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Appendices – Understanding Electric Utility Customers

What we know and what we need to know

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NOTE

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ABSTRACT

EPRI report 1023562 provides a synthesis of the body of evidence regarding the major factors that affect how customers value and use electricity; this companion report contains five appendices to support that document. Appendix A provides additional background on price elasticity of demand as a companion to the economics of demand discussion in Section 2 of 1023562. Appendix B provides tables detailing elements of the experimental designs for the 10 pricing pilots examined in Section 3 of 1023562; Appendix C details the analysis methods employed in those same 10 studies. The tables in Appendix D outline the six additional feedback studies examined in Section 4 of 1023562, and finally, Appendix E is a glossary of terms.

Keywords
Customer behavior
Pricing
Feedback
Control technology

CONTENTS

A
A CONCEPTUAL AND GEOMETRIC DERIVATION OF THE ELASTICITY OF SUBSTITUTION

It is relatively easy to derive and interpret the own-price elasticity of demand through a simple analysis if the demand model is as represented in Figure 2-3 of report 1023562. Deriving the elasticity of substitution is more complicated because it involves two electricity commodities, rather than one, and the customer's ability to substitute electricity consumption in one period for that in another period as the prices in each period change. By undertaking this more complex derivation below, we not only gain important insights into the nature of the demand response, but we can also examine the implications of moving to a dynamic rate structure that is designed to be revenue neutral.

The Customer's Utility Function—A Measure of Customer Satisfaction

To capture the nature of this substitution in a demand model, we must first specify a customer's utility function that depicts the customer's utility or level of satisfaction that he/she derives from the consumption of various collections of goods and services. Such a utility function that distinguishes between all other goods and peak and off-peak electricity consumption can be represented as:

$$V = V\left(x_1, x_2, ..., x_n, U\left(K_P, K_O\right)\right) \qquad \textbf{Equation A-1}$$

where V is the utility function for the customer, x_i are the goods and services other than electricity consumed, and K_P and K_O are the amounts of electricity consumed in peak and off-peak periods, respectively. In this very short run formulation, electricity is assumed to be separable in consumption from other goods and services. Therefore, the function $U\ (K_P,\ K_O)$ represents a sub-utility function for the customer. It reflects the fact that a customer can attain a given level of satisfaction from electricity consumption by consuming different amounts of peak and off-peak electricity that together yield a given level utility or satisfaction, say U_1.

This type of sub-utility function is depicted in Figure A-1, where the points on the curve U_1 represent all those combinations of peak electricity (K_P) and off-peak electricity (K_O) that would leave the customer equally well off (*i.e.*, at the same utility level or level of customer satisfaction, U_1). Because a customer derives the same utility from consuming peak and off-peak electricity in any combination on the curve, such a curve is referred to as an indifference curve. Similarly, all combinations of peak electricity (K_P) and off-peak electricity (K_O) on the curve labeled U_2 would leave the customer equally well off, but the level of satisfaction would be higher than on the curve labeled U_1.

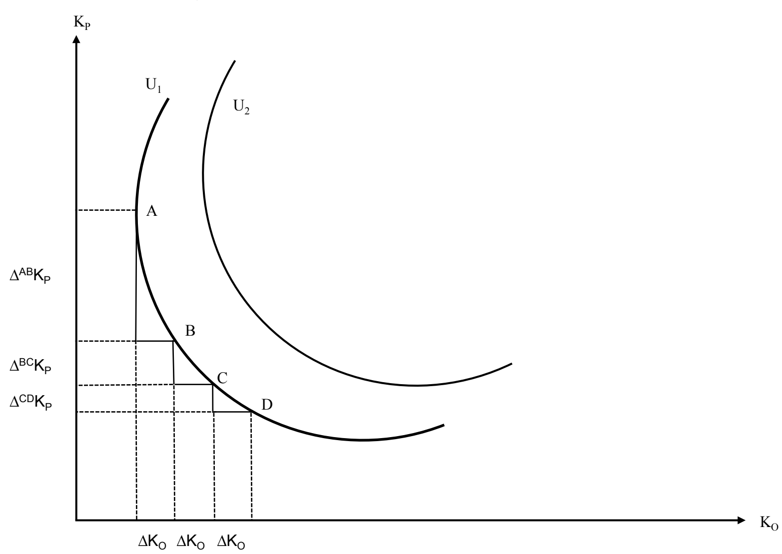

Figure A-1
Customer Sub-Utility Function for Peak and Off-Peak Electricity Consumption

To understand the concept of the *elasticity of substitution* between peak and off-peak electricity consumption, we must discuss three important properties of indifference curves:

1. Indifference curves do not intersect. If they did intersect, it would imply that one combination of peak and off-peak electricity usage would yield two separate and distinct levels of consumer satisfaction. This obviously cannot be the case.[1]
2. Indifference curves must have a negative slope. If this were not the case, then a consumer could consume more of both peak and off-peak electricity and be no better off than before.
3. The indifference curves are convex to the origin as depicted in Figure A-1.

The third property is perhaps the most critical aspect of indifference curves from the standpoint of understanding the elasticity of substitution. This property (of convexity) reflects the *decreasing marginal rate of substitution* of off-peak electricity usage for peak electricity usage, sometimes written as MRS_{OP}.

To illustrate, consider the peak and off-peak combination given at point A in Figure A-1. This point comprises a relatively small quantity of off-peak and a relatively large quantity of peak electricity usage. The shape of the curve reflects the fact that the consumer could give up a considerable quantity of peak electricity in order to obtain an additional unit of off-peak power and be just as well off (on the same indifference curve) as before. But, as the consumer uses more and more off-peak electricity, and is using less and less peak electricity, the amount of peak usage the consumer is willing to give up to obtain one more unit of off-peak electricity becomes

[1] We have drawn the curve U_1 so that it never crosses either axis. Thus, regardless of how high the peak price rises relative to the off-peak price, the customer will always consume some peak electricity as part of any equilibrium level of satisfaction. A similar assumption for commercial and industrial firms was tested by Boisvert, *et al*. (2007). In cases where some firms stopped purchasing electricity from the Grid when peak prices were very high, they were able to substitute power produced from available onsite backup generation.

increasingly smaller. That is, for the three equal increases in off-peak usage, ΔK_O, in moving from point A to point D on indifference curve U_I in Figure A-1, the reductions in peak electricity usage that can be sacrificed to keep the customer's level of satisfaction unchanged decreases from $\Delta^{AB}K_P > \Delta^{BC}K_P > \Delta^{CD}K_P$. The marginal rate of substitution is MRS_{OP} is defined as the amount of peak electricity usage a consumer is willing to give up to obtain one additional unit of off-peak usage. And, as in this case, the indifference curves are convex to the origin, then this MRS_{OP} is declining.

A couple of examples may help to clarify these assumptions about customer preferences. The first example could relate to a customer's desire to keep the house at a comfortable temperature throughout the day. One way to achieve a comfortable temperature would be to set a thermostat at a set temperature—which would call for electricity to run the air conditioning whenever the temperature rose above the setting on the thermostat. Setting a fixed temperature would likely result in some combined use of peak and off-peak electricity, depending upon how the ambient temperature varied throughout the day. Alternatively, the same (or nearly the same) level of comfort could be achieved by substituting off-peak electricity for peak electricity by pre-cooling the house prior to the hottest hours, and by letting the air conditioner run longer just after the hottest hours to cool the room. Clearly, the effectiveness of this strategy in maintaining the comfort of the house would diminish as more and more off-peak electricity (substituted for peak electricity) is used to run air conditioning during a hot summer afternoon.[2]

A second example relates to how a consumer chooses to run appliances such as dishwashers, washing machines and dryers during off-peak hours. As more and more appliances are operated off-peak, any further willingness to continue the substitution will diminish as these activities begin to interrupt other activities.

With these basic assumptions about consumer preferences, we can now examine how customers substitute off-peak for peak electricity usage when faced with a dynamic rate. Figure A-2 depicts the consumption of peak and off-peak electricity usage for customers on a flat rate. In this figure, the price of both peak and off-peak electricity are at the flat rate of P_p. Furthermore, given a consumer's budget for electricity of an amount B, the consumer could purchase any combination of peak and off-peak electricity that lies on the price and budget line (B/P_F). Since the customer faces a flat rate, the budget line has a slope of negative 45^{o}, indicating that if the entire budget were spent on either peak or off-peak usage, the same amount could be purchased. Furthermore, in moving along the budget line, there would have to be a one unit decrease in the use of peak electricity for every one unit increase in the purchase of off-peak electricity.

[2] A similar strategy for substituting off-peak for peak electricity use might also be employed by commercial establishments with a need to control the temperature at which food and other goods must be stored, but again, the effectiveness of the strategy will eventually begin to diminish as the substitution continues.

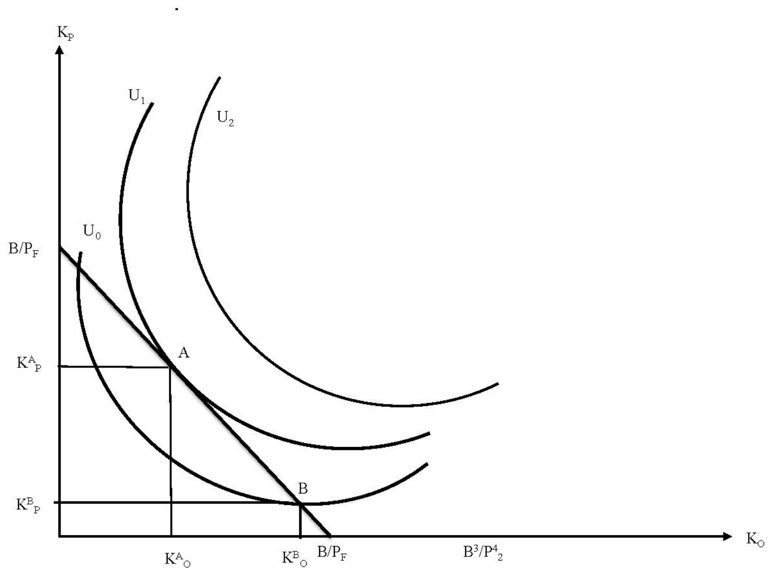

Figure A-2
Customer Utility and Peak and Off-Peak Electricity Consumption Based on a Flat Rate

Given this budget constraint depicted in Figure A-2, it is easy to see that the consumer maximizes satisfaction at point A, where the budget line is tangent to the utility curve, U_1. That is, a customer would maximize his/her utility by consuming K^A_P and K^A_O of peak and off-peak electricity, respectively.

To underscore the fact that point A is where the consumer would maximize his/her utility, we can compare point A to another combination of peak and off-peak usage that could be purchased with this fixed budget. Such a combination is at point B, where the customer would consume K^B_P and K^B_O of peak and off-peak electricity, respectively. Although this combination of peak and off-peak usage at point B can certainly be purchased with the existing budget, the consumer would be on a lower indifference curve (U_0 indicating that his utility level or level of satisfaction is lower that it is at point A. Through similar reasoning, one may conclude that when compared to point A, any other combination of peak and off-peak electricity usage that can be purchased with this budget (e.g. any point in the area between the horizontal and vertical axes and the budget line) would leave the consumer with a lower overall level of utility or satisfaction than at point A.

The Effect of Moving to Differential Peak and Off-Peak Rates

The initial point of peak and off-peak usage under the flat rate (point A in Figure A-2) provides the base of comparison in measuring the effect of going to a dynamic rate where the peak and off-peak electricity prices will differ. These effects are illustrated in Figure A-3, where it is assumed that the peak period price of electricity is $P_{P,}$ where $P_F < P_P$, and the off-peak prices is P_O, where $P_F > P_O$ (i.e., the peak period price is higher and the off-peak price is lower than the flat rate.)

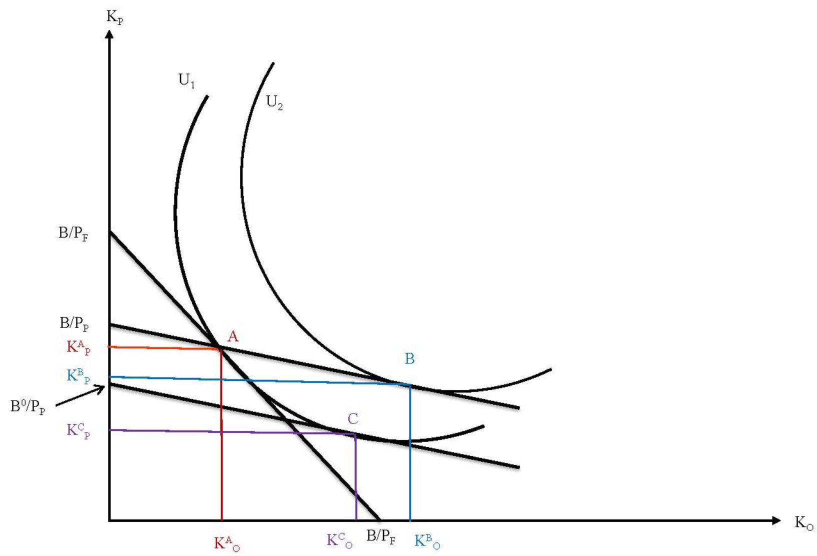

Figure A-3
Customer Utility and Effect on Peak and Off-Peak Usage from moving from a Flat Rate to a Time Differentiated Rate

Both of these price changes affect the slope of the customer's budget line. The increase in the peak price to P_P, means that less peak electricity can be purchased if all the initial budget B were spent on peak usage, while the decrease in the off-peak price to P_O means that more off-peak usage can be purchased if all the original budget B were spent on off-peak electricity usage. With these price changes moving in opposite directions, the budget line remains negatively sloped, but it is now flatter. It has an intercept on the K_P axis at B/P_P, which is below that of B/P_F under the flat rate. It also has an intercept on the K_O axis that would be well beyond the intercept under the flat rate of B/P_F.

We cannot be sure of the exact change in the slope of this budget line unless we know the exact changes in rates (and the customer's budget). However, if the new rate is indeed revenue neutral for this representative customer, we do know that this new budget line must also pass through point A, because the peak and off-peak rates have been increased and decreased, respectively, by the amounts necessary for this average customer to purchase existing peak and off-peak usage with the same expenditure as under the flat rate.

There are three possible effects in moving from this flat rate to a revenue neutral dynamic rate:

1. If the customer continues to spend the same amount on electricity, he/she can move to point B in Figure A-3 which is at a higher level of utility (U_2). This is accomplished by increasing off-peak usage from $K^A{}_O$ to $K^B{}_O$ and reducing peak usage from $K^A{}_P$ to $K^B{}_P$.
2. If rather than spend the same amount on electricity, the customer chooses to consume so that his/her level of satisfaction remains unchanged (e.g. at U_1), then consumption can be on the budget line (B^0/P_P) and at point C in Figure A-3. This is accomplished by increasing off-peak usage from $K^A{}_O$ to $K^C{}_O$ and reducing peak usage from $K^A{}_P$ to $K^C{}_P$. We know that total expenditures decline because the budge line for B^0/P_P lies everywhere inside the budget line B/P_P.

3. The situations in (1) and (2) above are at the two extremes in terms of customer response to moving to a dynamic rate. So the third, and perhaps the most likely scenario is that customer's new consumption levels will lie somewhere in between points B and C in Figure A-3. Where customers will end up after the implementation of the new rate is an empirical question, and any point between C and B will imply some change in the ratio of peak to off-peak usage relative to the change in the off-peak to peak prices.

However, in defining a measure such as the elasticity of substitution, it is necessary to decide on some base of comparison, and the base of comparison which leads to an unambiguous measure of the elasticity of substitution is one for which the customer's utility level is assumed to remain unchanged. This corresponds to case (2) above.

Thus, we define the elasticity of substitution for peak to off-peak electricity as a measure of the percentage change in usage in the two periods (e.g., the ratio of the peak to off-peak usage) for a one percent change in the *relative* prices in those periods (e.g., the ratio of the off-peak to peak price), holding the *level of customer utility unchanged*, and not, as some have suggested that it is total electricity consumption is unchanged. From Figure A-3, we can define the elasticity of substitution as:

$$E^s = \frac{\left\{\frac{K_P^C - K_P^A}{K_P^A}\right\}}{\left\{\frac{K_O^C - K_O^A}{K_O^A}\right\}} \div \frac{\left\{\frac{(P_O - P_F)}{P}\right\}}{\left\{\frac{(P_P - P_F)}{P_F}\right\}} \qquad \textbf{Equation A-2}$$

From equation for E^s, we can determine the signs on the four terms in { }. Since the off-peak price falls and the peak price rises in moving to a dynamic rate from a flat rate, we know that $\left\{\frac{(P_O - P_F)}{P_F}\right\} < 0$ and that $\left\{\frac{(P_P - P_F)}{P_F}\right\} > 0$. Similarly, we know that peak usage falls and off-peak usage rises in moving from a flat rate to the dynamic rate, so that $\left\{\frac{(K_P^C - K_P^A)}{K_P^A}\right\} < 0$ and $\left\{\frac{(K_O^C - K_O^A)}{K_O^A}\right\} > 0$. Therefore, $E^s > 0$.

In general, customers who are more willing to substitute off-peak for peak electricity usage, will have indifference curves that reflect that preference. That is, as the curvature or slope of the indifference curve U_1 in Figure A-3 becomes less pronounced (i.e., flatter), a customer's price responsiveness, as measured by the elasticity of substitution rises. Customers who are less willing to substitute off-peak for peak usage will have a more pronounced (curved) utility curve (such as the curve U_1) and E^s falls as price responsiveness decreases.

Some extreme values of the elasticity of substitution are of special interest. One such value is when $E^s = 0$. This is the case where peak and off-peak electricity use must be in fixed proportions, and this case is depicted where the indifference curves would be rectangles. This describes a situation in which peak and off-peak electricity usage are perfect complements, and such a situation might arise when a customer must run an electrical device 24/7 for medical reasons.[3] Another extreme case, where $\sigma = \infty$, is theoretically possible, but it is extremely

[3] There are also a number of production processes that must use electricity in fixed proportions during critical peak and off-peak hours.

unlikely in reality. This case is where the indifference curves are straight lines and peak and off-peak electricity are perfect substitutes.

Another value of special interest is where $E^s = 1$. This is the case where, as one moves to a dynamic rate, the ratio of peak to off-peak electricity usage changes in the same proportion as the ratio of off-peak to peak prices. This implies that after the change in rates, a customer's shares of total spending on electricity for peak and off-peak electricity will remain unchanged. However, in the extensive empirical literature to date, estimates of the elasticity of substitution between peak and off-peak electricity lie in the range where $0 < E^s < 1$, with most of them much closer to zero than to unity. With the elasticity of substitution less than unity, it can be shown that when there is a proportional decrease in the ratio of off-peak to peak electricity prices, such as would be the case in moving to a dynamic rate, the ratio of the shares of total expenditures for peak and off-peak electricity usage (e.g. P_pK_p / P_OK_O) will decrease in proportionately by a factor of E^s -1.[4]

In most studies where empirical estimates of the elasticity of substitution have been reported, the estimates have been between zero and unity ($0 < E^s < 1$). Therefore, there will be a negative decrease in this expenditure ratio, and any negative percentage translates into an actual percentage increase in the ratio of peak to off-peak expenditures.

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[4] This proportional decrease in the ratio of the shares of total expenditures for peak and off-peak electricity usage can be shown through an analysis of the formula for the elasticity of substitution (E^s:

$$\left(\frac{kWh_{peak}}{kWh_{off-peak}}\right) = a\left(\frac{Price_{off-peak}}{Price_{peak}}\right)^{E^S} .$$

The fact that the elasticity of substitution measures the percentage change in the ratio peak to off-peak usage due to a one percent change in the ratio of off-peak to peak prices is best represented by transforming this equation into logarithmic form:

$$ln\left(\frac{kWh_{peak}}{kWh_{off-peak}}\right) = lna + (E^s)ln\left(\frac{Price_{off-peak}}{Price_{peak}}\right)$$

In this form, the slope coefficient (Es) measures changes in percentage terms. To examine how the ratio of the shares of total expenditures for peak and off-peak electricity usage changes when the ratio of off-peak to peak prices changes, one can begin by dividing both sides of the first equation in this footnote by the ratio of off-peak to peak price. This division results in the following equation, where the left hand side of the equation is now:

$$\left(\frac{Price_{peak}}{Price_{off-peak}}\right) \cdot \left(\frac{kWh_{peak}}{kWh_{off-peak}}\right) = a\left(\frac{Price_{off-peak}}{Price_{peak}}\right)^{E^S-1}$$

Rather than being the ratio of peak to off peak usage, the left hand side of this equation is not the ratio of expenditures on peak electricity to expenditures on off-peak electricity. By taking the logarithms of both sides, we have:

$$ln\left(\frac{Price_{peak} \cdot kWh_{peak}}{Price_{off-peak}.kWh_{off-peak}}\right) = lna + (E^s - 1)ln\left(\frac{Price_{off-peak}}{Price_{peak}}\right)$$

The slope coefficient in this logarithmic equation is (Es – 1), and it is one less than the elasticity of substitution, Es. Using similar logic as above, this slope coefficient measures the percentage change in the ratio of expenditures on peak electricity to expenditures in off-peak electricity for a one percent change in ratio of the off-peak to the peak price of electricity. Thus, for every one percent decrease in the ratio of off-peak to peak electricity prices, such as would be the case in moving to a dynamic rate, the ratio of the shares of total expenditures for peak and off-peak electricity usage would decrease by a percentage of (Es – 1). Since it is likely that the elasticity of substitution for peak to off-peak electricity usage is between zero and unity (0 < Es < 1), this percentage decrease is in fact negative—which is then actually an increase.

Thus, by examining the elasticity of substitution we are able to gain important information about how the total expenditures on electricity are reallocated between purchases of peak and off-peak electricity usage. However, without information about initial levels of usage prior to the new rate, we cannot determine from the elasticity of substitution alone whether ***total*** usage will increase or decrease.

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[4] Results of CL&P's Plan-It Wise Energy Pilot. Connecticut Light and Power, Filing in Response to the Department of Public Utility Control's Compliance Order No. 4, Docket No. 05-10-03RE01, December 2009. Available at: http://nuwnotes1.nu.com/apps/clp/clpwebcontent.nsf/AR/PlanItWise/$File/Plan-it%20Wise%20Pilot%20Results.pdf.

[5] Evaluation of the (Commonwealth Edison) Residential Real Time Pricing (RRTP) Program, 2007-2010. Navigant Consulting, Inc., prepared for Commonwealth Edison Company, June 20, 2011.

[6] The Effect on Electricity Consumption of the Commonwealth Edison Customer Application Program: Phase 2 Final Analysis. EPRI Report No. 1023644. EPRI, Christensen Associates Energy Consulting, LLC, R. Boisvert, Cornell University. October 21, 2011.

[7] Hydro One Networks Inc. Time-of-Use Pilot Project Results. EB-2007-0086, Susan Frank, submitted to the Ontario Energy Board, Ontario, Canada, May 13, 2008.

[8] 2008 Ex Post Load Impact Evaluation for Pacific Gas and Electric Company's SmartRate™ Tariff. Stephen George and Josh Bode, Freeman, Sullivan & Co., San Francisco, CA, December 30, 2008.

[9] PowerCentsDC™ Power Program. eMeter Strategic Consulting for the Smart Meter Pilot Program, Inc., September 2010.

[10] Public Service Electric and Gas Company. Dan Violette, Jeff Erickson, Mary Klos, Summit Blue Consulting, Final Report for the myPower Pricing Segments Evaluation, Public Service Electric and Gas Company, December 21, 2007.

