashion. The PTR customers reduced their critical peak period usage by 2.7 to 4.1 percent while the CPP customers reduced their critical peak period usage by 1.7 to 7.2 percent. The total monthly consumption remained unchanged in response to the time-varying rates.

5. CONCLUDING REMARKS

We find evidence of statistically significant elasticities of substitution in Connecticut, which are only slightly lower than those observed in warmer climates with higher saturations of central air conditioning loads. We also find that equivalently designed PTR and CPP rates do not have equivalent impacts on peak demand. This finding contradicts the result found in the BGE pilot in Maryland during its first summer of operation in 2008, but is in line with the PowerCents DC pilot carried out by Pepco in the District of Columbia, which ran during the summers of 2008–09. This remains a topic for further research.

We also find that C&I customers are less price-responsive compared to the residential customers. TOU rates do elicit response for the residential class, but none for small C&I customers. This finding is consistent with those from earlier studies.

The Energy Orb did not boost price responsiveness, again in contrast to results observed in Maryland. However, cycling of residential air conditioners notably boosted price responsiveness for customers on dynamic pricing rates, but not for those on TOU rates.

We also found that within the subset of the PWEP residential customers who did respond to the income question, the elasticities of substitution for low income customers were essentially the same as those for the average customer with known income data. It is important to note that this result only holds for customers who responded to the survey, as only 552 out of 1,251 customers responded to the income question on the survey. Using the second definition of low income, hardship status as certified by the state, the results were slightly different. In this case, results indicated that hardship customers responded slightly less than the average treatment customer to the PTP rate, although they did still respond. The incremental effect of the PTR rate was similar for hardship and non-hardship customers.

The results of the PWEP experiment can be used to carry out a cost-benefit analysis of the deployment of smart meters and smart prices in the New England region. Such an analysis was indeed carried out for its Connecticut service territory and presented by CL&P to its regulatory commission in November 2010. The results of the cost-benefit showed a net societal benefit of $87 million and were supportive of the full scale deployment of smart metering and smart pricing (Connecticut Light & Power Company (2010)). However, the recommendation was opposed by the state's attorney general (State of Connecticut Department of Public Utility Control (2011)). The Commission has yet to rule on the matter.

REFERENCES

Allcott, Hunt (2011). "Rethinking Real-Time Electricity Pricing." *Resource and Energy Economics* 33(4): 820–842. http://dx.doi.org/10.1016/j.reseneeco.2011.06.003.

Borenstein, Severin (2005). "The Long-run Efficiency of Real-Time Pricing." *The Energy Journal* 26(3): 93–116. http://dx.doi.org/10.5547/ISSN0195-6574-EJ-Vol26-No3-5.

Chao, Hung-po (1983). "Peak-Load Pricing and Capacity Planning with Demand and Supply Uncertainty." *Bell Journal of Economics* 14(1): 170–90.

Charles River Associates (2005). *Impact Evaluation of the California Statewide Pricing Pilot.* March 16. The report can be downloaded from:
http://www.calmac.org/publications/2005-03-24_SPP_FINAL_REP.pdf.

Connecticut Light & Power Company, CL&P's Plan-it Wise Pilot Results, AMI & Dynamic Pricing Cost Benefit Analysis and Plan, Docket No. 05-10-03-RE04, *DPUC Hearing*, November 22, 2010.

Crew, Michael A., Chitru S. Fernando and Paul R. Kleindorfer (1995). "The Theory of Peak Load Pricing: A Survey." *Journal of Regulatory Economics* 8: 215–248. http://dx.doi.org/10.1007/BF01070807.

Enright, Toni and Ahmad Faruqui (2013). "A Bibliography on Dynamic Prices and Time-of-Use Rates Version 2.0," January. The bibliography can be downloaded from: http://papers.ssrn.com/sol3/papers.cfm?abstract_id = 2178674

Faruqui, Ahmad (2010). "The Ethics of Dynamic Pricing." *The Electricity Journal*, 23(6): 13–27. http://dx.doi.org/10.1016/j.tej.2010.05.013.

Faruqui, Ahmad and Stephen S. George (2005). "Quantifying Customer Response to Dynamic Pricing." *The Electricity Journal* 18(4): 53–63. http://dx.doi.org/10.1016/j.tej.2005.04.005.

Faruqui, Ahmad and Sanem Sergici (2009). "Household Response to Dynamic Pricing of Electricity – A Survey of 15 Experiments." *Journal of Regulatory Economics* 38(2): 193–225. http://dx.doi.org/10.1007/s11149-010-9127-y.

Faruqui, Ahmad and Sanem Sergici (2011). " Dynamic pricing of electricity in the mid- Atlantic region: econometric results from the Baltimore gas and electric company experiment." *Journal of Regulatory Economics* 40(1): 82–109. http://dx.doi.org/10.1007/s11149-011-9152-5.