<table>
<tr><td>Reference</td><td>Baltimore Gas & Electric Smart Energy Pricing Pilot - Summer 2008. Ahmad Faruqui and Sanem Sergici, BGE's Smart Energy Pricing Pilot, Summer 2008 Impact, The Brattle Group, Inc., April 28, 2009.</td></tr>
<tr><td>Location</td><td>Baltimore, Maryland</td></tr>
<tr><td>Customer Segment</td><td>Residential</td></tr>
<tr><td>Time/Duration</td><td>June 1, 2008 - September 30, 2008 (four months)</td></tr>
<tr><td>Sample Size</td><td>Treatment groups: 1,021
Control group: 354</td></tr>
<tr><td>Sample Size by Treatment Group (as of July 2008)</td><td>

Dynamic pricing + IHD + switch for AC cycling (>1,000) (8 treatment (technology/price combinations) groups, ~111-148 per treatment)
Control Group ~ 354

<table>
<tr><th>Group</th><th>Sample Size</th></tr>
<tr><td>Treatment (all)</td><td>1,021</td></tr>
<tr><td>DPP*</td><td>148</td></tr>
<tr><td>DPP+orb+switch</td><td>111</td></tr>
<tr><td>PTR-L**</td><td>126</td></tr>
<tr><td>PTR-L+orb</td><td>141</td></tr>
<tr><td>PTR-L+orb+switch</td><td>113</td></tr>
<tr><td>PTR-H**</td><td>127</td></tr>
<tr><td>PTR-H+orb</td><td>137</td></tr>
<tr><td>PTR-H+orb+switch</td><td>118</td></tr>
<tr><td>Control</td><td>354</td></tr>
</table>

Two types of pricing (with and without enabling technology)

DPP (dynamic peak pricing), which is a combination TOU with CPP rate structure
Peak time rebate (PTR), low and high levels:

PTRL = $1.16/kWh
PTRH = $1.75/kWh

Information treatments:

Energy orb only (a sphere that emits different colors to indicate peak, off-peak and critical peak hours)

Information plus control technology treatments:

Energy orb plus A/C switch to reduce AC load by 50%

</td></tr>
<tr><td>Experimental Design</td><td>Not randomized. Recruited customers from their load research sample; another 200 from their interval meter test sample. Then randomly selected 5,000 customers to be representative of their target population. (i.e., excluded TOU customers and those served by 3rd party ESPs.) Also, the control group was made up of the remaining customers in their load research and interval meter test sample.</td></tr>
</table>

Reference	**Baltimore Gas & Electric Smart Energy Pricing Pilot - Summer 2008.** Ahmad Faruqui and Sanem Sergici, BGE's Smart Energy Pricing Pilot, Summer 2008 Impact, The Brattle Group, Inc., April 28, 2009.
Recruitment method	Opt-in. Goal was to recruit 1,000 customers in total. • From the 440 customers in BGE's load research sample, recruited 84 customers were ultimately recruited • From the 200 customers within their interval meter test sample, 28 customers were ultimately recruited. • To recruit the remaining customers, BG&E randomly selected an additional pool of 5,000 customers. • Overall opt-in rate: 18% • Recruitment methods: direct mail, outbound telemarketing for non-respondents, education/informational materials, and one-time appreciation payment of $150 (DPP) and $100 (PTR)
Information?	• Energy Orb (by Ambient Technology, sphere that communicates pricing changes via a change in color) • Also DPP events communicated by phone, e-mail, SMS text messages; also on website (effects of this information were not tested as part of the pilot) • Website, customized welcome package (explaining details of the pilot, customer's specific pricing structure and technology info, tips to save) for treatment groups with pricing information (not tested in the pilot)
Feedback?	No. The effects of feedback were not tested in this pilot, but customers were provided the following: After each event, rebate (PTR) customers received a "savings report" from the event, as well as their overall performance; DPP customers received this, but on a monthly basis (in addition to, but around the same time as, their bill).
Control technology?	• Central AC switch (during critical event, utility decreased customers' air conditioning load, as it was at that time, by 50%). This treatment was always provided in combination with the Orb, so only Orb and Orb+switch were tested as per the design. • Provided free to the customer
Installation Method	• Orb: By customer. • Switches: By utility. Smart meters were required for all treatment and control customers, and switches were installed at the same time.

Reference	**Baltimore Gas & Electric Smart Energy Pricing Pilot - Summer 2008.** Ahmad Faruqui and Sanem Sergici, BGE's Smart Energy Pricing Pilot, Summer 2008 Impact, The Brattle Group, Inc., April 28, 2009.
Dynamic rate?	• Time of Use Rate + Dynamic Peak Pricing (on a limited number of critical peak days, the on-peak price was increased 9X; off-peak price lowered 6¢/kWh) • Peak Time Rebate (two levels, low = 1 9X base rate; high = 12.5X base rate) • Basic flat rate (flat, seasonal energy rate + customer charge) • Critical Peak Period for both CPP & PTR = 5 hours, 2:00 p.m. -7:00 p.m. weekdays • 12 events/year
Load impacts measured (pp. 22-24)	• Load reductions for CPP events on critical days, average weather: o without enabling technology = 20.11% o with Energy Orb + AC switch = 32.5% • Load reductions for PTR (PTRL + PTRH) events: o without enabling technology = 18-33% o with the Energy orb = 23-27% o with switch on AC = 29-33% Reductions were significant at the 95% level (p. 2)
Electricity Prices	• Substitution elasticities for DPP, PTRL & PTRH (not statistically different). Measures load shifting. • Elasticities based on average weather for all three rates was -0.096, "a one percent change in the ratio of peak to off-peak prices leads to a 0.096% change in the ratio of peak to off-peak consumption." (p. 17) • "It is important to note that the substitution elasticities for DP, PTRL and PTRH were not found to be statistically distinguishable from each other when tested separately in the estimation equations. This result has an important implication that the SEP customers show the same responsiveness to dynamic pricing whether it is expressed as a price increase during the critical hours or the availability of a peak time rebate." (p. 2) • Substitution elasticities (based on average weather, p. 17) for: o All three rates plus the energy orb: -0.136 o All three rates plus energy orb + A/C switch: -0.18 • Also estimated daily own price elasticity of -0.039 for average weather. (p. 16)
Estimation method	Constant Elasticity Model;[5] PRISM (Pricing Impact Simulation Model to simulate load impacts under different pricing scenarios.)
Price of substitutes?	No

[5] Constant elasticity model; "fixed effects" estimation routine that . . . controls for all customer specific characteristics that don't vary over time and isolate their impact on the dependent variable." p. 10.

Reference	**Baltimore Gas & Electric Smart Energy Pricing Pilot - Summer 2008.** Ahmad Faruqui and Sanem Sergici, BGE's Smart Energy Pricing Pilot, Summer 2008 Impact, The Brattle Group, Inc., April 28, 2009.
Income	Limited analysis based on follow-up survey data; found income of $75,000 + led to higher daily price elasticity. Limited survey response caused them to ignore the results.
Customer Circumstances	Limited analysis based on follow-up survey data; found having college + education increased the substitution elasticity. Limited survey response caused them to ignore the results.
Premise Circumstances	Appliance stock, central AC did not statistically affect substitution or daily elasticities; multi-family residence reduced the substitution elasticity. Limited survey response caused them to ignore the results.
Exogenous factors	Weather - modeled the impact of weather on load for all 8 treatment groups
Self-reports of behaviors changed?	Yes, mid-point through summer, both treatment and control groups, goal was to assess how appliances may have affected customers' ability to reduce consumption, although results not reported; final survey after the treatment period as well, but to obtain opinions about pilot
Persistence?	Mention of BG&E calling events on back-to-back days to estimate persistence, but didn't report any results. A follow-up analysis reported that substitution and own-price elasticities in 2009 were consistent with those in 2008.[6]

[6] Sanem Sergici and Ahmad Faruqui, "Evaluation of Baltimore Gas and Electric Company's Smart Energy Pricing Program," presented at the 9th International Industrial Organization Conference, Boston MA, p. 14. Available at: http://brattle.com/_documents/UploadLibrary/Upload940.pdf.

Reference	**Impact Evaluation of the California Statewide Pricing Pilot, (Residential Summary)** Charles River Associates, Oakland, CA, March 16, 2005.
Location	California - three major IOUs, SCE, PG&E, SDG&E
Customer Segment	Residential
Time/Duration	July 2003 - December 2004
Sample Sizes for all treatment groups & control group	This statewide pilot has a very complicated sample design. It was selected to represent four distinct weather zones in the state. Further, customers were divided into three tracks (p. 17): • Track A represented the general population of customers in the state • Track B represented the population of relatively low-income customers living in the vicinity of two power plants in the Hunters Point/Potrero division of San Francisco and a control group of customers in the city of Richmond. (Results for track B were reported in a different report.[7]) • Track C customers were recruited from a sample of customers that had previously volunteered for the AB970 Smart Thermostat pilot. All Track C customers had smart thermostats and central AC. (p. 9) Sample sizes are reported by track and by treatment on p. 26. Sample sizes were selected to accommodate a 20% opt-out rate. Total sample sizes (across zones) by treatment group are as follows: • Control Group: 813 • CPP-F: 606 • CPP-F (information only): 126 • CPP-V (SDG&E only): 520 • Information only (PG&E only): 126 • TOU: 300 • Total, all groups: 2491

[7] Results from the Track B analysis are contained in a separate report produced by San Francisco Community Power, the contractor that implemented and evaluated the Track B treatments. See *Statewide Pricing Pilot -- Track B: Evaluation of Community Based Enhanced Information Treatment*, Draft Final Report, March 8, 2005. (footnote 7, p. 17)

<table>
<tr><td>Reference</td><td>Impact Evaluation of the California Statewide Pricing Pilot, (Residential Summary) Charles River Associates, Oakland, CA, March 16, 2005.</td></tr>
<tr><td>Treatments (p. 4 & 5)</td><td>
Traditional TOU (peak price = 2X off-peak price)
Critical Peak Price ~ 5X the standard rate and 6X off-peak rate, with two different period definitions and advance notice:

CPP-F = fixed critical peak period and DA notice
Different price levels
CPP-V = variable peak period on critical days and same-day notice (SDG&E only)
Different price levels
CPP-V + control technology = customers on CPP-V offered free control technology to facilitate demand response (SDG&E only)
Different price levels
Choice of control technology (2/3 of customers accepted one of three 3 enabling technologies and about half of those selected a smart thermostat—see “control technology” cell below)

Information-only treatment: urged customers to reduce demand on critical days (PG&E territory only)
Control group: on standard rate
</td></tr>
<tr><td>Experimental Design</td><td>
Track A customers were randomly selected from the general customer population (both control and treatment groups)
Track C customers (both control and treatment groups) were selected from customers who had previously volunteered for the AB970 Smart Thermostat Pilot.
Goal: estimate the average impact of time-varying rates on energy use by rate period and develop models that can be used to predict impacts under alternative pricing plans
See description of treatment groups and estimation methods.
</td></tr>
<tr><td>Recruitment</td><td>
Originally proposed as opt-out; final was voluntary (opt-in) design for Tracks A & C; incentive payments for residential customers were $175 paid in 3 installments ($25 after completing a survey; $75 at the end of the summer 2003; $75 at the end of summer 2004 (pp. 30-31)
Response rates: A total of 63 customers (4%) elected to opt-out of the experiment between July 1 and Oct 31, 2003.
</td></tr>
<tr><td>Information?</td><td>
Yes: Information-only treatment: urged customers to reduce demand on critical days. No significant impact was found (pp. 9-10).
Also, Energy Orbs to a small subset of CPP-V customers. No statistically significant load impacts were found, but the authors state this is not surprisingly given the relatively low sample sizes.[8]
</td></tr>
</table>

[8] Martinez, M. S., & Geltz, C. R. (2005). Utilizing a pre-attentive technology for modifying customer energy usage. Paper presented at the ECEEE 2005 Summer Study Proceedings, Côte d'Azur, France, 3-11.

<table>
<tr><td>Reference</td><td>Impact Evaluation of the California Statewide Pricing Pilot, (Residential Summary) Charles River Associates, Oakland, CA, March 16, 2005.</td></tr>
<tr><td>Feedback?</td><td>As part of another study, a small subset of customers were provided feedback in the form of custom-made “enhanced bill analyses”, provided monthly by mail or email. These treatments were provided to a subset of customers on the CPP-V rate. No statistically significant load impacts were found, but the authors state this is not surprisingly given the small sample sizes.[9]</td></tr>
<tr><td>Control Technology?</td><td>

- Track A customers were offered three control technology options, which were free and voluntary:

<table>
<tr><td></td><td>CPP-V, Zone 2 (numbers deployed)</td><td>CPP-V, Zone 3 (numbers deployed)</td></tr>
<tr><td>Water heater controller (utility controllable)</td><td>7</td><td>15</td></tr>
<tr><td>Pool pump controller (utility controllable)</td><td>12</td><td>8</td></tr>
<tr><td>AC controller/smart thermostat (utility controllable)</td><td>14</td><td>3</td></tr>
<tr><td>Total controls</td><td>33 (out of 57, 60%)</td><td>29 (out of 38, 75%)</td></tr>
</table>

It is assumed that all controls are utility-controlled during critical events, although it is possible that the smart thermostats allowed for customer-control as well.

- All Track C customers (125 CPP-V and 20 control customers) had programmable thermostats based on their previous participation in the Smart Thermostat pilot (customer controlled, although it is assumed customers could program them as well; it is not known if customers could override the utility control)

</td></tr>
<tr><td>Dynamic rate?</td><td>

- Yes. (See Treatments)
- Base rates are inclining block rates

</td></tr>
</table>

[9] Ibid.

Reference	**Impact Evaluation of the California Statewide Pricing Pilot, (Residential Summary)** Charles River Associates, Oakland, CA, March 16, 2005.

Load Impacts measured for pricing treatment CPP-F	• Percent change in residential peak-period energy use (Avg. CPP-F prices/Avg. 2003/2004 Weather) on critical weekdays vs. normal week days
	• Average impacts by season:
	    o "inner summer" vs. "outer summer"
	    o "inner winter" vs. "outer winter"
	• Reduction in peak period energy use on critical days as a function of price (p. 7)
	    o inner summer, outer summer, summer average
	    o average summer (2003/04) by zone and statewide
	• Total energy use across the entire year: There was essentially no change in total energy use across the entire year based on average SPP prices. That is, the reduction in energy use during high-price periods was almost exactly offset by increases in energy use during off-peak periods. (p. 7)

Load Impacts measured for CPP-V	**Summer peak-period energy consumption** • Track A customers ~ 16% (almost 25% higher than the CPP-F rate average) • Track C customers ~ 27%. (about 2/3 attributable to enabling technology; remainder to price-induced behavioral changes)
Load Impacts measured for control technologies	Track A: No statistically significant effect was found for the control technology or the smart thermostat Track C: A 17% average peak period load reduction was attributed to the smart thermostats (~60% of the total reduction, the remaining 40% from the CPP-V rate).

Load Impacts measured for information-only treatment	• Energy use measured for critical peak periods, same as for CPP-F
	• Only measured for two zones
	    o In one zone in 2003, DR was statistically significant
	    o In the other zone, it was not
	    o In 2004, there was no response in either zone

Load Impacts for all treatments	Summarized in a detailed table, p. 11
Impact of Electricity Prices	Elasticities of substitution and daily elasticities were estimated and reported in great detail. (See pp. 66-70)

Reference	**Impact Evaluation of the California Statewide Pricing Pilot, (Residential Summary)** Charles River Associates, Oakland, CA, March 16, 2005.
Estimation method	• Demand models (p. 5) "were used to estimate the demand response impact for the average prices used in the SPP." • Energy use before and after being placed on the new rate is available for treatment customers. "This allows one to separate the impact of the experimental treatments from the impact of other factors that might influence energy use, including self-selection bias." (p. 5) • A constant elasticity of substitution (CES) demand system. "The demand system estimated for each tariff consists of two equations. One equation predicts daily energy use as a function of daily price and other factors. The second equation predicts the share of daily energy use by rate period. This type of demand system is commonly used in empirical analysis of energy consumption. While the complexity of the experimental design has created numerous empirical challenges, these challenges have been addressed through careful application of widely accepted statistical methods." (p. 5; for more detail, see pp. 33-38 and Appendix 7)
Price of substitutes?	No
Income	Not clear
Customer Circumstances	Yes. See p. 76. Elasticities of substitution and daily elasticities were estimated to determine the impact of 11 customer characteristics including demographic (income, education) as well as appliance stock (CAC, spas, swimming pools, electric cooking, etc.). Of all these variables, the presence of central air conditioning had the biggest response differential. (p. 74)
Premise Circumstances	Presence of central air conditioning. "HHs with central AC were more price responsive and produced greater absolute and percentage reductions in peak-period energy use than did HHs without AC." (p. 7; see also p. 74 for more detail)
Exogenous factors	Weather. Results were segmented by climate zone.

Reference	**Impact Evaluation of the California Statewide Pricing Pilot, (Residential Summary)** Charles River Associates, Oakland, CA, March 16, 2005.
Persistence?	Yes. "Differences in impacts across critical days when 2 or 3 critical days are called in a row were not statistically significant." (p. 6) The results indicated that ". . .the null hypothesis that the differentials are the same (for the elasticities of substitution and daily elasticities for 1st, 2nd and 3rd days of events) cannot be rejected . . . at the 5% level of significance." (p. 70) Also, with regard to persistence between the summer of 2003 and 2004 for the CPP-F rate: "While some relatively minor differences are found, we conclude that the most important variables (the critical day impacts and the elasticity of substitution) do not differ" (p. 45) • Comparing common customers in 2003 and 2004: There was no statistical difference in substitution elasticity between 2003 and 2004; the reduction in daily usage on critical days was statistically larger in 2004 than 2003 (daily price elasticity was -0.054, whereas it was -0.035 in 2003); and the increase in off-peak energy use was statistically less in 2004 than 2003. • Similar results are found when comparing all customers in 2003 and 2004 (not just common customers).

Reference	**California's Statewide Pricing Pilot, (Commercial & Industrial Analysis Update)** Freeman, Sullivan & Co. and Charles River Associates, Oakland, CA, June 28, 2006.[10]
Location	California - Southern California Edison only

Customer Segment	• C&I customers smaller than 200 kW, in two size categories:
	  o LT20 (demands <20 kW)
	  o GT20 (demands between 20 kW and 200 kW)

Time/Duration	Summers of 2004 and 2005 (defined as the first Sunday in June through the first Sunday in October) (p. 8 of June 2006 report)

Sample Sizes for treatment & control group	This pilot also has a very complicated sample design. C&I customers were divided into two tracks and two size categories reported above (p. 17 of March 2005 report):
	• Track A represented the general population of customers in the state
	• Track C customers were recruited from a sample of customers that had previously volunteered for the AB970 Smart Thermostat pilot. (p. 17 of 2005 Report)
	Sample sizes are reported by Track and by treatment on p. 26 (2005 Report). Total sample sizes at the beginning of the pilot were as follows. Control and treatment customers were selected from the AB970 Smart Thermostat Pilot:
	• Control Group = 84
	  o < 20 kW = 42
	  o > 20 kW= 42
	• CPP-V - Total = 132
	  o < 20 kW = 56
	  o > 20 kW= 76
	• Total, all groups: 216

Treatments (p. 2 of 2006 report)	• Critical Peak Pricing Periods
	  o On most weekdays, a peak period price was in effect between noon and 6:00 p.m.
	  o Critical peak periods were either 2 hours or 5 hours long
	• Standard Pricing (average prices) (Control group)
	  o for < 20 kW = 17¢/kWh
	  o for > 20 kW = 16 ¢/kWh
	• Critical Peak Pricing (average prices) (Treatment Groups)
	  o for < 20 kW = $1.00/kWh
	  o for > 20 kW = 60 ¢/kWh

[10] Note: This reference is for the updated analysis of the C&I results. The details about sample design, etc., are provided in the "Impact Evaluation of the California Statewide Pricing Pilot, (Residential Summary) Charles River Associates, Oakland, CA, March 16, 2005." Both reports are cited in this table.

Reference	**California's Statewide Pricing Pilot, (Commercial & Industrial Analysis Update)** Freeman, Sullivan & Co. and Charles River Associates, Oakland, CA, June 28, 2006.[10]
Experimental Design	Track A customers were randomly selected from the rate class (control and treatment). For Track C, control and treatment customers were selected from the customers who participated in the AB970 Smart Thermostat Pilot. Goal was to answer four questions (2006 report, p. 16): 1. Does demand response vary across the two summers of 2004 and 2005? 2. How much do peak period demand impacts vary across customers who do and don't have control technology? 3. Persistence: does DR vary across days in a multi-day CPP event sequence? 4. Does price responsiveness vary across 2-hour and 5-hour critical peak events?
Recruitment	• Opt-in recruitment design (but predicated on an opt-out approach). Randomly selected customers were mailed enrollment packages and then asked to affirm their participation. If customers did not respond, reminder mailers were sent, followed by phone calls. If they still did not respond, customers were dropped from the program. • Opt-out rates between summers of 2004 and 2005: o for LT customers: 19% o for GT customers: 23%
Information?	• No
Feedback?	• No
Control technology?	• Yes – all track A customers were offered a free smart thermostat that could be programmed to automatically respond to CPP price signals o Acceptance rates across both summer periods: ▪ for LT customers: roughly 33% accepted ▪ for GT customers: 59% accepted
Dynamic rate?	• Yes. CPP-V. (Same as CPP, except that the length of the time critical peak period can vary. Two time periods were tested, 2-hour and 5-hour. • Base rates are inclining block rates

Reference	**California's Statewide Pricing Pilot, (Commercial & Industrial Analysis Update)** Freeman, Sullivan & Co. and Charles River Associates, Oakland, CA, June 28, 2006.[10]
Load Impacts measured (pp. 3-4, 2006 report)	• *Average reduction in summer peak-period energy use on critical days (based on pooled data base)*: o for LT customers: 4.83% o for GT customers: 6.75% • *For LT customers, with and without control technology:* o without control technology: ~0% o with control technology: 13% • *For GT customers, with and without control technology:* o without control technology: 4.93% o with control technology: 9.57% • Detailed kWh estimates for different data sets (years and participants (pp. 19-20)
Load Impacts for all treatments	Summarized graphically on pp. 5-6 (2006 report)
Impact of Electricity Prices	Elasticities of substitution were estimated and reported in detail (see p. 17, 2006 report). Elasticities based on data pooled across both summers:[11] • for LT customers: -0.0316 • for GT customers: -0.0578 Elasticities of substitution with and without technology, estimated on critical days (See p. 24, 2006 report): • *For LT customers, with and without control technology:* o without control technology: -0.005 o with control technology: -0.0891 • *For GT customers, with and without control technology:* o without control technology: -0.0412 o with control technology: -0.0815
Estimation method	• CES demand models (see section 3.1 of 2005 report) • From the 2005 report: A constant elasticity of substitution (CES) demand system. "The demand system estimated for each tariff consists of two equations. One equation predicts daily energy use as a function of daily price and other factors. The second equation predicts the share of daily energy use by rate period. This type of demand system is commonly used in empirical analysis of energy consumption. While the complexity of the experimental design has created numerous empirical challenges, these challenges have been addressed through careful application of widely accepted statistical methods." (2005 report, p. 5; for more detail, see pp. 33-38 and Appendix 7.)

[11] Note: there were nominal differences in elasticities for different time periods for each customer segment, but the differences were not statistically significant.

Reference	**California's Statewide Pricing Pilot, (Commercial & Industrial Analysis Update)** Freeman, Sullivan & Co. and Charles River Associates, Oakland, CA, June 28, 2006.[10]
Price of substitutes?	No
Income	No
Customer Circumstances	No
Premise Circumstances	No
Exogenous factors	No. All customers were in SCE service territory, so weather would have been the same for all customers.

Persistence?	Persistence of response was measured for events that were called over multiple days. Results varied by size of customer.
	• *for LT20 customers - low response; no persistence*
	    o low level of price response on single days (or 1st day of a multi-day event)
	    o no response on 2nd or 3rd day of multi-day events
	• *for GT20 customers - moderate response, persisting across multiple days*
	    o moderate level of price response on single days (or 1st day of a multi-day event)
	    o consistent response on 2nd or 3rd days of multi-day events
	Persistence was also assessed from the summer of 2004 to the summer of 2005.