Faruqui, Ahmad and Lisa Wood (2008). *Quantifying the Benefits of Dynamic Pricing in the Mass Market*. Edison Electric Institute, Washington, D.C.

Faruqui, Ahmad, Ryan Hledik, Sanem Sergici (2009). "Piloting the Smart Grid." *The Electricity Journal* 22(7): 55–69. http://dx.doi.org/10.1016/j.tej.2009.06.012.

Faruqui, Ahmad, Sanem Sergici and Lamine Akaba (2012). "Dynamic Pricing of Electricity for Residential Customers: The Evidence from Michigan." *Energy Efficiency* 5(4): 1–14.

Faruqui, Ahmad, Sanem Sergici and Jennifer Palmer (2010). *The impact of dynamic pricing on low income customers*. The Institute for Electric Efficiency, Washington, DC, September. http://www.edisonfoundation.net/IEE/Documents/IEE_LowIncomeDynamicPricing_0910.pdf

Faruqui, Ahmad, Phil Hanser, Ryan Hledik and Jenny Palmer (2010). "Assessing Ontario's Regulated Price Plan," prepared for the Ontario Energy Board, December 8, 2010. http://www.smartgridinformation.info/pdf/4542_doc_1.pdf.

Faruqui, Ahmad, Doug Mitarotonda, Lisa Wood, Adam Cooper and Judith Schwartz (2011). *The Costs and Benefits of Smart Meters for Residential Customers*, IEE Whitepaper, July 2011. http://www.edisonfoundation.net/iee/Documents/IEE_BenefitsofSmartMeters_Final.pdf

Federal Energy Regulatory Commission (2012*). Assessment of Demand Response and Advanced Metering*. Staff Report, December. http://www.ferc.gov/legal/staff-reports/12-20-12-demand-response.pdf

Herter, Karen (2007). "Residential implementation of critical-peak pricing of electricity." *Energy Policy* 35(4): 2121–2130. http://dx.doi.org/10.1016/j.enpol.2006.06.019.

Herter, Karen, Patrick McAuliffe and Arthur Rosenfeld (2007). "An exploratory analysis of California residential customer response to critical peak pricing of electricity." *Energy* 32(1): 25–34. http://dx.doi.org/10.1016/j.energy.2006.01.014.

Littlechild, Stephen C. (2003). "Wholesale Spot Price Pass-Through." *Journal of Regulatory Economics* 23(1): 61–91. http://dx.doi.org/10.1023/A:1021883431400.

Newsham, Guy R. and Brent G. Bowker (2010). "The effect of utility time-varying pricing and load control strategies on residential summer peak electricity use: A review." *Energy Policy* 38(7): 3289–96. http://dx.doi.org/10.1016/j.enpol.2010.01.027.

Rowlands, Ian H. and Ian M. Furst (2011). "The cost impacts of a mandatory move to time-of-use pricing on residential customers: an Ontario (Canada) case-study." *Energy Efficiency* 4(4): 571–85. http://dx.doi.org/10.1007/s12053-011-9113-y.

State of Connecticut Department of Public Utility Control, Brief of George Jepsen, Attorney General for the State of Connecticut, Docket No. 05-10-03RE04, February 8, 2011. http://www.smartgridlegalnews.com/ConnAG_brief.pdf

Vickrey, W. S. (1971). "Responsive Pricing of Public Utility Services." *Bell Journal of Economics* 2(1): 337–46. http://dx.doi.org/10.2307/3003171.

Wolak, Frank A. (2011). "Do Residential Customers Respond to Hourly Prices: Evidence from a Dynamic Pricing Experiment." *American Economic Review: Papers and Proceedings*. http://www.stanford.edu/group/fwolak/cgibin/sites/default/files/files/hourly_pricing_aer_paper.pdf.

APPENDIX 1—RATE DETAILS

Table 1.1: PWEP All-in Rates ($/kWh)—Residential

	Rate 1		Rate 5		
	June	**July-August**	**June**	**July-August**	**Weighted Average**
Control	0.201	0.201	0.202	0.202	0.201
TOU_HI_PEAK	0.344	0.343	0.344	0.344	0.343
TOU_HI_OPEAK	0.144	0.143	0.144	0.144	0.143
TOU_LO_PEAK	0.273	0.272	0.273	0.273	0.272
TOU_LO_OPEAK	0.173	0.172	0.173	0.173	0.172
PTP_HI_PEAK	1.815	1.814	1.815	1.816	1.815
PTP_HI_OPEAK	0.165	0.164	0.165	0.166	0.165
PTP_LO_PEAK	0.857	0.856	0.857	0.857	0.856
PTP_LO_OPEAK	0.187	0.186	0.187	0.187	0.186
PTR_HI_PEAK	1.815	1.815	1.816	1.816	1.815
PTR_HI_OPEAK	0.201	0.201	0.202	0.202	0.201
PTR_LO_PEAK	0.856	0.856	0.857	0.857	0.856
PTR_LO_OPEAK	0.201	0.201	0.202	0.202	0.201

Note: Rates are shown for the customers who purchase their power from NU. For customers purchasing their power from 3rd party suppliers, generation charges are 10% lower on average.

Table 1.2: PWEP All-in Rates ($/kWh)—Small C&I

	Rate 30		Rate 35		
	June	**July-August**	**June**	**July-August**	**Weighted Average**
Control	0.203	0.205	0.180	0.181	0.203
TOU_HI_PEAK	0.341	0.342	0.318	0.319	0.341
TOU_HI_OPEAK	0.141	0.142	0.118	0.119	0.141
TOU_LO_PEAK	0.272	0.274	0.249	0.250	0.272
TOU_LO_OPEAK	0.172	0.174	0.149	0.150	0.172
PTP_HI_PEAK	1.805	1.806	1.781	1.782	1.804
PTP_HI_OPEAK	0.155	0.156	0.131	0.132	0.154
PTP_LO_PEAK	0.853	0.855	0.830	0.831	0.853
PTP_LO_OPEAK	0.183	0.185	0.160	0.161	0.183
PTR_HI_PEAK	1.804	1.806	1.781	1.782	1.804
PTR_HI_OPEAK	0.203	0.205	0.180	0.181	0.203
PTR_LO_PEAK	0.853	0.855	0.830	0.831	0.853
PTR_LO_OPEAK	0.203	0.205	0.180	0.181	0.203

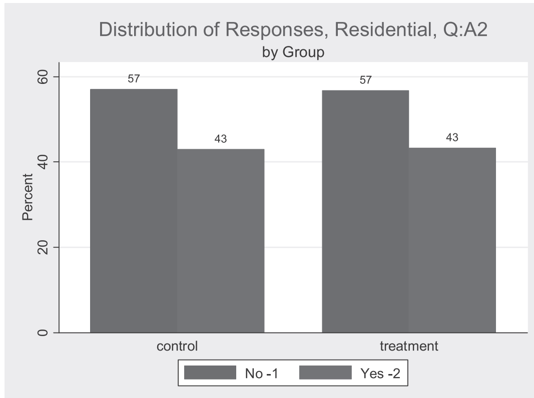
Note: Rates are shown for the customers who purchase their power from NU. For customers purchasing their power from 3rd party suppliers, generation charges are 10% lower on average.

Table 1.3: Weather Values used in the Elasticity Calculations

	TOU		Non-TOU	
	thi_diff	**ln_thi**	**thi_diff**	**ln_thi**
Residential	**4.75**	**4.25**	**4.75**	**4.29**
Small C&I	**5.13**	**4.25**	**5.19**	**4.29**

APPENDIX 2—SURVEY ANALYSIS

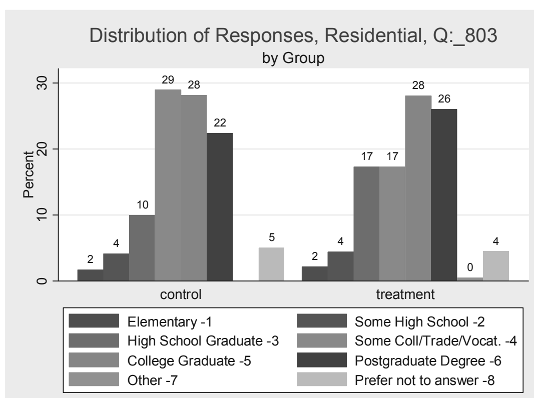
Table 2.1: Air Conditioning Ownership



Mean Comparison Test—Question A2

Group	Obs	Mean	Std. Err.	Std. Dev.	[95% Conf.	Interval]
Control	121	1.430	0.045	0.497	1.340	1.519
Treatment	1072	1.432	0.015	0.496	1.402	1.462
Combined	1193	1.432	0.014	0.496	1.404	1.460
Δ		–0.002	0.048		–0.095	0.091
Δ = mean (Control)– mean Treatment)				**Pr**(|**T**| > |**t**|) = 0.964		**t** = –0.045
H0: Δ = 0, HA: Δ ≠ 0				**Outcome**: Do Not Reject H0		

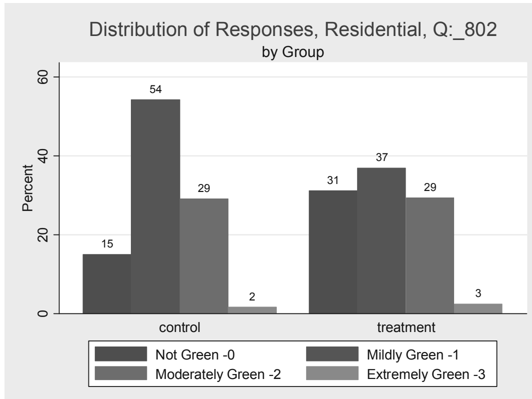
Table 2.2: Highest Level of Education Completed by the Head of Household