Reference	**Results of CL&P's Plan-It Wise Energy Pilot,** Connecticut Light & Power, Filing in Response to the Department of Public Utility Control's Compliance Order No. 4, Docket No. 05-10-03RE01, December 2009.
Location	Connecticut
Customer Segment	• Residential • Commercial & Industrial
Time/Duration	June 1, 2009 - August 31, 2009 (3 months)
Sample Sizes for treatment & control group (p. 6)	• Company designed 13 groups of 100 customers each for both residential and C&I customers (117 customers per cell were recruited to allow for attrition) • Control group - 200 (137 residential and 63 C&I) • Total customers - 2,437 customers

<table>
<tr><td>Reference</td><td>Results of CL&P's Plan-It Wise Energy Pilot,
Connecticut Light & Power, Filing in Response to the Department of Public Utility Control's Compliance Order No. 4, Docket No. 05-10-03RE01, December 2009.</td></tr>
<tr><td>Treatments (pp. 6-7)</td><td>

Control Group - Standard flat rate
Time of Use Rate Rates
On-peak period - 12:00 p.m. to 8:00 p.m. weekdays
Off-peak period - all other hours
Treatment - Critical Peak Pricing and PTR Overlays
Up to $1.60/kWh on 10 days from 2:00 p.m. to 6:00 p.m.; all other hours were discounted by 5¢/kWh
PTR rates provided a discount up to $1.60/kWh during event hours; base rate remained unchanged

Total feedback/information/control technology numbers (distributed across multiple rate treatments):
<table>
<tr><th></th><th>Residential</th><th>C&I</th></tr>
<tr><td>Feedback (IHD) and information (Orb)</td><td>307</td><td>409
(Orb only—IHD not provided for C&I)</td></tr>
<tr><td>PCT and switch</td><td>209</td><td>131</td></tr>
</table>
</td></tr>
</table>

<table>
<tr><th colspan="8">Time of Use Pricing - Differentials to Base Rates ($/kWh) (p. 6)</th></tr>
<tr><td rowspan="2">Customers</td><td>Rate</td><td colspan="2">TOU</td><td colspan="2">PTR</td><td colspan="2">CPP</td></tr>
<tr><td>Period</td><td>Low</td><td>High</td><td>Low</td><td>High</td><td>Low</td><td>High</td></tr>
<tr><td rowspan="2">Residential (Rate 1 & 5)</td><td>Peak</td><td>0.071</td><td>0.142</td><td>0.665</td><td>1.614</td><td>0.655</td><td>1.614</td></tr>
<tr><td>Off-peak</td><td>-0.029</td><td>-0.058</td><td>0.000</td><td>0.000</td><td>-0.015</td><td>-0.036</td></tr>
<tr><td rowspan="2">C&I (Rate 30 & 35)</td><td>Peak</td><td>0.069</td><td>0.138</td><td>0.650</td><td>1.601</td><td>0.650</td><td>1.601</td></tr>
<tr><td>Off-peak</td><td>-0.031</td><td>-0.062</td><td>0.000</td><td>0.000</td><td>-0.020</td><td>-0.049</td></tr>
</table>

<table>
<tr><td>Experimental Design</td><td>Goal was to test the three pilot rates with two price differentials, with and without technology
See sample sizes and rate differentials</td></tr>
</table>

Reference	**Results of CL&P's Plan-It Wise Energy Pilot,** Connecticut Light & Power, Filing in Response to the Department of Public Utility Control's Compliance Order No. 4, Docket No. 05-10-03RE01, December 2009.

Recruitment (pp. 7-8)	• Opt-in recruitment design
	• Recruitment approach:
	  o Direct mail
	  o Telephone follow up
	• Response rates:
	  o Residential - 3.1%
	  o C&I - 4.5%

Information?	• Ambient Technologies Orb that displayed real-time pricing information (in the form of changing color for peak, critical peak, etc.)
Feedback?	• In-home display (IHD), PowerCost Monitor by Blue Line Innovations • Website with hourly data (24 hours delay), although this was not separated out as its own treatment • Bill comparisons between base rate & TOU or CPP rates based on historical consumption (but the effects were not tested in the pilot) All provided free of charge to customer
Control technology?	• Automatic or smart switch device on central air conditioners • Programmable Communicating Thermostat designed to increase temperature settings during events, utility-controlled
Installation Method	• Feedback (IHD) and information (Orb): by customers • Control technology (PCT and switches): electricians (customers needed to be on the premise for PCT).
Dynamic rate?	• Yes. TOU, CPP and PTR

<table>
<tr><td>Reference</td><td>Results of CL&P's Plan-It Wise Energy Pilot,
Connecticut Light & Power, Filing in Response to the Department of Public Utility Control's Compliance Order No. 4, Docket No. 05-10-03RE01, December 2009.</td></tr>
<tr><td>Load impacts measured (See Appendix A, pp. 25-39)</td><td>
<table>
<tr><td></td><td></td><td colspan="2">TOU</td><td colspan="2">PTR</td><td colspan="2">CPP</td></tr>
<tr><td>Class</td><td>Period</td><td></td><td>With PCT and switch</td><td>High diff.</td><td>With PCT and switch</td><td>High diff.</td><td>With PCT and switch</td></tr>
<tr><td rowspan="2">Res. (Rates 1 & 5)</td><td>Peak load change</td><td>-3.1%</td><td>-3.1%</td><td>-10.9%</td><td>-17.8%</td><td>-16.1%</td><td>-23.3%</td></tr>
<tr><td>Monthly energy change</td><td>-0.1%</td><td>-0.1%</td><td>-0.2%</td><td>-0.3%</td><td>0.3%</td><td>0.2%</td></tr>
<tr><td rowspan="2">C&I (Rates 30 & 35)</td><td>Peak load change</td><td>0%</td><td>0%</td><td>0%</td><td>-4.1%</td><td>-2.8%</td><td>-7.2%</td></tr>
<tr><td>Monthly energy change</td><td>0%</td><td>0%</td><td>0%</td><td>0%</td><td>0%</td><td>0%</td></tr>
</table>

Load reductions were asserted to be "statistically measurable" but significance levels were not cited. (See p. 8.)
For the low version of each of the rates, effects were smaller (both for residential and commercial/industrial).

<u>Information and Feedback Effects</u>
The PowerCost Monitor and Orb were found to have no effect, on either load reduction or overall consumption reduction, in any of the pricing categories, for both residential and commercial.
<u>PCT and Switch Effects</u>
PCT had no effect on overall consumption reduction; PCT was found to have an effect on load reduction in most cases (see above table).
</td></tr>
<tr><td>Load Impacts for all treatments</td><td>See above cells.</td></tr>
</table>

<table>
<tr><td>Reference</td><td>Results of CL&P's Plan-It Wise Energy Pilot,
Connecticut Light & Power, Filing in Response to the Department of Public Utility Control's Compliance Order No. 4, Docket No. 05-10-03RE01, December 2009.</td></tr>
<tr><td>Impact of Electricity Prices</td><td>Yes. Elasticities of substitution (measures peak shifting). Also the daily price elasticity (measures conservation). See pp. 39-46 of Appendix A.

<u>Residential Elasticities of Substitution based on August weather</u>:
• TOU - Price only, Price + Orb and Price + TEC = -0.047
• PTP (aka CPP):
  o Price only = -0.081
  o Price + Orb = -0.081
  o Price + Orb + TECH = -0.128
• PTR
  o Price only = -0.052
  o Price + Orb = -0.052
  o Price + Orb + TECH = -0.100

<u>Residential Daily Elasticities based on August Weather</u>:
• TOU - Price only, Price + Orb and Price + TECH = 0.00
• PTP - Price only, Price + Orb and Price + TECH = -0.026
• PTP = Price only, Price + Orb and Price + TECH = -0.026

<u>Small C&I Elasticities of Substitution based on August weather</u>:
• TOU - Price only, Price + Orb and Price + TEC = 0.00
• PTP (aka CPP):
  o Price only = -0.016
  o Price + Orb = -0.016
  o Price + Orb + TECH = -0.042
• PTR
  o Price only = 0.00
  o Price + Orb = 0.000
  o Price + Orb + TECH = -0.026

<u>Small C&I Daily Elasticities based on August Weather</u>:
• TOU - Price only, Price + Orb and Price + TECH = 0.00
• PTP = Price only, Price + Orb and Price + TECH = 0.00
• PTR = Price only, Price + Orb and Price + TECH = 0.00</td></tr>
<tr><td>Estimation method (p. 7 and Appendix A)</td><td>• For load shifting: Measured elasticities of Substitution. (See Appendix A)
• For conservation effect: Estimated daily price elasticities</td></tr>
<tr><td>Price of substitutes?</td><td>No</td></tr>
</table>

Reference	**Results of CL&P's Plan-It Wise Energy Pilot**, Connecticut Light & Power, Filing in Response to the Department of Public Utility Control's Compliance Order No. 4, Docket No. 05-10-03RE01, December 2009.
Income?	No
Customer Circumstances	No
Premise Circumstances	No
Exogenous factors	No.
Self-reports of behaviors changed?	No
Persistence?	Not addressed, only 3 months

Reference	**Evaluation of the (Commonwealth Edison) Residential Real Time Pricing (RRTP) Program, 2007-2010.** Navigant Consulting, Inc., prepared for Commonwealth Edison Company, June 20, 2011.
Location	Chicago, Illinois
Customer Segment	Residential
Time/Duration	2007-2010
Sample Size	Treatment group: customers on RRTP (see table below) Control Group: ComEd's residential load research sample (RLS)
Sample Size by Treatment Group	• Total RRTP customers at year end: o 2007 - 3,334 o 2008 - 5,838 o 2009 - 8,007 o 2010 - 11,530 • RT-10 HHs: notice at the 10-cent level (customer must request)[12] • RT-14 HHs: notice at the 14-cent level (default notice) • PA (passive alert) receive no direct messages • Load Guard program - AC DLC program for RRTP • Control Group ~ 872 (p. 75)

[12] Participation numbers were graphed (p. 15) but tables showing exact numbers weren't in the report. From the graph on p. 15 it appears that as of year-end 2010, roughly 50% of the RRTP customers were in the RT-14 group (default notice); and approximately 27% were in the PA (passive alert) group. All other treatments were substantially smaller.

Reference	**Evaluation of the (Commonwealth Edison) Residential Real Time Pricing (RRTP) Program, 2007-2010.** Navigant Consulting, Inc., prepared for Commonwealth Edison Company, June 20, 2011.
Experimental Design	Not an experiment. It's a full scale program.[13] RRTP customers self-selected? Used ". . .a propensity score matching method to match each RRTP household to an RLS household, with the matched RLS household thereby serving as a control for the RRTP household. The basic regression model was run separately for all 24 hours of a day, for weekdays vs. weekends, and for each full season of the RRTP program. The model distinguishes the effect on consumption of a household's 'membership' in various subgroups of the RRTP program . . ."

Recruitment	• Opt-in. Customer recruitment was multifaceted, and included bill inserts, as well as direct marketing to targeted groups.
	    o Average direct mail response: 0.27%
	• In 2009, two other promotions were tested:
	    o *$100 sign-up bonus* offered to 6,000 targeted customers (with bills higher than $120/month). 65 customers (1.08%) enrolled in the program.
	    o *Free smart thermostats* were offered to 2,000 prospective RRTP customers (also with monthly bills >$120) in a second test promotion. Only 3 signed onto the program for a response rate of 0.15%.

[13] This excerpt from the 2010 Comverge report is relevant to understanding that the results of the ComEd pilot may not be extensible to other service territories (external validity) or even to ComEd's own system-wide service territory: "In 2009, Comverge disseminated 4,200,000 bill inserts and 856,000 direct mail pieces. Direct mail was suspended from June through August. Direct mail pieces in the first half of 2009 targeted college-educated with above average incomes in specific zip codes as well as AC Cycling customers. All direct mail pieces in the latter half of 2009 targeted customers with average electricity bills of $120 a month or higher. Current participants with average electricity bills of $120 a month or higher have shown to be able to save money on the RRTP program even during times with volatile hourly prices. The direct mail piece included a graph showing the average monthly savings incurred on the program in 2007-2008 of current RRTP participants with average electricity bills of $120 or higher.

"In 2009, the majority of RRTP Participants were college-educated with above average incomes, dual earners, and exhibited an older family skew (school-aged children and teenagers). These Participants tend to own the biggest homes with the most rooms and lowest average number of persons per room. These Participants experienced the largest potential for savings in 2009.

"Many RRTP Participants were top business executives, such as business managers, financial, and health care professionals. Additionally, many older families on fixed incomes also enrolled in the RRTP Program." Comverge, Inc. *ComEd Residential Real-Time Pricing Program, 2009 Annual Report*. East Hanover, NJ 07936. (Proprietary Report). March 31, 2010, pp. 17-18.

Reference	**Evaluation of the (Commonwealth Edison) Residential Real Time Pricing (RRTP) Program, 2007-2010.** Navigant Consulting, Inc., prepared for Commonwealth Edison Company, June 20, 2011.
Information?	• Yes - three different notice treatments of high prices o RT-10 HHs: e-mail or text messages of prices at the 10-cent level o RT-14 HHs: e-mail or text messages of prices at the 14-cent level o PA (passive alert) receive no direct messages; price information available on the RRTP web site
Feedback?	No, feedback was not explicitly tested as part of the program design.
Dynamic rate?	• Yes, Real-time Pricing (PJM's real-time hourly prices for the ComEd Zone). Hourly prices exceeded 16¢/kWh in fewer than 1% of the hours during the period of the study. (p. 19)
Control Technology?	• Free smart thermostats were offered as a sign-up bonus, but impact on usage was not estimated. (Only 3 accepted the offer)
Load impacts measured	• Conservation - load reductions during seasons and average annual (4% energy reductions across all seasons; 435 kWh/year) • Load shifting - simulated as described under "estimation methods"

Reference	**Evaluation of the (Commonwealth Edison) Residential Real Time Pricing (RRTP) Program, 2007-2010.** Navigant Consulting, Inc., prepared for Commonwealth Edison Company, June 20, 2011.

Impact of Electricity Prices	• Substitution elasticities? No?
	• Measured medium-run elasticities for the summer season only because analysis of other seasons indicated little, if any, price responsiveness (p. 9).
	• **<u>Medium-run elasticities are</u>**:
	  o Higher for RT-10 HHs than for RT-14[14] HHs
	  o Higher on weekdays than weekends
	  o Averaged -0.15 for RT HHs (a 1% increase in the average price for an hour reduces consumption by 0.15%)
	  o For RT-14, medium-run elasticities average about 0.05, about a third that of the RT-10 group
	• **<u>Short-run own-price elasticities</u>:**
	  o Low range: for hours 9 AM to 2 PM, and from 4-5 PM: -0.16
	  o High range: for hours 3-5 PM: -0.31
	Regarding statistical significance: Price elasticities were generally significant for the RT-10 group at the 99% level, and for the RT-14 group at the 90% level, except for the 2009 log model. See p. 61.

Estimation method	• For energy savings, used a *fixed effects regression analysis* of participants' monthly bills before and after being on RRTP • Medium-run elasticities were "measured using regression analysis based on the relationship between *average* hourly prices and *average* hourly deviations in consumption from the baseline where baseline consumption is derived from the consumption behavior of RLS matched control households." (p. 9) • For short-run price elasticities (on high priced days), used the Generalized Almost Ideal (GAI) demand system approach (p. 9)
Price of substitutes?	No
Income	No
Customer Circumstances	No
Premise Circumstances	No
Exogenous factors	Weather simulations were used in the simulations that went into the benefit/cost modeling. But it was not analyzed as part of the demand analysis.
Persistence?	Not explicitly addressed

[14] RT-14 price notice was the default for the program. Customers who wanted notice of price alerts at the 10-cent level had to request it. Thus, more price responsive customers self-selected into this group.

Reference	**The Effect on Electricity Consumption of the Commonwealth Edison Customer Application Program: Phase 2 Final Analysis.** EPRI, Christensen Associates Energy Consulting, LLC, R. Boisvert, Cornell University, prepared for Commonwealth Edison Company, EPRI: Palo Alto, CA. October 21, 2011. 1023644.
Location	Greater Chicago area, Illinois
Customer Segment	Residential
Time/Duration	June 2010 - April 2011 (eleven months)
Sample Size	• Treatment group: 8000 residences selected from a population of 130,000 AMI-metered customers, randomly assigned to treatment groups • Treatments = 6 rate structures with 4 types of education and/or enabling technology. • Control Group: 450 selected from a population of 130,000 AMI-metered customers

Reference	**The Effect on Electricity Consumption of the Commonwealth Edison Customer Application Program: Phase 2 Final Analysis.** EPRI, Christensen Associates Energy Consulting, LLC, R. Boisvert, Cornell University, prepared for Commonwealth Edison Company, EPRI: Palo Alto, CA. October 21, 2011. 1023644.
Sample Size by Treatment Group (see Section 3)	**<u>Treatment Groups</u>**[15] • Flat rate + AMI meter + eWeb education + BIHD = 300 • Flat rate + AMI meter + eWeb education + AIHD = 300 • IBR + AMI meter + eWeb education = 225 • IBR + AMI meter + eWeb education + BIHD = 300 • IBR + AMI meter + eWeb education + AIHD = 225 • CPP/DA-RTP + AMI Meter + eWeb education = 525 N(a), 225 N(b) • CPP/DA-RTP + AMI Meter + eWeb education + BIHD = 525 • CPP/DA-RTP + AMI Meter + eWeb education + AIHD = 525 • CPP/DA-RTP + AMI Meter + eWeb education + AIHD + PCT= 525 • PTR/DA-RTP + AMI Meter + eWeb education = 225 • PTR/DA-RTP + AMI Meter + eWeb education + BIHD = 525 • PTR/DA-RTP + AMI Meter + eWeb education + AIHD = 225 • PTR/DA-RTP + AMI Meter + eWeb education + AIHD + PCT= 225 • DA-RTP + AMI Meter + eWeb education = 225 N(a), 225 N(b) • DA-RTP + AMI Meter + eWeb education + BIHD = 525 • DA-RTP + AMI Meter + eWeb education + AIHD = 225 • TOU + AMI Meter + eWeb education = 225 • TOU + AMI Meter + eWeb education + BIHD = 525 N(a), 225 N(b) • TOU + AMI Meter + eWeb education + AIHD = 225 N(a), 225 N(b) • Other treatments: increased education, requirement for partial payment for enabling technology, and bill protection. NOTE: ComEd provided bill protection (a guarantee that customers would not pay higher bills under the pilot), " . . . but the majority of customers were not aware of it during the course of the pilot. Only two groups of customers (cells D1 and L1 in Figure 3-1) were informed of bill protection and ComEd only notified other customers in an attempt to prevent them from opting out of the pilot." (Section 2, p. 3, footnote 16)

[15] eWeb = enhanced Web education; IBR = inclining block rate; CPP = Critical Peak Pricing; DA-RTP = Day-ahead Real Time Pricing; PTR = Peak Time Rebate; TOU = Time of Use; BIHD = Basic in-home display; AIHD = Advanced in-home display; PCT = Programmable Communicating Thermostat.

<table>
<tr><td>Reference</td><td>The Effect on Electricity Consumption of the Commonwealth Edison Customer Application Program: Phase 2 Final Analysis. EPRI, Christensen Associates Energy Consulting, LLC, R. Boisvert, Cornell University, prepared for Commonwealth Edison Company, EPRI: Palo Alto, CA. October 21, 2011. 1023644.</td></tr>
<tr><td>Sample Size by Treatment Group, cont’d</td><td><u>Control Groups</u>
• Control Group F1 (flat rate + existing meter + no education) = 450 (from ComEd's load research sample)
• Control Group F2 (flat rate + existing meter + eWeb education = 225 (from ComEd's load research sample)
• Control Group F3 (Flat rate + AMI meter + basic AMI education = 225 (random sample selected from a population of 130,000 AMI-metered customers)</td></tr>
<tr><td>Sample Size by Treatment Group, cont’d</td><td>Feedback/control device quantities (across multiple treatments)
<table>
<tr><th></th><th>Intended to treat (i.e., number who received or had access to the intervention)</th><th>Actually treated (i.e., percentage who created a portal account or activated their device)</th></tr>
<tr><td>Web portal (eWeb)</td><td>8,100
- includes 225 households who comprised the control group</td><td>unknown</td></tr>
<tr><td>BIHD</td><td>2,925
- includes 225 who were offered a reduced rate to purchase the device</td><td>~17%</td></tr>
<tr><td>AIHD</td><td>2,625
- includes 225 who were offered a reduced rate to purchase the device</td><td>~12%</td></tr>
<tr><td>PCTs</td><td>750</td><td>< 10%</td></tr>
</table></td></tr>
<tr><td>Experimental Design</td><td>Randomized experimental design.</td></tr>
<tr><td>Recruitment</td><td>• Opt-out.
• All customer assigned to the appropriate group received reports, web portal and devices. However, customers still needed to activate their devices (for BIHDs) or make an appointment to have them installed for others (AIHDs and PCTs).</td></tr>
<tr><td>Information?</td><td>Pilot included several customer-facing elements, some of which were tested through the experimental design, while others were not.
• Education packages for rates, enabling technology
• Rate comparisons (shadow bills that show how they would be doing on other rates)</td></tr>
</table>

Reference	**The Effect on Electricity Consumption of the Commonwealth Edison Customer Application Program: Phase 2 Final Analysis.** EPRI, Christensen Associates Energy Consulting, LLC, R. Boisvert, Cornell University, prepared for Commonwealth Edison Company, EPRI: Palo Alto, CA. October 21, 2011. 1023644.
Feedback?	Opower monthly energy reports (originally planned) Opower website with consumption data, updated daily (this was provided to all treatment and control customers and therefore was not tested in the design) Tendril Insight in-home display ("basic" IHD) and OpenPeak IHD ("advanced" IHD); Cost to customers: • Free provision for most • Reduced rate offered to randomly selected customers via various marketing materials to purchase BIHDs and AIHDs
Installation Method	• By customer for B-IHD (once set up, customer needed to call to activate) • In the case of the A-IHD (with and without PCT capability), devices were mailed to customers, who then need to call to have them installed by a technician
Dynamic rate?	• Yes, four time-differentiated rates
Control Technology?	• Customer-controlled programmable communicating thermostat (PCT). This was provided to customers that also received an AIHD. In the end, so few of these were installed that their effect could not be assessed.

Reference	**The Effect on Electricity Consumption of the Commonwealth Edison Customer Application Program: Phase 2 Final Analysis.** EPRI, Christensen Associates Energy Consulting, LLC, R. Boisvert, Cornell University, prepared for Commonwealth Edison Company, EPRI: Palo Alto, CA. October 21, 2011. 1023644.
Load impacts measured (Section 5, pp. 4-5)	• Differences in overall consumption among treatment and control groups • Event day usage • Load shifting • Summary of results: Rate and technology application differences were not statistically significantly different from zero, with three exceptions: o For customers on DA-RTP, summer peak hour usage was 1.01 kWh higher and the summer peak to off-peak ratio was 0.037 kWh higher than for all other treatment groups. This result was counterintuitive because the DA-RTP peak-period prices were generally higher compared to prices in other hours o Event notification combined with full education reduced consumption 0.223 kWh/hour, independent of rate structure and enabling technology. o The impact of education combined with event notification was greatest when combined with: ▪ CPP + BIHD ▪ CPP + AIHD + PCT ▪ Flat rate structure + eWeb only o The impact of the other rates was not statistically significant, suggesting that more research is warranted. o The impact of the feedback (BIHD and AIHD), and the PCT/AIHD were not statistically significant, for both the energy and load impacts.
Impact of Electricity Prices	• Substitution elasticities (did not find statistically significant differences?)
Estimation method	• For energy savings, used ANOVA (analysis of variance) to measure differences in average consumption levels across groups • For elasticities of substitution, used the nested constant elasticity of substitution model and the Generalized Leontief (GL) models.
Price of substitutes?	No
Income	No
Customer Circumstances	No
Premise Circumstances	No

Reference	**The Effect on Electricity Consumption of the Commonwealth Edison Customer Application Program: Phase 2 Final Analysis.** EPRI, Christensen Associates Energy Consulting, LLC, R. Boisvert, Cornell University, prepared for Commonwealth Edison Company, EPRI: Palo Alto, CA. October 21, 2011. 1023644.
Exogenous factors	No
Self-reports of behaviors changed?	One question asked whether participants used appliances less during off-peak times as a result of ComEd's pricing pilot; however, responses are parsed by pricing treatments (not feedback or control technology treatment) as well as "responders" versus "non-responders."
Persistence?	Not explicitly addressed

<table>
<tr><td>Reference</td><td colspan="3">Hydro One Networks Inc. Time-of-Use Pilot Project Results, EB-2007-0086, Susan Frank, submitted to the Ontario Energy Board, Ontario, Canada, May 13, 2008.</td></tr>
<tr><td>Location</td><td colspan="3">Ontario, Canada</td></tr>
<tr><td>Customer Segment</td><td colspan="3">• Residential (low and high density)
• Farm
• Small general service (under 50 kW) distribution customers
Study was undertaken because they believed that the results from other pilots might not apply to Hydro One's customers since most are rural-based and have higher electricity usage due to greater reliance on electricity equipment such as space and water heating.</td></tr>
<tr><td>Time/Duration</td><td colspan="3">May - September 2007 (five months)</td></tr>
<tr><td>Sample Sizes for treatment & control group</td><td colspan="3"><table><tr><th>Group</th><th>Size</th></tr><tr><td>TOU with IHD</td><td>153</td></tr><tr><td>TOU without IHD</td><td>177</td></tr><tr><td>Standard rate with IHD</td><td>81</td></tr><tr><td>Standard rate without IHD (Control)</td><td>75</td></tr></table></td></tr>
<tr><td>Treatments (pp. 6-7)</td><td colspan="3">• Control Group - Standard rate: two-tiered inclining block
  • Tier 1 = 5.5¢/kWh
    o Up to 600 kWh, residential
    o Up to 750 kWh, non-residential
  • Tier 2 = 6.4 ¢/kWh (for both residential and non-residential, for amounts above the Tier 1 levels noted above)
• Treatment - Time of Use Rate
• Treatment – IHD</td></tr>
<tr><th colspan="4">Time of Use Pricing</th></tr>
<tr><td>Day of Week</td><td>Time of Day</td><td>Pricing</td><td>Rate (¢/kWh)</td></tr>
<tr><td>Weekends & Holidays</td><td>All day</td><td>Off-peak</td><td>3.4¢</td></tr>
<tr><td rowspan="4">Weekdays</td><td>7:00 a.m.-11:00 a.m.</td><td>Mid-Peak</td><td>7.1¢</td></tr>
<tr><td>11:00 a.m.-5:00 p.m.</td><td>On-Peak</td><td>9.7¢</td></tr>
<tr><td>5:00 p.m.-10:00 p.m.</td><td>Mid-Peak</td><td>7.1¢</td></tr>
<tr><td>10:00 p.m.-7:00 a.m.</td><td>Off-Peak</td><td>3.4¢</td></tr>
<tr><td>Experimental Design</td><td colspan="3">Stratified random sample was selected from about 23,000 customers who already had smart meters installed. Control group appears to have been selected from a different sample as the other three groups above.</td></tr>
</table>

Reference	**Hydro One Networks Inc. Time-of-Use Pilot Project Results**, EB-2007-0086, Susan Frank, submitted to the Ontario Energy Board, Ontario, Canada, May 13, 2008.
Recruitment (pp. 7-8)	• Opt-in recruitment design • Offered to 3,100 customers who already had smart meters installed and data communication system set up • 411 customer agreed to participate in the study, reflecting an overall response rate of 13% (see distribution to treatment groups above) • Recruitment approach: o Direct mail o Telephone follow up • Recruitment incentives - only one treatment group received a $50 participation incentive • See note on the control group in cell above: there is no mention about the way in which this group was selected • *Note*: only two general service customers agreed to participate. All others were residential or farm customers
Information?	• Tips, etc., were provided in the interim and final energy reports (the potential effects of which were not tested in the pilot)
Feedback?	• In-home displays (IHDs) (Blue Line PowerCost Monitor) • Interim and final energy report (effects not tested in the pilot)
Control technology?	• No
Dynamic rate?	• Yes. A TOU rate

Reference	**Hydro One Networks Inc. Time-of-Use Pilot Project Results**, EB-2007-0086, Susan Frank, submitted to the Ontario Energy Board, Ontario, Canada, May 13, 2008.
Load impacts measured[16] (pp. 8-9)	• *Load shifting impact for all days:* shifting of electricity use from peak hours to mid- to off-peak hours o For TOU + IHD = 5.5% o For TOU only = 3.7% o Incremental effect of IHD alone = 1.8% • *Load shifting impact for very hot days (>30^{o}C):* shifting of electricity use from peak hours to mid- to off-peak hours o For TOU + IHD = 8.5% o For TOU only = 2.9% o Incremental effect of IHD alone = 5.6% • *Conservation effect:* reduction in total electricity consumption, estimated by comparing consumption during the pilot to consumption in the same period in 2006 (weather normalized): o For TOU + IHD = 7.6% o For TOU only = 3.3% o Incremental effect of RTM alone = 4.3% o Base rate + IHD = 6.7% (effect of the feedback alone) • *Bill impacts:* comparison of what customers paid on the TOU rates vs. what they would have paid under the base IBR rate in the same time period. (Not a measure of performance per se, but rather of the windfall effects due to the difference in rate design.)
Load Impacts for all treatments	See above cell.

[16] Note on statistical significance of results for load shifting: The authors used a non-parametric econometric model. "The tests revealed the load-shifting impacts were statistically significant at 1% probability level (i.e., one chance in a hundred that the results could have happened by coincidence). (See p. 9)

Reference	**Hydro One Networks Inc. Time-of-Use Pilot Project Results**, EB-2007-0086, Susan Frank, submitted to the Ontario Energy Board, Ontario, Canada, May 13, 2008.
Impact of Electricity Prices	Not analyzed in this study.
Estimation method (p. 9-11)	• *For load shifting:* "A non-parametric econometric model was used to measure the load-shifting away from on-peak hours. Factors taken into account by the model include the different TOU pricing periods, treatment or control groups and type of day. Further details regarding the model can be found in "Ontario Energy Board Smart Price Pilot Final Report", Appendix E, Load Impact and Conservation Effect Analytical Model, prepared for the OEB, July 2007. • *For conservation effect:* reduction in total electricity consumption, estimated by comparing consumption during the pilot to consumption in the same period in 2006 (weather normalized). • *Bill impacts:* comparison of what customers paid on the TOU rates vs. what they would have paid under the base IBR rate in the same time period. (Not a measure of performance per se, but rather of the windfall effects due to the difference in rate design.)
Price of substitutes?	No
Income	No
Customer Circumstances	No
Premise Circumstances	No
Exogenous factors	No.
Persistence?	Not addressed.

<table>
<tr><td>Reference</td><td>2008 Ex Post Load Impact Evaluation for Pacific Gas and Electric Company's SmartRate™ Tariff.
Stephen George and Josh Bode, Freeman, Sullivan & Co. San Francisco, CA, December 30, 2008.</td></tr>
<tr><td>Location</td><td>California - Pacific Gas and Electric (PG&E). Offered in the Bakersfield and greater Kern Country region, a very hot area where maximum temperatures exceed 100° F on many summer days. This was the first region to receive new meters under PG&E’s advanced metering infrastructure deployment.</td></tr>
<tr><td>Customer Segment</td><td>Residential E-1 and E-8 customers (customers who were already on the PG&E SmartMeter program)
Non-residential customers on the A-1 tariff which applies to customers smaller than 200 kW</td></tr>
<tr><td>Time/Duration</td><td>Summer of 2008 (June - September)</td></tr>
<tr><td>Sample Sizes for treatment & control group</td><td>E-1 Residential customers - started at 3279, ended at 9913, average was 8758
A-1 (non-residential) customers - started at 185, peaked at 208, average was 185
There was no control group</td></tr>
<tr><td>Treatments (p. 3)</td><td>SmartRate is an overlay on top of the customer's otherwise applicable tariff, that has an incremental charge as well as a credit, all of which apply only to months of June through September
Peak Period Definition (on peak days)
2 to 7 p.m. for residential customers
2 to 6 p.m. for commercial customers
Incremental charge that applies during the peak period on SmartDays (up to 15 per year).
Residential charge = 60¢/kWh
Commercial charge = 75¢/kWh
Two credits for residential customers:
3¢/kWh that applies to all electricity use other than use during the peak period on SmartDays during the months of June-September
1¢/kWh credit that applies to tier 3 and higher usage for residential customers regardless of time period
Credits for non-residential customers:
2.7 ¢/kWh for A-1 customers (<200 kW)
0.5 ¢/kWh to all usage across all underlying tariffs</td></tr>
<tr><td>Experimental Design</td><td>Not a randomized design. Pilot customers were recruited in the Bakersfield and greater Kern County area. This region was the first in PG&E's service territory to receive new meters under the Company's advanced metering infrastructure deployment, branded as the SmartMeter™ Program." (p. 6)</td></tr>
</table>

Reference	**2008 Ex Post Load Impact Evaluation for Pacific Gas and Electric Company's SmartRate™ Tariff.** Stephen George and Josh Bode, Freeman, Sullivan & Co. San Francisco, CA, December 30, 2008.

Recruitment	• Opt-in recruitment design
	• Offered to 135,000 customers, of which more than 10,000 customers enrolled.
	    o 7.5% of residential customers accepted the offer
	    o 5% of small commercial customers who received the offer enrolled in the program
	• Recruitment approach:
	    o direct mail
	    o informational workshops (in English & Spanish)
	• Recruitment incentives
	    o $50 Visa gift card for residential customers who signed up early
	    o $150 rebate check for commercial customers who signed up early
	• First year bill protection

Information?	• Welcome kit with confirmation of enrollment letter • A Smart Tips guide providing information and recommendations on how to shift and/or reduce load during high price periods and other relevant material • Effects were not tested as part of the pilot
Feedback?	• No
Control technology?	• No
Dynamic rate?	• CPP rate, as outlined in Treatments section. • Base rates are inclining block rates. E-1 residential rate is a 5-tier inclining block rate with the Tier 5 rate roughly four times higher than the tier 1 rate • The ratio of the CPP price vs. "normal" pricing will vary by customers because it depends upon the customer's usage level when the event is called (i.e., which rate tier applies at that time)

Load impacts measured (pp. 41, 37 and 41)	• *Average reduction in load for the event window on the average event day:*
	    o For E-1 residential customers: 16.6%
	    o For A-1 non-residential customers: 16.0%
	• *Average load reduction on average event days for CARE vs. non-CARE customers:*
	    o CARE customers: 11%
	    o Non-CARE customers: 22.6%

Load Impacts for all treatments	Detailed tables for all event days are in the study appendices

Reference	**2008 Ex Post Load Impact Evaluation for Pacific Gas and Electric Company's SmartRate™ Tariff.** Stephen George and Josh Bode, Freeman, Sullivan & Co. San Francisco, CA, December 30, 2008.
Impact of Electricity Prices	Not analyzed in this study. The report was on load impacts, as required by CA PUC order.
Estimation method (p. 11)	For load impacts, "Time series regressions were estimated at the individual customer level rather than for all customers combined . . . . (because) the presence of air conditioning or lack thereof is a fixed effect that interacts with weather. By allowing individual customer coefficients to vary, the results are more accurate at the customer level -- an important feature when results are desired for various customer segments in addition to the average for all participants. In addition, individual customer regressions can be employed to describe accurately the distribution of customer load reductions as well as the distribution of percent load reductions." They developed regression models to predict: (1) what the load would have been without the DR, and (2) what the load would have been with the DR. They then compared the actual load (during the event day) to the two predictions. (pp. 22-23)
Price of substitutes?	No
Income	A disproportionate number of CARE (low-income) customers enrolled in the program. 35% of Kern County residential customers who were sent marketing customers were CARE customers, but 56% of the customers who enrolled in the program were CARE customers. However, load reductions for CARE customers were only half of the load reductions for non-CARE residential customers
Customer Circumstances	No
Premise Circumstances	No
Exogenous factors	No. All customers were in the Kern County area, so weather effects would be the same.
Persistence?	Not explicitly addressed

Reference	**PowerCentsDC™ Power Program,** eMeter Strategic Consulting for the Smart Meter Pilot Program, Inc., September 2010
Location	Washington, DC
Customer Segment	Residential
Time/Duration	July 2008 - October 2009 (analysis covers the summers of 2008 and 2009 and the winter of 2008-2009)
Sample Size	Total Sample Size: ~900, randomly selected across all eight wards of the District of Columbia Control Group: 400, randomly selected
Treatments (p. 10)	Three treatments: • Critical Peak Pricing • Critical Peak Rebate • Hourly Pricing Event hours for CPP and CPR: • Summer: 2:00 p.m. -6:00 p.m. summer • Winter: 6:00 a.m. -8:00 a.m. and 6:00 p.m. -8:00 p.m. • Number of events per year: 15, 12 summer and 3 winter Control group: standard offer prices (see below)

Sample Size by Treatment Group

Customer Type	CPP	CPR	Hourly Pricing
Regular (R)	175	202	175
All Electric (AE)	58	62	56
Regular, Limited Income (RAD)	-	36	-
All Electric Limited-Income (RAD-AE)	-	18	-

Residential standard offer prices by customer segment

Price Plan	Segment	Tier 1 Price ¢/kWh	Tier 2 Price ¢/kWh
R	Applies to most residential customers	12.9	14.7
AE	Residential w/electric heating	12.8	14.7
RAD	Limited income	5.4	14.8
RAD-AE	Limited income w/electric heating	5.4	12.3

For first three price plans, Tier 1 = 0-400 kWh; Tier 2 = 401+
For RAD-AE, Tier 2 = 401-700, Tier 3 = 701+. Tier 3 price is 14.6 ¢/kWh.

Reference	**PowerCentsDC™ Power Program,** eMeter Strategic Consulting for the Smart Meter Pilot Program, Inc., September 2010
Experimental Design	• Treatment and control groups were randomly selected, albeit from different populations. The control groups were randomly selected for the 4 strata of customers (R, AE, etc.); the potential treatment group customers were also randomly identified, but then each customer needed to opt-in to the program, thus potentially making the treatment and control groups statistically dissimilar. However, an analysis was performed to assess their statistical similarity (based on hourly consumption data of treatment and control group customers for a two-month pre-treatment period). No statistically significant difference was found between the hourly mean consumption of the treatment and control groups. • Customers were recruited independently for each price plan, and were not informed of the price plans being offered to other customers. Participants in the low income groups were over-sampled in order to obtain samples large enough to be statistically valid. (p. 15) • Low-income customers specifically recruited. • Customers with AC were offered a programmable thermostat (about a third of participants took the thermostat).
Recruitment	• Opt-in design • Response rates (population weighted) by demographic group: o Average total - 6.6 % o General residential - 6.4% o Low income - 7.6% • Response rates by rate option: o CPP - 6.5% o CPR - 7.4% o Hourly Pricing - 6.6%
Information?	• Prior to live billing, participants received an education package, including a pricing leaflet, conservation brochure, and refrigerator magnet displaying the critical peak hours and contact information • Real-time hourly prices were displayed on programmable thermostats for customers who elected to use them (p. 13).
Feedback?	Enhanced billing – customers received new bills with monthly graphical usage reports displaying daily usage by price, and information inserts. But effects of feedback alone were not tested.
Control Technology?	Customers with AC were offered a programmable thermostat. (About one-third accepted the offer.) Thermostats allowed for utility control during events, but customers could override the utility control (29% of CPR and 44% of HP and CPP participants indicated they overrode the signal during 2 or more events).

Reference	**PowerCentsDC™ Power Program,** eMeter Strategic Consulting for the Smart Meter Pilot Program, Inc., September 2010	
Dynamic rate?	• Yes. Approximate prices for Summer 2008 and winter 2008-2009: o Critical Peak Pricing ~ 75¢/kWh during 15 events/year, 12 Summer, 3 winter; all other hours 10.9¢/kWh o Critical Peak Rebate (synonymous with Peak Time Rebate) - same as for CPP o Hourly pricing - based on day-ahead wholesale market prices; prices range from 1¢/kWh to 37¢/kWh; high prices typically occur on summer weekday afternoons and winter mornings/evenings • Prices for Summer 2009 were significantly higher due to higher wholesale market prices • Base price for the control group are tiered (p. 10), although most residential customers fall within the first tier.	
Load impacts, summer vs. winter (p. 3)	Peak Load Reductions- Summer (during critical peak events) • CPP - 34% • CPR - 13% • Hourly Pricing - 4%	Peak Load Reductions – Winter (during critical peak events) • CPP - 13% • CPR - 5% • Hourly Pricing - 2%
Summer peak load reductions[17] with/without smart thermostats (p. 4)	No Smart Thermostats • CPP - 29% • CPR - 11% • Hourly Pricing - n/s	With Smart Thermostats • CPP - 49% • CPR - 17% • Hourly Pricing - 10%
Electricity Prices	Elasticities were not estimated	
Estimation method	• For energy savings and peak load reductions, the study employed a CBL (customer baseline load)[18] • Load reductions during peak and critical peak times, "a non-parametric conditional mean estimation framework was used. This framework uses customer-level fixed effects and day-of-sample fixed effects." (See p. 29-30 and Appendix B). This framework was also apparently used in the California Statewide Pricing Pilot	
Price of substitutes?	No	
Income	Low income customers were explicitly recruited, but into the CPR only. Found low income customers saw peak savings during summer critical hours of 11% (as compared to 13% for regular income customers).	
Customer Circumstances	Load response for low income customers vs. general residential customers were compared on the CPR rate only. Load reductions were comparable to those of the general residential customers.	

[17] These results are for regular, not all-electric homes.

[18] The baseline was based on the average of the highest non-event usage amounts on similar days (non-holiday weekdays) during the billing month. For example, the baseline for the August billing month (which might be, for example, for August 10 to September 9), was calculated based on the three highest non-event usage amounts for non-holiday weekdays during the August billing month. (p. 12)

Reference	**PowerCentsDC^{TM} Power Program,** eMeter Strategic Consulting for the Smart Meter Pilot Program, Inc., September 2010
Premise Circumstances	No
Exogenous factors	Impact of temperature on load reductions (p. 32)
Persistence?	Not explicitly addressed

<table>
<tr><td>Reference</td><td colspan="3">Public Service Electric and Gas Company. Dan Violette, Jeff Erickson, Mary Klos, Summit Blue Consulting, Final Report for the myPower Pricing Segments Evaluation, Public Service Electric and Gas Company, December 21, 2007.</td></tr>
<tr><td>Location</td><td colspan="3">PSE&G - New Jersey - Cherry Hill & Hamilton Townships</td></tr>
<tr><td>Customer Segment</td><td colspan="3">Residential</td></tr>
<tr><td>Time/Duration</td><td colspan="3">Summer 2006-Summer 2007 (~15 months)</td></tr>
<tr><td>Sample Size</td><td colspan="3">1,148 (total at 9/30/07)</td></tr>
<tr><td>Sample Size by Treatment Group</td><td colspan="3">• myPower Sense - TOU/CPP + Education Only - 379
• myPower Connection - TOU/CPP + Education + Technology - 319
• Control Group - 450</td></tr>
<tr><td colspan="4">Time of Use/Critical Peak Pricing Rate - Summer 2007 (June-September) (p. 51)</td></tr>
<tr><td>Day of Week</td><td>Time of Day</td><td>Pricing</td><td>Rate/kWh</td></tr>
<tr><td rowspan="3">Weekdays</td><td>9:00 a.m. -1:00 p.m.
6:00 p.m. - 10:00 p.m.</td><td>Medium</td><td>8.7¢</td></tr>
<tr><td>1:00 p.m.-6:00 p.m.</td><td>On-peak
Critical Peak</td><td>23.7¢
$1.46</td></tr>
<tr><td>10:00 p.m.-9:00 a.m.</td><td>Night</td><td>3.7¢</td></tr>
<tr><td rowspan="2">Weekends</td><td>9:00 a.m.-10:00 p.m.</td><td>Medium</td><td>8.7¢</td></tr>
<tr><td>10:00 p.m. -9:00 a.m.</td><td>Night</td><td>3.7¢</td></tr>
<tr><td>Control Group</td><td colspan="3">Base residential rate (~11.8¢/kWh, including base generation and distribution charges). See pp. 51, I-2 and J-5.</td></tr>
<tr><td>Experimental Design</td><td colspan="3">• Extent of randomization not clear.
• For treatment groups, customers were recruited into one or the other treatments. Recruitment was targeted at customers in Cherry Hill and Hamilton Township, NJ.
• Control group was "chosen to facilitate a detailed impact analysis of the energy and demand savings. In general, it is difficult to find estimates of energy savings for TOU programs since a large, matched control group is needed to answer the question of what customers would have done if they had not been on the TOU rate." (pp. 3-4)</td></tr>
<tr><td>Recruitment method</td><td colspan="3">Opt-in. Overall response rate to direct mail campaign: 4%. (Customers were then screened for other eligibility criteria (presence of AC, internet access, landline for telephone access, etc.) (pp. 10, 59)</td></tr>
<tr><td>Information?</td><td colspan="3">• Yes. Included education, energy-saving tips, rate information, and web access. Potential effects were not tested in the pilot.</td></tr>
<tr><td>Feedback?</td><td colspan="3">• No</td></tr>
</table>

Reference	**Public Service Electric and Gas Company.** Dan Violette, Jeff Erickson, Mary Klos, Summit Blue Consulting, Final Report for the myPower Pricing Segments Evaluation, Public Service Electric and Gas Company, December 21, 2007.
Control Technology?	• Yes. Smart thermostats for the myPower Connection treatment group; the thermostats were utility-controlled, but the set-point changes were based on customer-programmed preferences. Customers could override the automatic changes. • Seven members of this group received pool pump controllers and one received a water heater load controller although the potential load impacts of these were not tested. • Thirty-one members of this group also received a home energy management system which used a RF connection. It appears that this was a test for technology assessment purposes (i.e., no customer impacts were tested).
Dynamic rate?	• Time of Use Rate + Critical Peak Pricing • Basic flat rate (delivery charge + basic generation service rate)
Load impacts measured (see pp. 17-18)	• Summer peak day impacts • Summer kWh shifts • Summer energy conservation • Summer kWh shift impacts by size of participant • myPower Pricing TOU summer energy savings across treatment groups, with and without AC • "snap back" effects (not sure how measured)

<table>
<tr><td>Reference</td><td>Public Service Electric and Gas Company. Dan Violette, Jeff Erickson, Mary Klos, Summit Blue Consulting, Final Report for the myPower Pricing Segments Evaluation, Public Service Electric and Gas Company, December 21, 2007.</td></tr>
<tr><td>Load and Energy Impacts (p. 17)</td><td>Load Impacts
<table>
<tr><th>Segment</th><th>Baseline avg. on peak (kW)</th><th>TOU Only (% demand reduction on summer peak days)</th><th>CPP (% demand reduction on summer peak days)</th></tr>
<tr><td>myPower connection</td><td>2.85</td><td>21%</td><td>26%</td></tr>
<tr><td>myPower Sense w/Central AC</td><td>2.6</td><td>3%</td><td>14%</td></tr>
<tr><td>myPower Sense w/o AC</td><td>1.61</td><td>6%</td><td>14%</td></tr>
</table>
Statistical significance not stated

Energy Impacts (% overall kWh reduction for summer months compared to control)
<table>
<tr><th>Segment</th><th>TOU Only</th><th>CPP</th></tr>
<tr><td>myPower connection</td><td>3.3%</td><td rowspan="3">Not assessed</td></tr>
<tr><td>myPower Sense w/Central AC</td><td>3.7%</td></tr>
<tr><td>myPower Sense w/o AC</td><td>4.3%</td></tr>
</table>
Some numbers reported, but elsewhere it states that statistical significance was not clear .

Energy Impacts (% overall kWh reduction for winter and shoulder months compared to control)
“There was also little total energy savings in the winter and shoulder months. The one exception is the myPowerSense with central air conditioning group. They showed a 1.65% decrease in energy use during winter months which was statistically significant at the 90% confidence level.” (p. 19)</td></tr>
<tr><td>Impact of electricity prices?</td><td>Summer Substitution Elasticities for
• TOU/CPP + Education Only - w/AC = - 0.069
• TOU/CPP + Education Only - no/AC = - 0.063
• TOU/CPP + Education + Technology = - 0.125
Note on statistical significance of these estimates (p. 19): All three elasticity estimates were statistically significant (t-values of 14.6 to 44.9). However, the difference between the first two elasticities (for the myPower Sense program, with and without AC) were not statistically significantly different from each other.</td></tr>
</table>

Reference	**Public Service Electric and Gas Company.** Dan Violette, Jeff Erickson, Mary Klos, Summit Blue Consulting, Final Report for the myPower Pricing Segments Evaluation, Public Service Electric and Gas Company, December 21, 2007.
Estimation Method	Constant Elasticity of Substitution demand model (p. 102)
Price of substitutes?	No
Income	No
Customer Circumstances	No
Premise Circumstances	Customers with and without AC. Little difference in either load response or elasticities between these two groups.
Exogenous factors	Weather (temperature, humidity)
Persistence?	No?

C

SUMMARY OF MODELING TECHNIQUES USED TO ESTIMATE PRICE ELASTICITIES

Reference	**Baltimore Gas & Electric Smart Energy Pricing Pilot - Summer 2008.** Ahmad Faruqui and Sanem Sergici, BGE's Smart Energy Pricing Pilot, Summer 2008 Impact, The Brattle Group, Inc., April 28, 2009.
Location	Baltimore, Maryland
Customer Segment	Residential
Time/Duration	June 1, 2008 - September 30, 2008 (four months)

The analysis of demand response for this SEP Pilot is conducted by the same firm that did the analysis for the CL&P's Plan it Wise Energy Pilot. The analyses are very similar; the major differences are in the specification of pilot specific variables that reflect differences in the pricing options or in the other data available.