Mean Comparison Test—Question 803

Group	Obs	Mean	Std. Err.	Std. Dev.	[95% Conf.	Interval]
Control	121	4.694	0.126	1.383	4.445	4.943
Treatment	668	4.716	0.057	1.464	4.604	4.827
Combined	789	4.712	0.052	1.451	4.611	4.814
Δ		–0.021	0.143		–0.303	0.260
Δ = mean (Control)–mean Treatment)				**Pr**(|**T**| > |**t**|) = 0.882		**t** = –0.149
H0: Δ = 0, HA: Δ ≠ 0				**Outcome**: Do Not Reject H0		

Table 2.3: Degree of "Green Home"

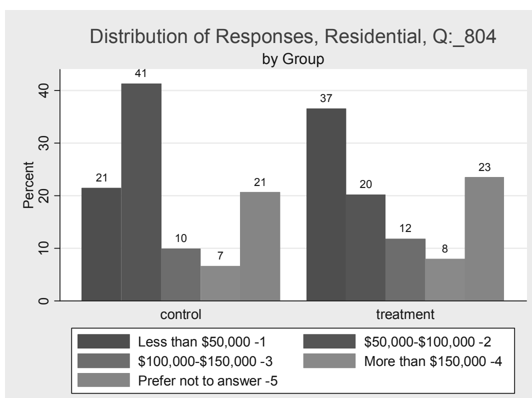


Mean Comparison Test—Question 802

Group	Obs	Mean	Std. Err.	Std. Dev.	[95% Conf. Interval]	
Control	120	1.175	0.063	0.694	1.050	1.300
Treatment	668	1.034	0.033	0.848	0.970	1.099
Combined	788	1.056	0.029	0.828	0.998	1.114
Δ		0.141	0.082		−0.020	0.302

Δ = mean (Control)–mean Treatment) **Pr(|T| > |t|)** = 0.087 **t =** 1.714
H0: Δ = 0, HA: Δ ≠ 0 **Outcome**: Do Not Reject H0

Table 2.4: Total Annual Household Income



Mean Comparison Test—Question 804

Group	Obs	Mean	Std. Err.	Std. Dev.	[95% Conf. Interval]	
Control	121	2.636	0.130	1.432	2.379	2.894
Treatment	667	2.672	0.062	1.609	2.549	2.794
Combined	788	2.666	0.056	1.583	2.556	2.777
Δ		−0.035	0.156		−0.342	0.272

Δ = mean (Control)–mean Treatment) **Pr(|T| > |t|)** = 0.822 **t =** −0.226
H0: Δ = 0, HA: Δ ≠ 0 **Outcome**: Do Not Reject H0

APPENDIX 3—REGRESSION SENSITIVITY

Table 3.1: Substitution Equation with both Linear and Non-linear Price Terms

VARIABLES	TOU & Control RESID	PTP/PTR & Control RESID
thi_diff	−0.002	0.001
	(0.120)	(0.355)
thi_diffxjune	−0.001	0.000
	(0.567)	(0.870)
thi_diffxjuly	0.007*	0.005*
	(0.018)	(0.018)
thi_diffxaug	0.014**	0.008**
	(0.000)	(0.001)
TreatCustomerxTreatPeriod	−0.061**	−0.065**
	(0.003)	(0.000)
ln_price_ratio	−0.045	−0.071**
	(0.131)	(0.008)
ln_price_ratioxthi_diff	−0.005	−0.003
	(0.222)	(0.540)
ln_price_ratioxPTR		0.004
		(0.882)
ln_price_ratioxthi_diff_PTR		0.005
		(0.362)
ln_price_ratioxORB	−0.068	0.031
	(0.102)	(0.370)
ln_price_ratioxthi_diff_ORB	0.016**	−0.000
	(0.008)	(0.980)
ln_price_ratioxTECH	−0.092	−0.120**
	(0.115)	(0.001)
ln_price_ratioxthi_diff_TECH	0.009	0.018*
	(0.211)	(0.010)
june	0.066**	0.078**
	(0.000)	(0.000)
july	0.039	0.080**
	(0.052)	(0.000)
aug	0.037	0.019
	(0.067)	(0.306)
weekend	0.062**	0.084**
	(0.000)	(0.000)
Constant	0.106**	−0.009
	(0.000)	(0.349)
Observations	59,669	102,384
R-squared	0.013	0.014
Number of customer	498	890

Robust pval in parentheses
** $p<0.01$, * $p<0.05$