To measure the demand response impacts of each SEP Pilot pricing option, the analysts specify two demand models for each class of customers. This alternative was chosen, instead of models of analysis of variance or covariance, in large measure because of their capacity to provide estimates of price elasticities.

- One model, the constant elasticity of Substitution (CES) model, is used to explain the percentage changes in the ratio of peak to off-peak usage as a function of the ratio of peak to off-peak prices, and other terms to control for weather and some important fixed effects associated with month, time of the week, and customer treatment and treatment period.

- A second model is used to estimate average daily electricity consumption as a function of average daily price of electricity and other fixed effects similar to those in the CES model.

The two equations constitute a system for predicting electricity consumption by time period. The first equation essentially predicts the changes in the load shape caused by changes in the peak to off-peak price ratios. The second equation predicts the changes in the level of daily electricity consumption caused by changing average daily electricity price. New levels of daily electricity consumption implied by the second equation are partitioned between peak and off-peak periods using the new load shape implied by the first equation.

- **Peak Load Reduction—CES Models for Elasticity of Substitution**

By assuming that the demand model is one for which there is a constant elasticity of substitution, it can be shown that the logarithm of the ratio of peak to off-peak usage is a function of the ratio of the peak to the off-peak price. The exact specification of each of the variables is in the report. With a couple of exceptions, the important variables are rather transparent from the variable names. Others are defined as necessary. The model is:

$$
\begin{aligned}
ln\left(\frac{Peak\_kWh}{offPeak\_kWh}\right)_{it} \\
&= \alpha_0 \\
&+ \alpha_1 THI_{DIFFt} + \sum_{k=1}^{6} \delta_k (THI_{DIFFt} \cdot D\_Month_k) \\
&+ \{\alpha_2 ln\left(\frac{Peak\_Price}{offPeak\_Price}\right)_{it} + \alpha_3 ln\left(\frac{Peak\_Price}{offPeak\_Price}\right)_{it} \cdot THI_{DIFF_t} \\
&+ \alpha_4 ln\left(\frac{Peak\_Price}{offPeak\_Price}\right)_{it} \cdot ORB_i + \alpha_5 ln\left(\frac{Peak\_Price}{offPeak\_Price}\right)_{it} \\
&\cdot ET\_ORB_i\} + \alpha_6 D_{TreatPeriod_t} + \alpha_7 D_{TreatPeriod_t \cdot TreatCustomer_i} \\
&+ \sum_{k=1}^{6} \beta_k (D_{Month_k}) + + \sum_{k=1}^{12} \gamma_k D\_CPP_k + \alpha_8 D_{WEEKEND_t} + v_i + u_{it}
\end{aligned}
$$

where
D_CPP_k = dummy variable that is equal to 1 for the k^{th} CPP day.

The important terms from the standpoint of the elasticities of substitution are the coefficients α_2 through α_5 associated with the four variables in { }. The second term is an interaction term between the price ratio and weather, as measured by the difference between average hourly peak and off-peak Temperature Humidity Index. For the last two terms, these variables are also interacted with dummy variables for customers with an Energy Orb, but no A/C switch (ORB_i) and those customers with both (ET_ORB_i).

This specification allows for the elasticity of substitution to differ by weather and whether or not a customer has an energy orb or an energy orb plus an A/C switch. To account for these differences, there are a total of three estimates of the elasticity of substitution of off-peak for peak electricity usage. It is important to note that since there was no statistical differences between the price elasticities for DPP, PTRO and PTRH rates, there is only a single price variable in this equation.

The three equations for the elasticities of substitution are:

Subst_Elasticity $_{\text{price}}$ = $\alpha_2 + \alpha_3 * THI_{DIFFt}$ (Price, Weather)

Subst_Elasticity $_{\text{price + ORB}}$ = $\alpha_2 + \alpha_3) * THI_{DIFFt} + \alpha_4$ (Price, Weather, ORB)

Subst_Elasticity $_{\text{price + ET\_ORB}}$ = $\alpha_2 + \alpha_3) * THI_{DIFFt} + \alpha_5$ (Price, Weather, ET_ORB)

- **Daily Demand Equation**

This is the second equation in the 2-equation system that is estimated. (These equations, although used in conjunction with one another to estimate electricity usage by time period, are estimated separately, not jointly).

The daily demand models measure the change in average daily electricity usage from to changes in the average price of electricity due to the rate treatments. The model has a similar structure to that of the CES model, particularly with respect to the several variables specified to control for fixed effects. The exact variable specifications are in the report, but some of the important variables are also defined below. The model can be written as:

$$
\begin{aligned}
ln(kWh)_{it} = \alpha_0 + \alpha_1 \ln(THI)_t + \sum_{k=1}^{6} \delta_k (ln(THI)_t \cdot D\_Month_k) + \{\alpha_2 ln(Price)_{it} \\
+ \alpha_3 ln(Price)_{it} \cdot \ln(THI)_t + \alpha_5 ln(Price)_{it} \cdot \ln(THI)_t \cdot ORB_i \\
+ \alpha_6 ln(Price)_{it} \cdot \ln(THI)_t \cdot ET_i\} + \alpha_4 D_{TreatPeriod_t} \\
+ \alpha_5 D_{TreatPeriod_t \cdot TreatCustomer_i} + \sum_{k=1}^{6} \beta_k \left(D_{Month_k}\right) + \sum\nolimits_{k=1}^{12} \gamma_k D\_CPP_k \\
+ \alpha_6 D_{WEEKEND\,t} + v_i + u_{it}
\end{aligned}
$$

where
$\ln(kWh)_{it}$ = natural logarithm of daily average of the hourly load on day t for customer i;
$\ln(THI)_{it}$ = natural logarithm of the daily average of the hourly temperature humidity index for customer i on day t;
$\ln(Price)_{it}$ = natural logarithm of average daily price of electricity for customer i on day t;
D_CPP_k = dummy variable that is equal to 1 for the k^{th} CPP day.

This is a log-linear model, so the coefficients on the price terms have the immediate interpretation as the own price elasticity of demand for daily electricity where the price is the average daily price. Again the important terms from the standpoint of these price elasticities are the coefficients α_3 through α_6 associated with the four variables in { }. Each of these variables involves the interaction of the logarithm of the ratio of peak to off-peak prices and the logarithm of the average temperature humidity index for a given day (THI_t). For the last three terms, these variables are also interacted with dummy variables for PTR customers, and customers with and Energy Orb, but no thermostat or A/C switch. For the TOU regressions, α_4 is set to zero.

This specification allows for the own price elasticities of demand to differ by weather. It is important to note: since there are no statistical differences between the price elasticities for DPP, PTRO and PTRH rates, there is only a single price variable in this equation, as in the CES model above. In contrast to the CES model, the results for this daily demand equation do not differ with enabling technology, so these interaction terms with price were eliminated as well. Given the statistical insignificance of differential effects by rate and enabling technology, there is only one equation for the daily own price elasticity of demand:

Daily_Elasticity = $\alpha_2 + \alpha_3 * THI_{DIFFt}$

- **Hour-Specific Elasticities of Substitution**

The analysts also estimate hour-specific elasticities of substitution for each of the peak hours, and for at least two of the non-peak hours adjacent to the peak period. However, the analysts don't provide any rationale for calculating these elasticities.

For the hour-specific peak elasticities, the dependent variable is the ratio of the load for the i^{th} peak hour to the average load during off-peak hours, and the price ratio is defined as the ratio of the price in the i^{th} peak hour to the average price during all non-peak hours. Other variables are redefined in a similar fashion.

For the non-peak hour elasticities, the dependent variable is the ratio of the average load for peak period to the load for the j^{th} non-peak hour and the price ratio is defined as the ratio of the average price in the peak hours to the price during the j^{th} non-peak hour. Other variables are redefined in a similar fashion.

- **Effects of Socio-demographic Characteristics**

The analysts also estimate alternative specifications of the demand models to examine the price responsiveness that may differ by customer socio-demographic variable by introducing an interaction term between the price variables and a dummy variable for the relevant customer characteristic. Based on survey responses, they examine the effects central A/C (0), multi-family residence (-), college education (+), pool ownership (+), and incomes above $75,000 (+). While all but the A/C were statistically significant, they were not used because about 20% of the customers failed to respond to respond to the survey.

Reference	**Impact Evaluation of the California Statewide Pricing Pilot, (Residential Summary)** Charles River Associates, Oakland, CA, March 16, 2005.
Location	California - three major IOUs, SCE, PG&E, SDG&E
Customer Segment	Residential
Time/Duration	July 2003 - December 2004

The methodology for estimating demand response for each tariff consists of two equations. One equation predicts daily energy use as a function of daily price and other factors. The second equation predicts the ratio of daily energy use in the peak and off-peak period.

The analysts argue that this two equation system can model several behavioral changes. As one example, if there is a reduction in peak period energy use with no change in off-peak energy use, this would be registered by a reduction in the ratio of peak-to-off-peak energy use in the substitution equation. An increase in off-peak energy use, with no change in peak-period energy use, would also show up in as a change in the same ratio. In contrast, energy conservation would be reflected by a change in daily energy use and, in the absence of any change in the ratio of peak-to- off-peak energy use, would still lead to a reduction in peak-period energy use because the peak-period share would be multiplied by a lower daily use value. They claim in appendix 9 to show how the own and cross-price elasticities can be derived from the elasticity of substitution and the daily price elasticities for small changes in price.

The analysts also argue that the elasticity of substitution and/or the daily price elasticity could very well differ between hot and cool days and across customers who have different socio-economic characteristics (e.g., different appliance ownership, different income levels, etc.).

- **The CES Model**

This version of the CES model below accounts for differences in weather and the ownership of central air conditioning affect the estimates of the elasticities of substitution:

$$ln\left(\frac{Q_p}{Q_{op}}\right) = \alpha + \sum_i \theta_i D_i + \sigma ln\left(\frac{P_p}{P_{op}}\right) + \delta\left(CDH_p - CDH_{op}\right)$$
$$+ \mu\left(CDH_p - CDH_{op}\right) ln\left(\frac{P_p}{P_{op}}\right) + \vartheta(CAC) ln\left(\frac{P_p}{P_{op}}\right) + \varepsilon$$

where

Q_p = average daily peak energy use per peak hour;
Q_{op} = average daily peak energy use per peak hour;
P_p = a usage weighted average of the peak prices for the day;
P_{op} = a usage weighted average of the off-peak prices for the day;
D_i = a binary variable equal to 1 for the *ith* customer, 0 otherwise;
CAC = 1 if a household owns a central air conditioner, 0 otherwise;

CDH_p = cooling degree hours for peak hours during the day;
CDH_{op} = cooling degree hours for off-peak hours during the day;
ε = regression error term.

Thus, the elasticity of substitution (*ES*) in this model contains three terms:

$$ES = \sigma + \mu\left(CDH_p - CDH_{op}\right) + \vartheta(CAC)$$

- **The Daily Demand Model**

The daily demand model also allows for the temperature and the ownership of central air conditioning to affect the own price elasticity of demand:

$$\ln(Q_D) = \alpha + + \sum_i \theta_i D_i + \rho \ln(P_D) + \mu(CDH_D) + \tau(CDH_D)\ln(P_D) + \omega(CAC)\ln(P_D) + \varepsilon$$

where
Q_D = average daily energy use per hour;:
P_D = average daily price;
CDH_D= average daily cooling degree hours per hour (base 72 degrees)
CAC = 1 if a household owns a central air conditioner, 0 otherwise;
D_i = a binary variable equal to 1 for the i^{th} customer, 0 otherwise;
ε = regression error term.

The composite daily own price elasticity(*DPE*) in this model now includes three terms:

$$DPE = \rho + \tau(CDH_D) + \omega(CAC)$$

- **Some Estimation Issues**

The analysts argue for the need to correct for heteroscedasticity and autocorrelation, and when a panel data set is balanced, then the correction can be made using Generalized Least Squares (GLS). For an unbalanced panel, one approach involves averaging across the daily observations for each day type. An alternative approach to addressing the autocorrelation problem involves transforming the daily observations using a procedure known as "first differencing," a common technique for dealing with serial correlation in which the previous day's observation is subtracted from the current day's observation for each of the variables.

To obtain the most efficient parameter estimates and to account for the statistical correlations between the daily equation and the substitution equation, the two equations are estimated jointly using a seemingly unrelated regressions (SUR) technique.

Reference	**California's Statewide Pricing Pilot, (Commercial & Industrial Analysis Update)** Freeman, Sullivan & Co. and Charles River Associates, Oakland, CA, June 28, 2006.
Location	California - Southern California Edison only
Customer Segment	C&I customers smaller than 200 kW, in two size categories: LT20 (demands <20 kW) GT20 (demands between 20 kW and 200 kW)
Time/Duration	Summers of 2004 and 2005 (defined as the first Sunday in June through the first Sunday in October) (p. 8 of June 2006 report)
	In this updated final report, the analysts state that the methods used in the analysis of price response and load impacts are in Section 3.1 of an earlier report dated March 16, 2006. The methods appear to be nearly the same (differing only in the specification of independent variables in addition to prices) as used in the analysis of residential customers described in the preceding table. Thus, that level of detail is not repeated here. The CES demand system is used to estimate changes in energy use by rate period. The 2-equation system consists of one equation that relates the logarithm of the ratio of peak-to off-peak energy use to the logarithm of the ratio of peak-to-off-peak prices and other determining factors such as weather. Thus, the independent variables in this equation are the logarithm of the price ratio, interaction terms to allow price responsiveness to vary with ownership of air conditioning and weather, the difference between cooling degree hours per how between peak and off-peak periods, and a binary variable for the weekend. The coefficient on the price ratio term is the elasticity of substitution. The second equation in the demand system relates the logarithm of daily energy use to the logarithm of daily average price, and some other relevant variables. The daily price variable was dropped in this equation because it was not statistically significant. Therefore, the equation for daily electricity use relates the logarithm of daily electricity use to the number of daily cooling degree hours on that day and a binary variable to represent the weekend. As in the case for the analysis of residential customers, the 2-equation system was estimated jointly using a seemingly unrelated regression (SUR) estimator. There is a first difference transformation to correct for autocorrelation of the error terms.

Reference	**Results of CL&P's Plan-It Wise Energy Pilot,** Connecticut Light & Power, Filing in Response to the Department of Public Utility Control's Compliance Order No. 4, Docket No. 05-10-0RE01, December 2009. Available at: http://nuwnotes1.nu.com/apps/clp/clpwebcontent.nsf/AR/PlanItWise/$File/Plan-it%20Wise%20Pilot%20Results.pdf
Location	Connecticut
Customer Segment	Residential Commercial & Industrial
Time/Duration	June 1, 2009 - August 31, 2009

The analysis of demand response for this Plan it Wise Energy Pilot is conducted by the same firm that did the analysis for the BG&E's Smart Energy Pricing Pilot. The analyses are very similar. The major differences are in the specification of pilot specific variables that reflect differences in the pricing options or other data available.

To measure the demand response impacts of the PWEP pricing options, the analysts specify two demand models for each class of customers. This alternative was chosen, instead of models of analysis of variance or covariance, in large measure because of their capacity to provide estimates of price elasticities.

Two demand models are specified.

1. One model, the constant elasticity of Substitution (CES) model is used to explain the percentage changes in the ratio of peak to off-peak usage as a function of the ratio of peak to off-peak prices, and other terms to control for weather and some important fixed effects associated with month, time of the week, and customer treatment and treatment period.

2. The second model is for average daily electricity consumption as a function of average daily price of electricity and other fixed effects similar to those in the CES model.

The two equations constitute a system for predicting electricity consumption by time period. The first equation essentially predicts the changes in the load shape caused by changing peak to off-peak price ratios. The second equation predicts the changes in the level of daily electricity consumption caused by changing average daily electricity price. New levels of daily electricity consumption implied by the second equation are partitioned between peak and off-peak periods using the new load shape implied by the first equation.

- **Peak Load Reduction—CES Models for Elasticity of Substitution**

By assuming that the demand model is one for which there is a constant elasticity of substitution, it can be shown that the logarithm of the ratio of peak to off-peak usage is a function of the ratio of the peak to the off-peak price. The exact specification of each of the variables is in the report. With a couple of exceptions, the important ones are rather transparent from the variable names themselves. Others are defined as necessary Thus, the model is specified as:

$$
\begin{aligned}
ln\left(\frac{Peak\_kWh}{offPeak\_kWh}\right)_{it}
&= \alpha_0 \\
&+ \alpha_1 THI_{DIFFt} + \sum_{k=1}^{3} \delta_k (THI_{DIFFt} \cdot Month_k) \\
&+ \{\alpha_3 ln\left(\frac{Peak\_Price}{offPeak\_Price}\right)_{it} \cdot THI_{DIFF_t} \\
&+ \ \alpha_4 ln\left(\frac{Peak\_Price}{offPeak\_Price}\right)_{it} \cdot THI_{DIFF_t} \cdot PTR_i \\
&+ \alpha_5 ln\left(\frac{Peak\_Price}{offPeak\_Price}\right)_{it} \cdot THI_{DIFF_t} \cdot ORB_i \\
&+ \alpha_6 ln\left(\frac{Peak\_Price}{offPeak\_Price}\right)_{it} \cdot THI_{DIFF_t} \cdot ET_i\} + \alpha_7 D_{TreatPeriod_t} \\
&+ \alpha_7 D_{TreatPeriod_t \cdot TreatCustomer_i} + \sum_{k=1}^{3} \beta_k \left(D_{Month_k}\right) \\
&+ \alpha_{10} D_{WEEKEND_t} + v_i + u_{it}
\end{aligned}
$$

The important terms from the standpoint of the elasticities of substitution are the coefficients α_3 through α_6 associated with the four variables in { }. Each of these variables involves the interaction of ratio of peak to off-peak prices and the difference between the peak and the off-peak temperature humidity index for a given day (THI_{DIFFt}). For the last three terms, these variables are also interacted with dummy variables for PTR customers, and customers with an Energy Orb, but no thermostat or A/C switch. For the TOU regressions, α_4 is set to zero.

This specification allows for the elasticity of substitution to differ by weather and whether or not a customer is a PTP/PTR customer or if the customer has an energy orb or a thermostat or an A/C switch. To account for these differences, there are a total of six estimates of the elasticity of substitution of off-peak for peak electricity usage. The six equations for the elasticities of substitution are:

Subst_Elasticity $_{\text{price\_PTP/TOU}}$ = $\alpha_3 * THI_{DIFFt}$ (Price, Weather)
Subst_Elasticity $_{\text{price\_PTR}}$ = $(\alpha_3 + \alpha_4) * THI_{DIFFt}$ (Price, Weather)

Subst_Elasticity $_{\text{price+ORB\_PTP/TOU}}$ = $(\alpha_3 + \alpha_5) * THI_{DIFFt}$ (Price, Weather, Orb)
Subst_Elasticity $_{\text{price+ORB\_PTR}}$ = $(\alpha_3 + \alpha_4 + \alpha_5) * THI_{DIFFt}$ (Price, Weather, Orb)

Subst_Elasticity $_{\text{price+ET\_PTP/TOU}}$ = $(\alpha_3 + \alpha_6) * THI_{DIFFt}$ (Price, Weather, ET)
Subst_Elasticity $_{\text{price+ET\_PTR}}$ = $(\alpha_3 + \alpha_4 + \alpha_6) * THI_{DIFFt}$ (Price, Weather, ET)

- **Daily Demand Equation**

This is the second equation in the 2-equation system that is estimated. (It should be noted that these equations, although used in conjunction with one another to estimate electricity usage by time period, are estimated separately, not jointly.

The daily demand equation models the change in average daily electricity usage due to changes in the average price of electricity due to the rate treatments. The model has a similar structure to that of the CES model, particularly with respect to the several variables specified to control for fixed effects. The exact variable specifications are in the report, but some of the important variables are also defined below. The model can be written as:

$$
\begin{aligned}
ln(kWh)_{it} = \alpha_0 \\
&+ \alpha_1 \ln(THI)_t + \sum_{k=1}^{3} \delta_k (ln(THI)_t \cdot D\_Month_k) + \{\alpha_3 ln(Price)_{it} \\
&\cdot \ln(THI)_t + \alpha_4 ln(Price)_{it} \cdot \ln(THI)_t \cdot PTR_i + \alpha_5 ln(Price)_{it} \\
&\cdot \ln(THI)_t \cdot ORB_i + \alpha_6 ln(Price)_{it} \cdot \ln(THI)_t \cdot ET_i\} \\
&+ \alpha_7 D_{TreatPeriod_t} + \alpha_7 D_{TreatPeriod_t \cdot TreatCustomer_i} \\
&+ \sum_{k=1}^{3} \beta_k (D_{Month_k}) + \alpha_{10} D_{WEEKEND_t} + v_i + u_{it}
\end{aligned}
$$

where

$\ln(kWh)_{it}$ = logarithm of daily average of the hourly load on day t for customer *i*;

$\ln(THI)_{it}$ = logarithm of the daily average of the hourly temperature humidity index for customer *i* on day *t*;

$\ln(Price)_{it}$ = logarithm of average daily price of electricity for customer *i* on day *t*.

In this is a log-linear model the price coefficients are the own price elasticity of demand for daily electricity. The important coefficients are α_3 through α_6 associated with the four variables in { }. Each of these variables involves the interaction of ratio of peak to off-peak prices and the logarithm of average temperature humidity index for a given day (THI_t). For the last three terms, these variables are also interacted with dummy variables for PTR customers, and customers with an Energy Orb, but no thermostat or A/C switch. For the TOU regressions, α_4 is set to zero.

The own price elasticities of demand to differ by weather and whether a customer is a PTP/PTR customer or if the customer has an energy orb or a thermostat or an A/C switch. There six separate estimates of the own price elasticity of demand are:

Daily_Elasticity $_{\text{price\_PTP/TOU}} = \alpha_3 * THI_{DIFFt}$ (Price, Weather)
Daily_Elasticity $_{\text{price\_PTR}} = (\alpha_3 + \alpha_4) * THI_{DIFFt}$ (Price, Weather)

Daily_Elasticity $_{\text{price+ORB\_PTP/TOU}} = (\alpha_3 + \alpha_5) * THI_{DIFFt}$ (Price, Weather, Orb)
Daily_Elasticity $_{\text{price+ORB\_PTR}} = (\alpha_3 + \alpha_4 + \alpha_5) * THI_{DIFFt}$ (Price, Weather, Orb)

Daily_Elasticity $_{\text{price+ET\_PTP/TOU}} = (\alpha_3 + \alpha_6) * THI_{DIFFt}$ (Price, Weather, ET)
Daily_Elasticity $_{\text{price+ET\_PTR}} = (\alpha_3 + \alpha_4 + \alpha_6) * THI_{DIFFt}$ (Price, Weather, ET)

Reference	**Evaluation of the (Commonwealth Edison) Residential Real Time Pricing (RRTP) Program, 2007-2010.** Navigant Consulting, Inc., prepared for Commonwealth Edison Company, June 20, 2011.
Location	Chicago, Illinois
Customer Segment	Residential
Time/Duration	2007-2010

The analysts conducting this study estimated conservation effects, hourly demand impacts, and the price responsiveness of RRTP participants.

- **Conservation Effects**

Although the analysts argue that the main purpose of hourly pricing for residential customers may be to promote shifting of energy use rather than conservation, there may also be some conservation by RRTP customers, particularly if there is joint participation with other ComEd energy efficiency programs. These conservation effects are estimated for each of four seasons using a “fixed effects” regression model. It is a semi-logarithmic model of daily average energy consumption over a billing period. It has the form (which implies that the marginal effect of explanatory variables is proportional to initial consumption):

$$\begin{aligned} lny_{it} = \alpha_i &+ \beta_1 CDD_{it} + \beta_2 HDD_{it} + \beta_3 RRTP_{it} + \beta_4 (RRTP_{it} \cdot CDD_{it}) \\ &+ \beta_5 (RRTP_{it} \cdot HDD_{it}) + \beta_6 EE_{it} + \beta_7 (RRTP_{it} \cdot EE_{it}) \\ &+ \beta_8 (RRTP_{it} \cdot CDD_{it} \cdot EE_{it}) + +\beta_9 (RRTP_{it} \cdot HDD_{it} \cdot EE_{it}) + \beta_{10} LG_{it} \\ &+ \beta_{11} (RRTP_{it} \cdot LG_{it}) + \beta_{12} (RRTP_{it} \cdot CDD_{it} \cdot LG_{it}) + \beta_{13} (RRTP_{it} \\ &\cdot HDD_{it} \cdot LG_{it}) + \varepsilon_{it} \end{aligned}$$

where
y_{it} = customer *i*’s average daily consumption (kWh) for billing period *t*;
α_{it} = customer *i*’s fixed effect;
CDD_{it} = average number of cooling days per day experienced by customer *i* in time *t*;
HDD_{it} = average number of heating days per day experienced by customer *i* in time *t*;
$RTTP_{it}$ = dummy variable equal to 1 if customer *i* is participating in the RTTP program during billing month *t*;
EE_{it} = dummy variable equal to 1 if customer *i* is participating in ComEd’s Appliance Recycling or AC Efficiency program during billing month *t*;
LG_{it} = dummy variable equal to 1 if customer *i* is participating in ComEd’s Load Guard program during billing month *t*.

The final model, after eliminating the insignificant terms is:

$$\begin{aligned} lny_{it} = \alpha_i &+ \beta_1 CDD_{it} + \beta_2 HDD_{it} + \beta_3 RRTP_{it} + \beta_4 (RRTP_{it} \cdot CDD_{it}) \\ &+ +\beta_5 (RRTP_{it} \cdot HDD_{it}) + \beta_6 EE_{it} + \varepsilon_{it} \end{aligned}$$

- **Hourly Demand Impacts**

This analysis is to estimate the shifting of consumption from high-priced to low-priced periods. It does so through the generation of a difference-in-difference criterion for comparing conservation effects between RRTP participants before and after entering the program with control group customers. Thus, it is a 2-step process. First, customers in the control group are matched with those in the participant group using a propensity scoring method (PSM). The second step involves the estimation of regression equations for every hour for every season in the program for week days and weekends. The impacts were then estimated by comparing participants and their matched control customers.

Step 1: The PSM
This method is to estimate the probability of program participation for both participants and control customers using a logit regression. The matching criterion for the RRTP customer is the RLS customer with the closest propensity score.

In the PSM, seasonal electricity consumption in monthly bills is used to predict participation. The logit regression for estimating the probability of participation is:

$$\Pr(y_i = 1) = \frac{e^{\beta x}}{1 + e^{\beta x}}$$

where:
β is a vector of parameters; and
x a vector of variables which include:
Average kWh/day in summer 2009;
Average kWh/day in summer 2010;
Average kWh/day in winter 2008;
Average kWh/day in winter 2009; and
the squares of all four variables.

Step 2: The Hourly Demand Impact Equations
The regression equations (of which there are a total of 720) are specified as:

$$\begin{aligned} HEC_{kt} = a_0 &+ a_1 RRTP_k + a_5 RT10alert_t + a_6 RT14alert_t + a_7 \mathrm{LG10}_t + a_8 \mathrm{LG14}_t \\ &+ a_9 ACC50_t + a_{10} ACC100_t + a_{11} RRTP_k Temp_t \\ &+ a_{12} RRTP_k PreConsumption_t + a_{13} RRTP_k DAalert_t \\ &+ a_{14} RRTP_k RT10alert_t + a_{15} RRTP_k RT14alert_t + a_{16} RRTP_k LG10alert_t \\ &+ a_{17} RRTP_k LG14alert_t + a_{18} RT10HH_{kt} + a_{19} RT14HH_{kt} + a_{20} LG10HH_{kt} \\ &+ a_{21} LG14HH_{kt} + a_{22} RT10HH_{kt} DAalert_t + a_{23} RT10HH_{kt} RT10alert_t \\ &+ a_{24} RT14HH_{kt} DA14alert_t + a_{25} RT14HH_{kt} RT14alert_t \\ &+ a_{26} LG10HH_{kt} LG10_t + a_{23} LG14HH_{kt} LG14_t + e_{kt} \end{aligned}$$

where:
$Temp_t$ = temperature of the hour on day t;
$PreConsumption_k$ = average consumption of household k in the preprogram year, 2006;
$RRTP_k$ = a 0/1 binary variable with a value of 0 if household k is a control household, and 1 if a program household;
$DAalert_t$; $RT10alert_t$; $RT14alert_t$ = binary 0/1 variable's with values of 1 if there is a Day Ahead and RT10 or an RT14 alert in the specified hour of day t;
$LG10_t$; $LG14_t$ = binary 0/1 variables with values of 1 if there is a load guard event with a 10 or 14 cent threshold in the specified hour of day t;

IH$_{kt}$; *RT10HH*$_{kt}$ = binary 0/1 variables with values of 1 if household k is to receive real-time alerts via e-mail or text message for 14 or 10 cent thresholds; there

LG10HHkt; *LG14HH*$_{kt}$ = binary 0/1 variables with values of 1 if household k enrolled in load guard on day t with events called at 10 or 14 cent thresholds, respectively.

- **Price Responsiveness of RRTP Participants**

There are two components to the measurement of price responsiveness. The first is for what the analysts call the "***medium run***" in which households "respond to differences in average hourly prices with a broad shift in energy consumption of behavior, as compared to a fixed-price regime, forming new habits and modes of operation…" The second is the "***short run*** " response, where the analysts argue that even after response to average hourly price changes, customers can respond in the short run to large deviations in prices from their means.

Comment:

1. This characterization of short and medium term demands is distinct. The analysts suggest that the short-run demand can be more elastic than the medium term. The diagrams in the report are supposed to illustrate these behaviors. These arguments are less than convincing. If average hourly prices in the peak are higher than in the non-peak, then much of the response should be picked up in the "medium term". If there is significant load reduction on peak due to a large deviation from average peak prices (e.g. a critical peak price) the relatively large load reduction is likely due to a large movement up an inelastic demand curve in response to a large price change. The analysts' logic seems to suggest that the short term response is due to a small movement up a somewhat more elastic demand curve.

Medium Run Price Response

The analysts estimate both semi-logarithmic and double-logarithmic forms of this model. Only the semi-log form is outlined here.

Average hourly electricity consumption by program participants in hour *t* is specified by:

$$ln\bar{y}_{tp} = \alpha_{0p} + \alpha_1\bar{X}_t + \alpha_2\bar{p}_t + \varepsilon_{tp}$$

where:

vector $\bar{X}_t$ contains the mean values in hour *t* of variables influencing energy consumption—temperature, etc.; and

$\bar{p}_t$ is the average price in hour *t*.

A corresponding equation for non-participants is:

$$ln\bar{y}_{t,np} = \alpha_{0,np} + \alpha_1\bar{X}_t + \alpha_2 p^f + \varepsilon_{t,np}$$

where p^f is the fixed price of electricity.

Subtracting the second equation from the first, we have:

$$ln\bar{y}_{tp} - ln\bar{y}_{t,np} = \tilde{\alpha}_0 + \alpha_1\bar{X}_t + \alpha_2\bar{p}_t + \tilde{\varepsilon}_t$$

where

$$\tilde{\alpha}_0 = \alpha_{0p} - \alpha_{0,np} - \alpha_2 p^f.$$

For the semi-log specification, the price elasticity of demand is given by $\alpha_2 p$, indicating that demand is more elastic at high prices.

This equation was estimated by ordinary least squares for customer subgroups and seasons and weekdays and weekends. It uses mean hourly consumption by the participant subgroup of interest for $\bar{y}_{tp}$ and the subgroup's baseline mean hourly consumption derived from the hourly regressions from the hourly impact equations from above as an estimate of $\bar{y}_{t,np}$.

Short Run Demand Model
In contrast to any other study, these analysts attempt to estimate a complete daily demand system for electricity by aggregating the 24 hours of the day into nine periods. Through this process, they estimate own and cross-price elasticities for electricity for the nine groups of hours. This is in stark contrast to others' attempts to estimate elasticities of substitution between two or at most three groups of hours. In so doing, the analysts, in theory, capture both the income and substitution effects of a price change, rather than just the substitution effect (e.g. remaining on the same indifference curve) as is measured by the elasticity of substitution.

They also specify and attempt to estimate a Generalized Almost Ideal demand system (GAIDS), arguably the most demanding complete demand system in terms of data requirements and in terms of the econometric sophistication needed in its estimation.

The demand model is given by:

$$w_i = \frac{s_i p_i}{x} + \frac{\tilde{x}}{x}\left[\alpha_i \sum_j \gamma_{ji} log(p_j) + \beta_i log\left(\frac{\tilde{x}}{P}\right)\right] + \varepsilon_i$$

where
$w_i = \frac{q_i p_i}{\sum_i q_i p_i}$ = the day's expenditure share of time block i.
s_i = the parameter representing the "pre-committed quantity" for block i;
p_i = the day's price ($ per kilowatt-hour) for block i;
x = the day's electricity expenditures;
$\tilde{x} = x - \sum_i s_i p_i$ = the day's "supernumerary expenditure";
α_i, γ_{ji}, β_i = parameters to be estimated for block i;
P = the price index for the day;
ε_i = the error term for block i.

$$\log(P) = \alpha_0 + \sum_i \alpha_i \log(p_i) \sum_i \sum_j \gamma_{ij} \log(p_i) \log(p_j)$$

where the following constraints must be placed on the parameters to ensure linear homogeneity of this price aggregate:

$$\sum_i \alpha_i = 1, \sum_i \beta_i = 0, \sum_i \gamma_{ij} = 0 \sum_j \gamma_{ij} = 0, \gamma_{ij} = \gamma_{ji}.$$

In the estimation, the pre-committed quantity (s_i) was specified as functions of demand shifting variables such as cooling degree days, a binary variable indicating AC and Load Guard events, and the maximum temperature from the previous day. The estimation involved 102 parameters.

Reference	**The Effect on Electricity consumption of the Commonwealth Edison Customer Application Program: Phase 2 Final Analysis.** EPRI, Christensen Associates Energy Consulting, LLC, R. Boisvert, Cornell University, prepared for Commonwealth Edison Company, EPRI: Palo Alto, CA. October 21, 2011. 1023644.
Location	Greater Chicago area, Illinois
Customer Segment	Residential
Time/Duration	June 2010 – May 2011 (one year)

In this study, there are a number of separate analyses of the participant responses to the CAP rate and the several technology treatments in this pilot. These are discussed in turn below.

- **Aggregate Average Impacts on Usage**

Methods of Analysis of Variance (ANOVA) are used to identify the impacts on aggregate average electricity usage that are due to the various rates and other treatments. These analyses are conducted using ordinary least squares regression models in which indicator (0,1) variables are included for each treatment.

The primary regression model is:

$$\begin{aligned} Usage_i = \alpha + \beta_{CPP} \times CPP_i + \beta_{RTP} \times RTP_i + \beta_{PTR} \times PTR_i + \beta_{TOU} \times TOU_i + \beta_{BIHD} \times BIHD_i \\ + \beta_{AIHD} \times AIHD_i + \beta_{PCT} \times PCT_i + \beta_{Bill\ Prot} \times Bill\ Prot_i + \beta_{Purch} \times Purch_i \\ + \beta_{Educ} \times Educ\ Not_i + \beta_{SFSH} \times SFSH_i + \beta_{MFNS} \times MFNS_i + e_i \end{aligned}$$

where:
Usage$_i$ is defined three different ways: Average overall usage (conservation), average peak period usage, and Peak to Off-peak usage;
i is an index for customers;
α is the constant term (e.g. the effect associated with the specified control group);
β's are estimated parameters (the treatment effects);
SFSH denotes single family residences with space heat;
MFNS denotes multi-family residences with no space heat; and
MFSH denotes multi-family residences with space heat.

There were a total of 46 hypotheses tested. To test most hypotheses, the dependent variable is specified as metered usage (e.g. monthly usage or average hourly usage in peak periods). To test some hypotheses, it was necessary to construct ordinal or cardinal measures from the CAP system process, measurement, and validation databases (e.g. number of times a customer accessed the CAP website).

- **Event Day Load Impacts of CPP and PTR**

The event day load impacts for the CPP and PTR treatments are estimated using a fixed-effects regression model. The dependent variable in the model is the natural logarithm of average daily usage over the peak-hours (1:00 p.m. to 5:00 p.m.) on non-holiday weekdays. As explanatory variables, the model includes customer-specific intercept terms to account for differences in average usage, as well as variables to account for weather conditions, day type and month. The model is specified as:

$$ln(Q_{ct}) = \alpha + \beta^{Event} \times Event_t + \beta^{Event7} \times Event7_t + \beta^{PKTHI} \times PKTHI_t + \beta^{PKTHI2} \times PKTHI_t^2 + \beta^{PREPKTHI} \times PREPKTHI_t + \beta^{PREPKTHI2} \times PREPKTHI_t^2 + \beta^{MORTHI} \times MORTHI_t + \beta^{MORTHI2} \times MORTHI_t^2 + \beta^{LAGTHI} \times LAGTHI_t + \beta^{LAGTHI2} \times LAGKTHI_t^2 + \sum_{i=2}^{5}\left(\beta^{DTYPE} \times DTYPE_{i,t}\right) + \sum_{i=7}^{9}\left(\beta^{MONTH} \times MONTH_{i,t}\right) + v_c + e_t$$

where:
$Q_{c,t}$ represents the average usage from 1:00 to 5:00 p.m. for customer *c* on day *t*;
β's are estimated parameters;
$Event_t$ is an indicator variable that equals one if day *t* is an event day;
$Event7_t$ is an indicator variable that equals one if day *t* is September 21;
THI_t is the temperature-humidity index, which is calculated across four different time periods;
$PKTHI_t$ is the average temperature-humidity index from 1:00 to 5:00 p.m. on the current day;
$PREPKTHI_t$ is the average temperature-humidity index from 10:00 a.m. to 1:00 p.m. on the current day;
$MORTHI_t$ is the average temperature-humidity index from 12:00 a.m. to 10:00 a.m. on the current day;
$LAGTHI_t$ is the average temperature-humidity index for the entire previous day;
$DTYPE_{i,t}$ is a series of dummy variables for each day of the week;
$MONTH_{i,t}$ is a series of dummy variables for each month;
v_c is the customer-specific fixed effect for customer *c*; and
e_t is the error term.

Comments:

1. In this pilot, customers were recruited based on an "opt-out" approach. In the "opt-out" approach, customers are simply assigned to a dynamic rate. The customer must take specific action in order to opt out of the program. This is perhaps one reason for why both the ANOVA analysis and the fixed effects models failed to identify significant load reductions across the entire sample. Thus, in an attempt to identify a subset of customers in the sample that may be "price responders", the analysts estimated customer-specific regression models for each customer.

- **Identification of Customers who Respond to Events**

The models to identify the sub-set of customers who are "event responders: are identical to the fixed effects models except that the variables for the customers' fixed effects were removed, and the dependent variable was the average hourly peak period usage for each customer. Since customers on all rate treatments were notified of events, these regressions were also estimated for customers other than those on CPP and PTR rates. Using these regression models, customers were classified as even-responders if the estimated coefficient for the event-day variable was negative and statistically significant at the 80 percent level or greater.

Hourly Regression Model

To identify the load response of these "event" responders, the analysts estimated a regression model in which the dependent variable was the average usage by event responders in any hour. This model was designed to identify whether customers reduced load during only event hours, during non-event hours of the event day, or during all hours of the event day. The analysts claim that this strategy would help identify customers whose loads would have been low anyway—thus being incorrectly identified as an event responder. There may well be some potential for this method to identify customers who may anticipate the peak period by pre-cooling or those with significant "snapback" usage after the event hours. This model is:

$$
\begin{aligned}
ln(Q_t) = {} & \sum_{i=1}^{24}\left(\beta_i^{EVT} \times h_{i,t} \times EVT_t\right) + \sum_{i=1}^{24}\left(\beta_i^{THI} \times h_{i,t} \times THI_t\right) \\
& + \sum_{i=1}^{24}\left(\beta_i^{THISQ} \times h_{i,t} \times THISQ_t\right) \\
& + \sum_{i=1}^{24}\left(\beta_i^{LAGTHI} \times h_{i,t} \times LAGTHI_t\right) + \sum_{i=1}^{24}\left(\beta_i^{MON} \times h_{i,t} \times MON_t\right) \\
& + \sum_{i=1}^{24}\left(\beta_i^{FRI} \times h_{i,t} \times FRI_t\right) + \sum_{i=2}^{24}\left(\beta_i^{h} \times h_{i,t}\right) + \sum_{i=2}^{5}\left(\beta_i^{DTYPE} \times DTYPE_{i,t}\right) \\
& + \sum_{i=2}^{5}\left(\beta_i^{MONTH} \times MONTH_{i,t}\right) + e_i
\end{aligned}
$$

where:
Q_t represents average event-responder customer usage in hour t;
β's are estimated parameters;
$h_{i,t}$ is a dummy variable for hour i;
EVT_t is an indicator variable for event days;
THI_t is the temperature-humidity index;
$THISQ_t$ is the temperature-humidity index squared;
LAGTHIt is the temperature-humidity index from the same hour on the previous day;
MON_t is a dummy variable for Monday;
FRI_t is a dummy variable for Friday;
$DTYPE_{i,t}$ is a series of dummy variables for each day of the week;
$MONTH_{i,t}$ is a series of dummy variables for each month; and
e_t is the error term.

- **Elasticities of Substitution**

For the sub-set of customers identified as "event responders", the analysts specified two separate models to estimate elasticities of substitution between peak and off-peak electricity usage. One model is a nested CES model that allocates a customer's electricity usage both across hours within a day, but also between days. The second model is based on a Generalized Leontief specification which allows elasticities of substitution to differ by customer and by day.

The Nested CES Model

The nested CES model is derived from a cost function that allocates a customer's electricity costs separately within a day and between days. This model is estimated only for CPP and PTR "event-responders". The model is:

$$ln\left(\frac{E_{dh}}{\overline{E_h^m}}\right) = \sigma_w \left[ln\left(\frac{D_d}{\overline{D^m}}\right) - ln\left(\frac{P_{dh}}{\overline{P_h^m}}\right)\right] + \sigma_b \left[ln\left(\frac{M_m}{\overline{M^m}}\right) - ln\left(\frac{D_d}{\overline{D^m}}\right)\right] + e_d$$

where:

E_{dh} represents electricity usage in hour (or time period) h on day d;

P_{dh} is the price in that time period on day d;

D_d and M_m represent daily and monthly price indexes of a CES form;

σ_w and σ_b are the between-day elasticity of substitution and within-day elasticity of substitution parameters, respectively; and

e_d is an error term.

The variables with the bars above the capital letter in the denominator of each term are averages of the variable for the comparable time period in the reference period (*e.g.*, the average load in time period h on weekdays in a given month). The daily and monthly price indexes are constructed as weighted averages of relevant rate structure prices, where the weights are load shape parameters (α_{hd} and β_d), which characterize the inherent shape of the customer's load pattern. A series of indicator variables for the different time periods and months are also added, as well as a weather variable (daily THI) of the same log ratio form relative to the reference period as the other variables.

The GL Demand Model

This model is based on a Generalized Leontief demand model. To estimate the elasticities one must first estimate an equation in with the dependent variable is the logarithm of the ratio of peak and off-peak expenditure shares:

$$ln\left(\frac{ES_{pd}}{ES_{od}}\right) = \beta \times CDD_d + ln\left[H_p H_d + \gamma_{pp} P_{pd} + \gamma_{po}\sqrt{P_{pd} P_{od}}\right] + ln\left[H_o H_d + \gamma_{oo} P_{od} + \gamma_{po}\sqrt{P_{pd} P_{od}}\right] + e_d$$

where:

ES_{pd} and ES_{od} are peak and off-peak electricity expenditure shares, respectively, on day d,

β is a parameter that controls for daily differences in cooling degree days (CDD_d),

P_{pd} and P_{od} are peak and off-peak prices, respectively, on day d,

H_d is a variable that is set to be equal to unity on days where the temperature exceeded 85 degrees F, and was zero otherwise;

γ_{ij} are estimated parameters; and

e_d is error term.

Once this model is estimated, the parameters are used to predict expenditure shares, which, in turn, are used to estimate the daily elasticities of substitution. Since the calculations are rather involved, they are not repeated here. The calculations are, however, reported in Appendix A of the Phase 1 report for this pilot.

- **Analysis of the Inclining Block Rate**

Of the 10 pilots reviewed for this report, this is the only one in which there was a treatment for an inclining block rate. Sampling issues, as well as complications encountered by the fact that the last block of the rate reduced prices to the flat rate, precluded any ANOVA analysis of this rate treatment.

As an alternative, the analysts compared electricity usage for IBR customers the CAP and the pre-pilot time periods, covering a period of 22 months. The model for this analysis is:

$$\ln(Q_m) = \alpha + \beta_c CDD_m + \beta_h HDD_m + \beta_{IBR} IBR_m + \varepsilon_m$$

where:
Q_m electricity usage in billing month m;
CDD_m and HDD_m are the total cooling degree days and total heating degree days, respectively, during the billing month; and
IBR_m is a dummy variable which equals unity for the months the customer is on the IBR rate (e.g. the CAP pilot period), and zero otherwise (e.g. months prior to the CAP pilot when the customer was on a conventional ComEd tariff).

Reference	**Hydro One Networks Inc. Time-of-Use Pilot Project Results**, EB-2007-0086, Susan Frank, submitted to the Ontario Energy Board, Ontario, Canada, May 13, 2008.
Location	Ontario, Canada
Customer Segment	Residential Farm Small general service (under 50 kW) distribution customers
Time/Duration	May - September 2007 (five months)

In this pilot, the load impact and conservation econometric analyses were 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.

The analysts argue that the nonparametric conditional mean estimation framework used is the most general model that one can estimate to recover the impact of a critical peak event. They suggest that, unlike other pilot results, it is hard to think of any omitted variable that could be causing the results for which there is no control.

The fixed effects approach embodies a separate intercept term for each customer to control for effects that are unique to that customer and constant over the time period. Because of its fixed effects nature, the model does not need to include unchanging customer characteristics such as square footage, number of floors, equipment, etc. Since each customer has a different base load, a different response to weather, and a different pattern of consumption that changes over time, the inclusion of these fixed effects controls for the amount of variance (noise) in the model. By including time effects, 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.

There are two separate models estimated, one for demand response, and the other for the conservation effect. The specifications of the two models are nearly identical in terms of the independent variables. The major differences are in the specification of the dependent variable, as is indicated below.

- **Model for Demand Response and/or Conservation Effect**

The analytical models are specified as:

$$y_{(i,t)} = \alpha_i + \gamma_t + Treat_i * TOU_t * \beta 1 + Treat_i * CPP_t * \beta 2 + Treat_i * CPR_t * \beta 3 + \varepsilon_{(i,t)}$$

where:
(*Dependent Variable--Demand Response Model*)
$y_{(i,t)}$ is logarithm of consumption for customer *i* during the peak hours on day *t*,

(*Dependent Variable--Conservation Effect Model*)

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

(*Independent Variables—Common to Both Models*)

α_i is the customer-level fixed effects,
γ_t is the day of sample fixed effect,
$Treat_i$ is the dummy variable whether a customer is treatment or control,
β1, β2, β3 are the changes 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*.

(*For the Demand Response Model*)

TOU_t, CPP_t, and CPR_t are defined as respective dummy variables indicating whether a day is a critical peak day or not,
$\varepsilon(i,t)$ is the error term for customer *i* during the peak hours on day *t*.

(*For the Demand Response Model*)

TOU_t, CPP_t, and CPR_t are defined as respective dummy variables indicating whether a period is for the previous year or not,
$\varepsilon(i,t)$ is the error term for customer *i* during the bimonthly billing period for period *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 γ_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.

Reference	**2008 Ex Post Load Impact Evaluation for Pacific Gas and Electric Company's SmartRate™ Tariff,** Stephen George and Josh Bode, Freeman, Sullivan & Co. San Francisco, CA, December 30, 2008.
Location	California - Pacific Gas and Electric (PG&E). Offered in the Bakersfield and greater Kern Country region, a very hot area where maximum temperatures exceed 100°F on many summer days. This was the first region to receive new meters under PG&E advanced metering infrastructure deployment.
Customer Segment	Residential E-1 and E-8 customers Non-residential customers on the A-1 tariff which applies to customers smaller than 200 kW
Time/Duration	Summer of 2008 (June - September)

This study contains no analysis of the impact of electricity prices. The focus is exclusively on the load impacts as required by CA PUC order.

- **Load Impacts**

To estimate load impacts, separate models were specified for both residential and non-residential customers. For several reasons, time series regressions were estimated at the *individual customer level* rather than pooling the data for all customers. In the case of residential customers, the most important reason was that PG&E did not collect data on the size and type of air conditioning for each household. Thus, the presence of air conditioning is a fixed effect that interacts with weather. The analysts go on to argue that by allowing individual customer coefficients to differ, the results are more accurate at the customer level. This facilitates the calculation of the effects by customer segments in addition to the average for all participants.

In both model specifications, the explanatory variables are be classified into three categories—those that: (1) reflect the average load shape of customers, absent the need for cooling; (2) explain deviations in hourly usage from the average load shape; and (3) capture the change in energy use during event days and the factors that influence the load reductions. The actual variables included in each model were somewhat different.

The results from the regression models are used to predict: (1) what the load would have been without the DR, and (2) what the load would have been with the DR. They then compare the actual load (during the event days) with the two predictions. The models for residential customers and non-residential customers are given below.

The Residential Model

$$KW = \alpha_0 + \sum_{i=2}^{24} \beta_i \cdot Hour_i \cdot NS \cdot WEEKDAY + \sum_{i=2}^{24} \omega_i \cdot Hour_i \cdot S \cdot WEEKDAY$$
$$+ \sum_{i=2}^{24} \omega_i \cdot Hour_i \cdot WEEKEND + \sum_{i=1}^{24} \mu_i \cdot Hour_i \cdot CDH$$
$$+ \sum_{i=1}^{24} \delta_i \cdot Hour_i \cdot CDH^2 + \sum_{k=7}^{10} \vartheta_k \cdot MONTH_k \cdot EVENT$$
$$+ \sum_{i=2}^{24} \pi_i \cdot Hour_i \cdot EVENTDAY$$
$$+ \sum_{k=7}^{10} \vartheta_k \cdot MONTH_k + \sum_{i=1}^{24} \theta_i \cdot Hour_i \cdot EVENTDAY \cdot CDH + \sum_{i=1}^{24} \theta_i \cdot Hour_i$$
$$\cdot EVENTDAY \cdot CDH^2 + \sum_{k=1}^{3} \tau_k \cdot INROW_k \cdot EVENT + \rho \cdot CUMEVENTS$$
$$\cdot EVENT + \sum_{k=2}^{7} \tau_k \cdot DOW_k \cdot EVENT + \varphi \cdot S \cdot CHD + \sigma \cdot S \cdot CDH^2 + \varepsilon$$

The Non-Residential Model

$$KW = \alpha_0 + \sum_{i=2}^{24} \beta_i \cdot Hour_i \cdot WEEKDAY$$
$$+ \sum_{i=2}^{24} \omega_i \cdot Hour_i \cdot WEEKEND + \sum_{i=1}^{24} \mu_i \cdot Hour_i \cdot CDH$$
$$+ \sum_{i=1}^{24} \delta_i \cdot Hour_i \cdot CDH^2 + \sum_{k=7}^{10} \vartheta_k \cdot MONTH_k \cdot EVENT$$
$$+ \sum_{i=2}^{24} \pi_i \cdot Hour_i \cdot EVENTDAY$$
$$+ \sum_{k=7}^{10} \vartheta_k \cdot MONTH_k + \sum_{i=1}^{24} \theta_i \cdot Hour_i \cdot EVENTDAY \cdot CDH + \sum_{i=1}^{24} \theta_i \cdot Hour_i$$
$$\cdot EVENTDAY \cdot CDH^2 + \sum_{k=1}^{3} \tau_k \cdot INROW_k \cdot EVENT + \rho \cdot CUMEVENTS$$
$$\cdot EVENT + \sum_{k=2}^{7} \tau_k \cdot DOW_k \cdot EVENT + \varphi \cdot S \cdot CHD + \sigma \cdot S \cdot CDH^2 + \varepsilon$$

where:
KW = Electricity usage in Hour *i* for Customer *j*;
NS = No School (period in summer when school is NOT in session);
S = Period during the summer when school is in session;
WEEKDAY = Monday – Friday;
WEEKEND = Saturday – Sunday;
$HOUR_i$ = Hours of the day, numbered 1-24;
$MONTH_j$ = Months of the year, numbered 1-12;
CDH_i = Cooling Degree Hours, Max(0, Temperature(F) -70);
CDH^2 = CDH squared;
EVENTDAY = SmartRate event day (all 24 hours);
EVENT= SmartRate event window (2-7 pm);
INAROW = Number of consecutive events in a row;
CUMEVENTS= Cumulative number of events in season;
DOW = Day of week;
ε = the error term;
i = Subscript indicating the hour of day (1-24);
j = Subscript indicating the month of the year (1-12);
k = Subscript indicating the number of consecutive events in a row
l = Subscript indicating the day of week (1-7).

Reference	**PowerCentsDC™ Power Program,** eMeter Strategic Consulting for the Smart Meter Pilot Program, Inc., September 2010
Location	Washington, DC
Customer Segment	Residential
Time/Duration	July 2008 - October 2009 (Analysis covers the summers of 2008 and 2009 and the winter of 2008-2009)

The analysts argue that the demand response impact and conservation effect analyses are based on a non-parametric conditional mean estimation framework with customer-level and day of sample fixed effects. Thus, the data were pooled across customers to estimate the model.

In the analysis, they focus exclusively on the impact of the pricing programs on electricity use during the peak hours of the day.

- **The Impact on Electricity Use During the Peak Hours of the Day**

To model these demand response impacts, the analysts used a model with customer-level fixed effects and day-of-sample fixed effects. It has the general form:

$$y_{(i,t)} = \alpha_i + \mu_t + Treat_i * HP_t * \beta_1 + Treat_i * CPP_t * \beta_1 + Treat_i * CPR_t * \beta_1 + \varepsilon_{(i,t)}$$

where

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

α_i = customer level fixed effects;

λ_t = the day of sample fixed effect;

$Treat_i$ = a dummy variable whether a customer is treatment or control;

HP_t, or CPP_t or CPR_t = a dummy variable indicating whether a day is a critical peak day or not;

B_1, B_2, B_3 = parameters that measure the change in customer consumption due to the respective pricing plans HP, CPP, and CPR;

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

Reference	**Public Service Electric and Gas Company.** Dan Violette, Jeff Erickson, Mary Klos, Summit Blue Consulting, Final Report for the myPower Pricing Segments Evaluation, Public Service Electric and Gas Company, December 21, 2007.
Location	PSE&G - New Jersey - Cherry Hill & Hamilton Townships
Customer Segment	Residential
Time/Duration	Summer 2006-Summer 2007 (~15 months)

To assess the impact of the various rate designs, the analysts for this study measured Summer Peak Day Impacts, Summer kWh Shifts, and the Elasticity of Substitution Between Peak and Off-peak Usage. They also estimated the Winter and Shoulder Month Impacts.

- **Summer Peak Day Impacts**

The methods used to estimate summer peak day impacts differ for TOU & CPP customers.

TOU—

Demand impacts from the TOU rate alone (minus the impact of the CPP) were based on a comparison of participant group to control group kWh usage on the hottest summer days of 2006 and 2007 that did not have CPP events.

The control group of customers closely matched the participant group in each participant segment and size strata.

CPP—

This analysis of CPP impacts is based on a "fixed effects" regression model using pooled time-series and cross-sectional data—summer hourly observations for all households in the same customer segment are combined into one model.

Algebraically, the fixed-effect panel data model is:

$$y_{it} = \alpha_i + \beta x_{it} + \varphi c_t + \varepsilon_{it} ,$$

where:
y_{it} = energy consumption for customer i during hour t
α_i = constant term for customer i
β = vector of coefficients
x_{it} = vector of variables that represent factors causing changes in energy consumption for customer i during hour t (i.e., weather, hour of the day);
φ = vector of estimated impacts during and after critical peak events;
c_t = vector of variables for presence of control or snapback for hour t;
ε_{it} = error term for customer i during hour t.

It is difficult to know from the write up what was actually done, but here is what appears to be the correct specification: There is a dummy variable in the model for each hour of the day. Furthermore, they model each hour of the peak period separately, arguing that load impacts ***degrade*** over the period. To estimate the hourly impact on load during the peak control period:

- There is a dummy variable created for each of these hours on an event day. These dummy variables are part of the vector C_t , and one would expect the coefficient on the corresponding element of the φ vector $\varphi_t < 0$, indicating a reduction in load in that hour, relative to load in the same hour on non-event days. If the impacts do in fact ***degrade*** over the period, then the absolute values of these coefficients would decline over the peak hours.
- The vector C_t includes dummy variables for each of several hours after the peak on critical event days. The coefficients on these hourly variables are used to measure ***snapback***, an increase in consumption after the event is over as air conditioners catch up. One would thus expect the coefficient on the corresponding element of the φ vector $\varphi_t >$ 0, for these snapback hours indicating an increase in load in that hour, relative to load in the same hour on non-event days. The size of these coefficients could rise for a couple of hours after the end of the peak.

- **Summer kWh Shifts**

The analysts argue that the effects of TOU and CPP rates on summer peak days are primarily related to reducing the need for system capacity and the associated avoided costs. Since TOU rates apply to all days, they also examine how much load is shifted from one price period to another over the entire summer—the effect on the average daily load curve.

The analysis is based on a comparison of participant group with the control group kWh usage during summer days without CPP events. That is, average kWh usage per customer for each hour of the study period for each study group was estimated. (They argue that using average kWh usage per customer, per hour, minimized the problem of missing data. If a kWh reading was missing for a particular customer during a particular hour, the impact on the calculated average for that hour was small.) The average kWh usage for each hour was then assigned to the proper rate period: Night, Base or On-Peak. The result was the average kWh per customer used during each rate period during the summer study period.

- **Summer Energy Conservation**

The analysis of kWh shifts is based on the assumption that overall energy use is fixed, but it is also possible that due to the TOU rate, overall energy consumption would be reduced.

The TOU summer energy savings analysis is based on a difference of differences approach since each participant group has a matched control group. These savings were estimated by calculating simple averages of monthly use before and after the program initially calculated for each program group, including separate estimates for the matched control groups. The differences before and after the start of the program for each group provided an estimate of the impact of the program on monthly energy use during summer months. These differences for the program groups are then compared to the differences for the control groups to estimate the effect of the program on energy use compared to what it would have been without the program.

To account for the fact that weather during the four study years may not have been normal, they estimated a fixed effects regression model for customers with and without central air.

A logarithmic transformation of the monthly kWh variable was used to focus on the percentage change in use. The energy savings models are specified as follows:

ln(Monthly kWh) = f (Monthly THI, Billing Days,
myPower Connection Customer after program began,
myPower Sense Customer after program began,
Control Group Customer after program began).

After these models were estimated, the logarithm of monthly kWh was predicted for normal monthly THI (temperature humidity index), before and after the start of the program, and a difference of differences approach with matching control groups provided an estimate of normalized energy savings under different weather conditions.

- **The Elasticity of Substitution**

The only effects of electricity prices on demand for electricity in this study are measured through an elasticity of substitution, which the analysts suggest provides an indication of how much electricity usage will be shifted from the peak period to the off-peak period as the relative prices change.

The analysts specify a Constant Elasticity of Substitution (CES) model, in which the ratio of peak electricity use to off-peak electricity use is regressed on the ratio of peak to off-peak prices. The coefficient on the ratio of peak to off-peak prices is the elasticity of substitution The model is:

$$ln\left(\frac{kWh_{peak}}{kWh_{offpeak}}\right) = \alpha + \sigma ln\left(\frac{Price_{peak}}{Price_{offpeak}}\right) + \epsilon_{it}$$

where:
kWh_{it} = energy consumption for home *i* during peak and off-peak periods;
α_i = constant term;
β = vector of estimated coefficients;
x_{it} = vector of variables that represent weather factors (temperature and humidity) causing changes in household energy;
σ = elasticity of substitution for electricity between peak & off-peak periods;
Price = the price of electricity during peak and off-peak periods;
ε_{it} = error term for home *i* during hour *t*.

D

SUMMARY OF FEEDBACK STUDIES REVIEWED

[1] Impact Evaluation of 2007 In-Home Display Pilot: Submitted to Progress Energy—Carolinas (Final Report). Summit Blue Consulting, LLC, Boulder, CO: October 2008.

[2] Hydro One Pilot, Real Time Monitoring Pilot, Summer 2004-2005. Dean C. Mountain, Mountain Economic Consulting and Associates, Inc., March 2006.

[3] Dominion Virginia Power, Power Cost Monitor Pilot – May 2008 to July 2009. Dean C. Mountain, Mountain Economic Consulting and Associates, Inc., January 2010.

[4] Focus On Energy – PowerCost Monitor Study: Final Report. Energy Center of Wisconsin, April 16 2010.

[5] Evaluation Report: OPOWER SMUD Pilot Year 2. Navigant Consulting, February 2011.

[6] H. Allcott. "Social Norms and Energy Conservation," Journal of Public Economics. Vol. 95, No. 9-10, p. 1082 (2011).

Reference	**Impact Evaluation of 2007 In-Home Display Pilot: Submitted to Progress Energy—Carolinas (Final Report).** Summit Blue Consulting, LLC, Boulder, CO: October 2008.
Type of Feedback	IHD (PowerCost Monitors by Blue Line Innovations)
Cost to Customer	Free
Installation Method	Meter collar installed by utility, IHD left on front step (not reported whether there was follow-up to ensure proper functioning of the IHD)
Location	Raleigh, Wilmington, Southern Pines and Asheville, North Carolina
Customer Class	Residential (single-family, owner-occupied homes)
Time/Duration	August 2007 – July 2008 (one year)
Sample Size by Treatment Group	Treatment group: 293 (this is the number who received IHDs—presumably this is the number also used in the analysis, although it is not explicitly stated). Control group (no IHD): 293 (or identical number as in treatment group) Customers included those on Progress Energy's flat rate and "Balanced Bill" rate (one type of levelized rate); those on "Budget Billing" (another type of levelized rate) or time-of-use rates not eligible. Customers from billing groups 1 and 2 randomly selected to be solicited (each billing group represents customers whose meters are read on the same day). All customers had 24 months of prior billing history (no estimated readings). Participants screened to ensure half of treatment customer were household heads 45 years of age or less, and half greater than 45 years.
Experimental Design (pp. 6-8)	A random selection of the approximately 10,000 customers that were eligible for the pilot (based on screening criteria in "Sample Size" above) were solicited to participate. The number that was solicited and did not volunteer was not reported, but ultimately 293 customers received IHDs. The control group was developed using the remaining customers of the 10,000. For each treatment group member, a group of potential control group matches was developed based on characteristics known to Progress through their database (region, family composition, household head age, income group, housing type, PRIZM segment, and rate type). The best match for each treatment group member was then determined by finding the person in that group with the closest pre-test annual electricity usage.

Reference	**Impact Evaluation of 2007 In-Home Display Pilot: Submitted to Progress Energy—Carolinas (Final Report).** Summit Blue Consulting, LLC, Boulder, CO: October 2008.

	The overall annual usage and standard deviation of the treatment and resulting control groups were almost identical.
	
	Chi-square calculations comparing other characteristics of the treatment and control group yielded the following results:
	• No differences based on operating region or county (95% confidence level)
	• Treatment group members were:
	  o Less likely to be in a 1000 to 2000 sq ft home (presumably not the smallest size category, and not the largest)
	  o More likely to have income between \$15,000 to \$40,000, and less likely to have income between \$50,000 to \$70,000 (could suggest a lower income cohort, but not certain)
	  o More likely to have children in the home
	  o More likely to be 25-45 years of age, and less likely to be 55-75 (could suggest a younger cohort)
	  o On the “Balanced Bill” program at a lower proportion: 4% compared to 9% for the control group

Recruitment method	Phone recruitment with screener questionnaire. Details of number of calls and number of initial volunteers were not reported.
Other information provided to customers?	Instructions provided with the IHD, along with energy savings tips. These were not evaluated separately (therefore impact evaluation incorporates effects of IHDs and tips together).
Control technology?	No
Dynamic rate?	No (those on TOU were excluded from the sample)
Energy impacts measured (kWh)	2.4% annual savings (calculated from model coefficients that are significant at the 93% level). Model estimated 420 kWh savings annually over total average annual consumption of 17,235 kWh. 263 of the 420 kWh savings found to be attributable to changes in electricity usage behaviors that could occur year-round (e.g., turning off appliances, lights, installing more efficient lights); 157 of the 420 kWh savings found to be attributable to cooling-related actions; model found no electricity savings attributable to heating (half of participants did not have

Reference	**Impact Evaluation of 2007 In-Home Display Pilot: Submitted to Progress Energy—Carolinas (Final Report).** Summit Blue Consulting, LLC, Boulder, CO: October 2008.
	electric heating, so this finding was not unexpected). An additional analysis performed on treatment group customers with electric heating that reported taking 6 actions that would affect space heating consumption (during a condensed 182-day winter period), compared to treatment group customer that reported they did not take such actions. Found a 1.3 kWh savings per 182 winter days per action taken (they assumed that each of 6 heating related savings would have the same value savings value) (95% confidence level). Additional analysis was also performed on treatment group customers with electric water heating that reported taking 2 savings actions (clothes washing with cold water, fewer dishwasher loads) that would affect water heating consumption (over the course of the year), compared to treatment group customer that reported they did not take such actions. No statistically significant electricity savings were found. Additional analysis was also performed on treatment group customers that reported taking 3 savings actions (turning off lights & appliances, installing efficient lights, and installing efficient appliances), and comparing them to treatment group customer that reported they did not take such actions. Effect of turning off lights and other appliances: 1.49 kWh savings per day (at 99% confidence level). Effect of installing energy efficient lights: 0.71 kWh savings per day (at 86% confidence level). Effect of installing energy efficient appliances: 1.43 kWh savings per day (at 84% confidence level).
Load impacts measured (kW)	Monthly data only, no hourly data. However, analysis included an engineering model to estimate average hourly demand, and thus potential hourly savings impacts from each of the self-report actions taken for which statistically significant savings were found. Assuming a later afternoon summer peak (~2-5 p.m.): • Effect of summer AC actions: 50 watts per summer peak hour per participant • Effect of other year-round actions: 20 watts per summer peak hour per participant • Effect of turning off lights and appliances: 40 watts per summer peak hour per participant that took the action • Effect of installing energy efficient lights: 10 watts per summer peak hour per participant that took the action

Reference	**Impact Evaluation of 2007 In-Home Display Pilot: Submitted to Progress Energy—Carolinas (Final Report).** Summit Blue Consulting, LLC, Boulder, CO: October 2008.
	• Effect of installing other energy efficient appliances: 55 watts per summer peak hour per participant that took the action
Self-reports of behaviors changed?	Three surveys, #2 (after installation) and #3 (after one year) asked what actions people took (presumably because of the IHD). Control group customers were not surveyed. Largest reported actions (#2 and #3): turning off lights and appliances Some self-reports of actions declined from #2 to #3 Three actions showed an increase in frequency from #2 to #3; two of these were purchase-oriented (installing energy efficient lights and energy efficient windows). Similar levels of electric and non-electric space/water heating reported adjusting heating, dishwashing and clothes washing. This could mean a number of things, including: self-report bias (socially desirable answers), conservation behavior crossed over to other fuels, even though usage behavior wouldn't be reported via the IHD, customers didn't realize their space/water heating appliances were not electrically fueled.
Electricity Prices	Customers included those on Progress Energy's flat rate and "Balanced Bill" rate (one type of levelized rate); those on "Budget Billing" (another type of levelized rate) or time-of-use rates not eligible.
Estimation method (pp. 6-8, 15-18 for kWh savings, p. 20 for kW savings estimations)	Year-round and weather-dependent electricity savings (kWh) attributable to the IHD. Difference of difference using a control group (tests if bill difference between the pre-test and post-test period is due to the displays) Fixed effects model was with weather-normalized data. Monthly billing data is dependent variable in a regression equation that controls for weather and household characteristics Several model specifications were tried The t-values show that estimates of daily year-round (i.e., not weather dependent) savings and daily summer cooling-related saving were statistically significant at the 93% confidence level. Appliance/behavior-specific electricity (kWh) savings attributable to the IHDs Used treatment group survey respondents only, compared electricity usage of those who reported taking specific actions to those that did not report

Reference	**Impact Evaluation of 2007 In-Home Display Pilot: Submitted to Progress Energy—Carolinas (Final Report).** Summit Blue Consulting, LLC, Boulder, CO: October 2008.
	taking the actions Appliance/behavior-specific load (kW) savings attributable to the IHDs Used an engineering model to estimate daily loads in the summer, then applied the above estimated electricity savings over the peak period (~2-5:00 p.m.) to estimate potential loads savings
Income	This information was known by Progress Energy, and was also obtained for the treatment groups in the first survey (before IHDs were installed)
Customer Circumstances	Known prior to pilot. Treatment was similar to match control group in consumption and region, but was lower income and younger than the control group. See "Sample Size" and "Experimental Design" above. Energy and load impacts not reported for different demographic traits.
Premise Circumstances	Model using self-reports of actions suggest electric space-heating actions contributed to annual savings, but electric water heating savings did not. However, model results interpreted with caution. Other than this, energy and load impacts not reported for different premise traits.
Exogenous factors	Weather, and particularly hot post-test summer period (although controlled for in model)
Persistence?	Savings of 2.4% was estimated after one year. Interim savings were not reported. Self-reports indicate small decline in persistence of most actions from second to third (final) survey; two of the three actions for which self-reports *increased* over this time period were purchase-oriented in nature (installing energy efficient lights and energy efficient windows)

Reference	**Hydro One Pilot, Real Time Monitoring Pilot, Summer 2004-2005**. Dean C. Mountain, Mountain Economic Consulting and Associates, Inc., March 2006.
Type of Feedback	IHD (PowerCost Monitors by Blue Line Innovations)
Cost to Customer	Free
Installation Method	By customer (although not mentioned in above reference)
Location	Ontario
Customer Segment	Residential
Time/Duration	April/May 2004 – July 2005 (thirteen month post-test period)
Sample Size	Treatment: 382 with IHD used in analysis (500 were originally provided IHDs) Control: 42 with no IHD
Experimental Design (pp. 9-13)	Pre/post treatment/control comparison, treatment group comprised of volunteers from a stratified random sample based on 6 consumption strata and 5 geographic regions. Control group also appears to be proportionately representative of consumption strata and geographic regions, and randomly drawn from the same initial sample frame.
Recruitment method	Phone recruitment to solicit volunteers from a stratified random sample based on 6 consumption strata and 5 geographic regions Excluded apartment addresses, multi-family premises, condominiums, town homes, and row homes Excluded customers whose meters were not 7.2 kHz Additional exclusions after telephone screening: customers who planned to move within 6 months; seasonal customers; premises with meters located inside the house. After screening, less than 2% of customers rejected the offer for the free IHD. 500 customers received IHDs, but for various reasons (customers moving away, data problems, not completing surveys), the number of treatment and control customers available for the analysis was 382 and 42 respectively. It appears that the treatment and control customers initially came from the same sampling frame, although the control customers did not go through the telephone screening, and did not have to opt-in for anything (even though the opt-in rate was very high, 98%).

Reference	**Hydro One Pilot, Real Time Monitoring Pilot, Summer 2004-2005**. Dean C. Mountain, Mountain Economic Consulting and Associates, Inc., March 2006.
Other Information?	No provision of conservation literature or goal setting materials No interventions
Control technology?	None
Dynamic rate?	None
Energy impacts measured (kWh)	Average impact of IHD on electricity consumption over 13 months: 6.5% Significant at the 95% confidence level See 'premise characteristics' below for savings breakdown based on appliance stock.
Load Impacts Measured (kW)	Not evaluated, household energy consumption measured
Self-reported Conservation Behaviors	Questionnaires were not designed to measures self-reports on actions taken as a result of the feedback (or at least it was not reported 38.9% consulted the monitor at least once per day
Electricity Prices	Not evaluated

Reference	**Hydro One Pilot, Real Time Monitoring Pilot, Summer 2004-2005**. Dean C. Mountain, Mountain Economic Consulting and Associates, Inc., March 2006.
Estimation method (pp. 13-23; results 24-37)	The study uses a panel based econometric methodology using sub-models to control for weather, appliance stock, housing, and demographic determinants. Monthly billing data and meter reads were collected for participant households, and historical billing data was also compiled. An initial survey provided snapshots of appliance and demographic characteristics of the participants and their opinion of the monitor itself. Weather data was also collected and used in the analytic models where participant usage without the monitor is controlled for. The analysis attempts to isolate the impact of the IHD by controlling for factors that contribute to the control groups' consumption. First, the historical monthly billing data was collected for up to 18 months prior to receiving the IHD for the treatment participants, allowing for pre-/post-treatment comparisons. Second, a parallel control sample that received no IHD was monitored simultaneously with the treatment group. Finally, the model controls for changes in electricity consumption that arise from traditional factors such as weather, appliance configurations, and demographic characteristics. Sub-Models included electric heating, electric water heating, air conditioning, other electricity load, time trend, IHD impact R-squared value of econometric model: 0.9439 Excluded observations where participants had technical difficulties with monitor Excluded observations corresponding to installation period Excluded participants who failed to respond to any of the three administered questionnaires
Price of substitutes?	Not evaluated

Reference	**Hydro One Pilot, Real Time Monitoring Pilot, Summer 2004-2005**. Dean C. Mountain, Mountain Economic Consulting and Associates, Inc., March 2006.
Premise and Customer Circumstances	Three surveys at the beginning, mid-point, and end of the pilot sought information on dwelling and demographic characteristics and appliance holdings before, during, and years leading up to the pilot. Education, income, and occupant age appear not to affect IHD impacts. Average savings (over 13 months) by households with: • Electric heating, water heating, and air conditioning: 0.87% (reported elsewhere that savings from electrically heated homes not significant) • Electric heating and water heating, no air conditioning: 1.16% (reported elsewhere that savings from electrically heated homes not significant) • Electric water heating and air conditioning, no electric heat: 16.74% • Electric water heating, no electric heat or air conditioning: 16.74% • Air conditioning, no electric heat or water heating: 5.05% (significant at the 95% level) No electric heat, water heating, or air conditioning: 5.05% (significant at the 95% level)
Exogenous factors	Weather – accounted for the impact of weather on load for control and treatments Higher savings observed in the summer when temperatures are warmer, especially in the hot days of summer.
Persistence?	The time trend in the model no reduction in conservation effect observed over 13 month Survey Responses: 65.1% planned to continue using the Monitor after pilot

Reference	**Dominion Virginia Power, Power Cost Monitor Pilot – May 2008 to July 2009.** Dean C. Mountain, Mountain Economic Consulting and Associates, Inc., January 2010.
Type of Feedback	IHD (PowerCost Monitors by Blue Line Innovations)
Cost to Customer	Free
Installation Method	By customer (although not discussed in above reference)
Location	Virginia
Customer Segment	Residential
Time/Duration	April/May 2008 – July 2009 (fifteen months)
Sample Size by Treatment Group	Treatment: ~ 180 with IHDs (number in analysis; ~1,000 provided to customers) Control Group: ~ 40
Experimental Design	Pre/post treatment/control comparison.
Recruitment method	Randomly selected 1000 pilot participants to receive meter. Excluded: apartment addresses, multi-family premises, and TOU households Control group selection was not discussed. Methodology appears very similar to the Mountain 2006 (Hydro One) study.
Other information provided to customers?	None reported
Control technology?	None
Dynamic rate?	None

Reference	**Dominion Virginia Power, Power Cost Monitor Pilot – May 2008 to July 2009.** Dean C. Mountain, Mountain Economic Consulting and Associates, Inc., January 2010.
Energy impacts measured	Observations where participants had technical difficulties with monitor were excluded. Also, participants who failed to respond to any of the three administered questionnaires were excluded from analysis. Annual consumption savings (modeled with 15 months of data used to produce annual load impact) • Electric Heat and WH: 1.66% • No Electric Heat, Electric WH: 14.69% • No Electric Heat or WH: 1.66% Seasonal impacts reported as well Significant at the 90% level
Load Impacts Measured	Not evaluated, household energy consumption measured
Self-reported Conservation Behaviors	Yes, final questionnaire asked customers about individual actions taken to reduce energy consumption. Multiple actions reported, the top three being: • Used CFLs: 37.8% • Adjusted Temperature Set points: 35.4% • Turn TV/PC/Other Off When Not In Use: 28.9%
Electricity Prices	Not evaluated

Reference	**Dominion Virginia Power, Power Cost Monitor Pilot – May 2008 to July 2009.** Dean C. Mountain, Mountain Economic Consulting and Associates, Inc., January 2010.
Estimation method (pp. 7-21)	The study uses a panel based econometric methodology using sub-models to control for weather, appliance stock, housing, and demographic determinants. Monthly billing data was collected for participant households, and historical billing data was also compiled. An initial survey provided snapshots of appliance and demographic characteristics of the participants and their opinion of the monitor itself. Weather data was also collected and used in the analytic models where participant usage without the monitor is controlled for. The analysis attempts to isolate the impact of the IHD by controlling for factors that contribute to the control groups' consumption. First, the historical monthly billing data was collected for at least one year prior to receiving the IHD for the treatment participants, allowing for pre-/post-treatment comparisons. Second, a parallel control sample that received no IHD was monitored simultaneously with the treatment group. Finally, the model controls for changes in electricity consumption that arise from traditional factors such as weather, appliance configurations, and demographic characteristics. Sub-Models include: electric heating, electric water heating, air conditioning, other electricity load, time trends, the IHD R-squared of econometric model: 0.7126
Price of substitutes?	Not evaluated
Premise and Customer Circumstances	Some determinants to the responsiveness to the IHD included "the heating configuration, presence of electric heating, size of the dwelling, number of residents, appliance holdings, levels of education, number of senior citizens, attitudes toward conservation and seasonality…" (p. 18). See impacts differences based on existence of electric space and water heating above. Key relationships: • Higher education (of occupants >14 years?), higher consumption reduction due to IHD • Lower number of occupants, higher consumption reduction due to IHD • Lower number of appliances, higher consumption reduction due to IHD

Reference	**Dominion Virginia Power, Power Cost Monitor Pilot – May 2008 to July 2009.** Dean C. Mountain, Mountain Economic Consulting and Associates, Inc., January 2010.
Exogenous factors	Weather – accounted for the impact of weather on load for control and treatments The higher the temperature rise on hot summer days, the lower the consumption reduction due to IHD
Persistence?	Electricity savings reported based on a 12-month period. Author also states that "While there is some reduction in conservation as the pilot proceeded, the remaining conservation is statistically significant" but details of effect decay are not provided. Survey analysis: 63.1% self-report plans to continue using the Monitor after pilot

Reference	**Focus On Energy – Powercost Monitor Study: Final Report**. Prepared by Energy Center of Wisconsin. April 16 2010.
Type of Feedback	IHD (PowerCost Monitors by Blue Line Innovations)
Cost to Customer	Free, but offered only to participants who stipulated they were willing to pay $25 for monitor
Installation Method	Installed by customers
Location	Various Locations, Wisconsin
Customer Segment	Residential
Time/Duration	~ May 2008-June 2009, about one year
Sample Size by Treatment Group	Sample size used in main billing analysis: • 149 treatment participants with IHD and tip sheets (those who successfully installed and for which there were clean data only) • 91 control participants (no IHD or tip sheets) Initial sample size: • 287 treatment participants • 166 control participants Participants were omitted from the billing analysis for various reasons, see recruitment method below. Ultimately, the number that received an IHD (regardless of the installation status or whether they'd dropped out of the pilot) was 240 (212 of which there were utility billing data)
Experimental Design (pp. 10-12; 14-15)	Randomly assigned participants to treatment and control groups (see recruitment method below).

Reference	**Focus On Energy – Powercost Monitor Study: Final Report**. Prepared by Energy Center of Wisconsin. April 16 2010.
Recruitment method	Participants were randomly selected from general population using a random-digit-dialing system (listed sample, effect of unlisted and cell phones not mentioned). Recruited using a telephone survey with several layers of screening questions to meet pre-determined characteristics. Participants were screened for housing characteristics (home ownership, single-family home, resided in home for more than a year, not using electricity for primary heat source); whether electric utility was part of study; willingness to pay $25 for PowerCost Monitor (they were not required to pay that much). Also, participants needed to provide written permission to obtain two years of electric billing data from their utility; they also agreed to respond to two surveys throughout the course of the study. Study participants were not offered an IHD or told they might receive one during survey. Total number agreeing to participate from two recruitment periods (735) were then randomly assigned to treatment and control groups based on utility, and release forms were sent out. 453 returned forms: 287 treatment and 166 control (release forms slightly different, not known how the response rate varied between treatment and control group). Treatment reduced from 287 to 149 for various reasons outlined in study. Control group reduced from 166 to 91 for reasons outlined in the study.
Additional information provided to customers?	Three tip sheets provided to treatment groups at three separate dates with energy saving tips Effect of tips not measured explicitly in the pilot (pilot instead measured effect of IHD and tips together)
Control technology?	None
Dynamic rate?	Some appeared to be on TOU (presumably both treatment and control group customers), but effects not measured explicitly.

Reference	**Focus On Energy – Powercost Monitor Study: Final Report**. Prepared by Energy Center of Wisconsin. April 16 2010.
Energy impacts measured	Note: all effects assess median impacts of IHD+tips (not just IHD alone) By sub-test: Test 1: Treatment group that successfully installed IHD vs. control (70% of 212 who were distributed IHDs, or 149 treatment; 91 control). Results: Reduction not significantly different from zero at 90% confidence level; a 38% probability the savings for these treatment homes would exceed the 2% (cost/benefit threshold value). Test 2: Treatment group where IHD was functional and consulted at least occasionally at end of study vs. control (44%, or 55 of presumably the 129 homes that reported successfully install the IHD at the end of the study; 91 control). Results: Reduction not statistically different from zero at 90% confidence level; a 81% probability the savings for these treatment homes would exceed the 2% (cost/benefit threshold value). Test 3: Treatment group where IHD was consulted at least as often at mid-study survey as when it was initially installed vs. control (49, or 41% of presumably the respondents to that question; 91 control). Results: Not statistically different from zero at 90% confidence level; a 83% probability the savings for these treatment homes would exceed the 2% (cost/benefit threshold value). Test 4: Treatment group where IHD was perceived as useful in saving electricity vs. control (70, or 53% of study-end survey respondents with IHDs at end of study and regardless of how often it was consulted after its installation; 91 control). Results: 5.4% reduction, statistically significant at 90% confidence level; a 96% probability the savings for these treatment homes would exceed the 2% (cost/benefit threshold value). Test 5: Treatment group comprised of top three quartiles of pre-treatment power usage vs. top three quartiles of control group (using 107 of 212 treatment and 64 of 95 control customers for which there were data). Results: Reduction not statistically significant at 90% confidence level; a 77% probability the savings for these treatment homes would exceed the 2% (cost/benefit threshold value).
Load Impacts Measured	Not evaluated, household energy consumption measured.

Reference	**Focus On Energy – Powercost Monitor Study: Final Report**. Prepared by Energy Center of Wisconsin. April 16 2010.
Self-reported Conservation Behaviors	Post-test survey questions asked (at mid-point and then after ~one year) what behaviors people changed in general since the same time last year, as well as in response to the feedback. Most prolific savers reported turning IHD consultations into a game (in particular homes with children)
Electricity Prices	Not evaluated
Estimation method (pp. B1-B5)	Non-parametric bootstrap simulation, testing for relative energy savings across several participant groups compared to the control utilizing billing data provided by the utilities.
Price of substitutes?	Not evaluated
Income	Not evaluated
Premise and Customer Circumstances	When customers with annual consumption in the lowest quartile are excluded from analysis, savings becomes 3.4%, and although still not significant, the authors state that the probability that the true medium is at least above the threshold of 2% is 77%. This sub-group represents 75% of the treatment group. It is not know whether comparisons to original control group are appropriate.
Exogenous factors	Not evaluated, weather and other exogenous factors controlled for with control group.
Persistence?	Analysis based on approximately 1 year, long-term performance not evaluated.

Reference	**Evaluation Report: OPOWER SMUD Pilot Year2**. Navigant Consulting, February 2011.
Type of Feedback	Enhanced billing reports (Home Energy Report by OPOWER)
Cost to Customer	Free
Installation Method	NA, monthly and quarterly reports
Location	Sacramento, CA
Customer Class	Residential (single family homes)
Time/Duration	April 2008-August 2010 (29 months evaluation period—reports continue to be provided to customers, the Year 3 evaluation is due in May 2012)
Sample Size by Treatment Group	Numbers used for the analysis (to ensure adequate number of bills before/after treatment periods): • Monthly/high consumer treatment group: 20,200 (also called "high consumption" households because the monthly reports were provided mainly to the higher consumers) • Monthly/high consumer control group: 29,800 • Quarterly/low consumer treatment group: 8,300 (also called "low consumption" households because the quarterly reports were provided mainly to the lower consumers) • Quarterly/low consumer control group: 12,200 Total numbers to which reports were provided: • Monthly/high consumer treatment group: 24,761 (called "high consumer" households because the monthly reports were provided mainly to the higher consumers) • Quarterly/low consumer treatment group: 9,903 (called "low consumer" households because the quarterly reports were provided mainly to the lower consumers)
Experimental Design (pp. 6-8)	Quasi-experimental, due to the non-random nature of the control group selection (see 'recruitment method' description below)

Reference	**Evaluation Report: OPOWER SMUD Pilot Year2**. Navigant Consulting, February 2011.
Recruitment method	Note: some details taken from another study: *The Impact of Home Energy Reports—Final Report*. ADM Associates, September 2009. Opt-out. 85 census tracts were selected that were geo-codable and had a high prevalence of single-family homes Residences screened for: billing cycle type, active SMUD customer, residence but not an apartment building, size between 250-99,998 sq ft, has at least 12 months of pre-test data. This resulted in 84,000 eligible houses. Census block batches (consisting of 5 contiguous census blocks, about 5-200 homes per batch) were then randomly assigned to the treatment and control groups. The batches were randomly assigned, not the individual homes, so therefore not completely random. This was done until 35,000 homes were in each treatment and control group; the remaining 14,000 were then assigned to the control group Also, assignment to monthly and quarterly treatments was not random—monthly report recipients were on average higher electricity consumers.
Other information provided to customers?	Customer usage compared to both a normative and a historic standard, as well as tips to reduce electricity consumption (some of which are customer-specific). All these piece of information are provided together, and as such, the evaluation does not test their individual effects.
Control technology?	No
Dynamic rate?	No

Reference	**Evaluation Report: OPOWER SMUD Pilot Year2**. Navigant Consulting, February 2011.
Energy impacts measured (kWh)	Difference in difference results: For 29-month period (April 2008-Aug 2010): • 2.6% savings for monthly reports/high consumers • 1.5% savings for quarterly reports/low consumers For year 1 (April 2008-March 2009): • 2.4% savings for monthly reports/high consumers • 1.3% savings for quarterly reports/low consumers For year 2 (April 2009-March 2010): 2.9% savings for monthly reports/high consumers 1.7% savings for quarterly reports/low consumers Trend results for monthly reports/high consumers: • Year 2 savings are higher than Year 1 savings (increase is statistically significant) • But also states that long-term trends level off after 12 months, then savings remained fairly constant; long term savings trends of approx. 2.9% annually projected Trend results for quarterly reports/low consumers: • Year 2 savings are higher than Year 1 savings (not mentioned if increase is statistically significant) • Long-term trends suggests savings appear to continue upward Seasonal results: • For both monthly reports/high consumers and quarterly reports/low consumers, savings are highest in months where consumption is highest—summer and winter All results at a 95% confidence level.
Load impacts measured (kW)	Not measured
Self-reports of behaviors changed?	Not in this evaluation, but in others

Reference	**Evaluation Report: OPOWER SMUD Pilot Year2**. Navigant Consulting, February 2011.
Electricity Prices	Not mentioned, assumed flat
Estimation method (pp.8-11)	i) Difference in difference and ii) linear fixed effect regression (seems like equations 3 and 4 on p. 9 are missing a variable)
Income	Not mentioned
Customer Circumstances	Not mentioned
Premise Circumstances	Low versus high consumers; higher users appeared to save more (in percentage terms), although usage level is confounded with quarterly and monthly reports, respectively.
Exogenous factors	Fixed effect model used (controls for weather, etc.).
Persistence?	Yes, evidence that effects persist, and in the case of quarterly report recipients/low consumers, increased over a 29 month period.

Reference	H. Allcott. **"Social Norms and Energy Conservation,"** Journal of Public Economics. Vol. 95, No. 9-10, p. 1082 (2011)
Type of Feedback	Enhanced billing: periodic (monthly, bimonthly, quarterly) reports that compared a customer's consumption to their neighbors (called a normative comparison), as well as energy savings tips (reports provided by OPOWER). This study is a meta-analysis of 14 different experiments using a similar enhanced billing intervention (17 pilots are mentioned, but 3 of them were not designed as experiments with a control group).
Cost to Customer	None
Installation Method	None
Location	Research data set for 14 experiments conducted by 11 utilities in the US (West, Midwest, and Northeast). Individual utilities were not identified, except in one case Connexus Energy (MN)
Customer Class	Residential households
Time/Duration	All site were operational by late 2009 Three pilots had two full years of data
Sample Size by Treatment Group	Ranged from 11,000 to 79,000 residences for treatment(s) and control Treatment groups ranged from: 3,852 to 39,024
Experimental Design	Random assignment of either the entire population of the utility's households (with a few exceptions) or a selected segment to treatment and control in most cases. In three cases, construction of a randomized control was not possible. In some cases, the target population was larger users. The analysis considered all these factors. Pre-treatment consumption of treatment and control group appear to be balanced (in all but three cases) supporting the randomness of assignment.
Recruitment method	Opt-out: customer received the report unless they requested to be un-enrolled. Opt out rates were 0.1 to 3.3%. Attrition rates, where residents moved out during the trial, were 5-20%.

Reference	H. Allcott. **"Social Norms and Energy Conservation,"** Journal of Public Economics. Vol. 95, No. 9-10, p. 1082 (2011)
Other information provided to customers.	Yes, although the report constituted the entire treatment (information effects not teased out). Each report provided an indicative score of the month's usage relative to neighbors (no indication of how neighbors are chosen). Indicative score are: Great: less than 20% of neighborhood comparisons Below average: usage ore than the neighborhood mean Good: between below average and great between In addition, the reports provided tips on how to reduce usage ranging from more efficient equipment to efficient usage suggestions
Control technology?	None.
Dynamic rate?	None reported- study implies that virtually all were on standard uniform energy rates.
Energy impacts measured (kWh)	The base reported impact is Average Treatment Effect (ATE): For the entire experimental set (all controlled utilities): 2.0% For individual utilities (anonymously): 1.37% to 3.32% Monthly and bimonthly delivery: 2.2% Quarterly delivery: 1.7% Seasonal: larger in winter and summer Persistence: higher after two years (from 3 experiments) Larger versus smaller users: treatment effect larger for those with larger load pre-treatment Injunctive effect (motivation by the grade given of great, good, below average): not a substantial influence Cost effectiveness: average cost of reduced kWh, about $.0331/kWh (ranging from ~1-6 cents/kWh)
Load impacts measured (kW)	None reported

Reference	H. Allcott. **"Social Norms and Energy Conservation,"** Journal of Public Economics. Vol. 95, No. 9-10, p. 1082 (2011)
Self-reports of behaviors changed?	One program implemented a survey that asked treatment participants what actions they took (but apparently did not ask controls the same questions). Some reported capital stock changes (weather stripping, AC service) but more frequent were day-to-day behaviors like turnings off lights and lowering the thermostat; actions consumers presumably knew would lower energy use. This provides evidence that the reports "increase the moral cost" of energy use (i.e., act as a reminder to do what one knows is the "right thing"), rather than provide new information.
Electricity Prices	Calculated the equivalent price change that would have been required to achieve the same result, based on assumed SR (-0.10 to -0.18) and LR (-0.39) elasticities (own price). SR effect of HER: 11-20 % short-term price increase LR effect: equal to sustained 5% increased in price
Estimation method	ATE effects for experiments with randomized control (14 of 17) estimated using estimated using differences in difference model with: dummy variable to treatment of control, fixed customer effects, and monthly dummy variables. Experiments are larger than the number of utilities because some utilities implemented in more than one state. Demonstrate the bias associated with non-randomized control by estimating the effect using synthetic controls constructed from bill of customers of other utilities in the state. Estimated ATEs from differences in differences was 3.75%, almost twice the estimate ATE (2%) using randomized controls.
Customer Circumstances	Injunctive effects: examined whether the suggestive scoring mechanism (great, good, below average) have motivational effects (are viewed as injunctions to change) that mitigate a potential boomerang effect. Used a regression discontinuity model to demonstrate that the injunctive effect is less than 20% of the percentage savings (i.e., being classified as one category or another has a relative small effect). The treatment effect therefore likely comes from responses to the descriptive norms or "by aspects of the injunctive norms that affect households in the different categories by similar amounts." (p. 12)

Reference	H. Allcott. **"Social Norms and Energy Conservation,"** Journal of Public Economics. Vol. 95, No. 9-10, p. 1082 (2011)
Premise Circumstances	Pre-treatment consumption effects were examined, and the largest pre-treatment users reduced the most: 6.3% for users whose pre-treatment consumption was in the highest decile; the lowest decile users saved close to zero percent. Suggests that targeting by size may be more cost effective, because larger users may have more way to save easily than smaller ones. Also, examining the quintile treatment effects (QTE), those with lower pre-treatment usage did not use more after the treatments (i.e., the so-called "boomerang effect" where lower users use more in response to the reports was not exhibited).
Persistence?	Three experiments with 2 full years of data all showed higher second year effects. Effects also found to be seasonal – higher in the summer and winter – and to exhibit ramping up over the initial months.

E
GLOSSARY OF SELECTED TERMS AND ACRONYMS

AMI. Advanced Metering Infrastructure

Analysis of variance (ANOVA). Formal statistical protocols that compare differences between the mean values of measured outcomes (e.g., differences in overall energy consumption or peak-period usage) associated with the applications.[19]

CPP (C**ritical Peak Pricing).** An overlay option which typically allows the utility to call a limited number of critical events during pre-specified time periods based on short-term system conditions (called events), high costs, or both, and charge a much higher critical peak price for all usage during the event.[20]

CPR (Critical Peak Rebate). Also called Peak time rebate (PTR). CPR is conceptually very similar to CPP, except that the participant is paid an event credit ($/kWh) for energy reductions measured relative to a customer baseline load.[21]

EoS or E_s. Elasticity of Substitution. Usually refers to the substitution between energy use during high-priced periods and energy use during low priced periods. It is defined as the percentage change in the ratio of electricity usage between time periods that is due to a one percent change in the ratio of those period's electricity prices, all other factors held constant.

Default Service. In competitive retail markets, default service defines the terms and conditions under which a customer will be supplied and billed if they do not buy electricity from another supplier. Default service is almost always provided by the distribution utility.

DR. **Demand Response**. Refers to a change in electricity usage that results from the customer responding to an inducement that overlays a base pricing agreement. That inducement may be the posting of a high price that overrides the base price, the possibility of paying a penalty if load is not reduced, or programs where customers agree to allow certain devices to be externally controlled.[22]

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[19] *The Effect on Electricity Consumption of the Commonwealth Edison Customer Application Program Pilot: Phase 2*. EPRI, Palo Alto, CA: 2011. 1023644, p. 2-5.

[20] A System for Understanding Retail Electric Rate Structures. EPRI, Palo Alto, CA: 2011.1021962, p. 3-6.

[21] *Ibid*., p. 3-6.

[22] *A Proposed Framework for a Demand Response Product Database: Preliminary Results for Selected ISO/RTO and Utility Programs*. EPRI, Palo Alto, CA: 2008. 1016086, p. 2-2.

Feedback. In the context of electricity consumption, feedback refers to information provided to customers about their electricity usage. It includes both indirect feedback (provided after consumption occurs) and direct feedback (provided in real time).[23]
IBR (Inclining Block Rate). A rate structure under which prices are higher as usage increases above a given level.

Opt-in. A form of customer recruitment where customers are offered the opportunity to participate in a program (dynamic pricing program, in the context of this report) and must affirmatively choose to do so.

Opt-out. A form of customer recruitment where customers are assigned to a program (dynamic pricing program, in the context of this report) and must take action in order to be removed from it.

Own-price Elasticity. The percentage change in electricity usage due to a one percent change in the price of electricity, all other factors held constant.

Price Elasticity. See own-price elasticity and elasticity of substitution.

Price Response. Refers to a change in electricity usage that is undertaken by the consumer based on the prices s/he pays under a firm service agreement, which typically involves prices that are known in advance and apply to any quantity the consumer elects to use.[24]

PTR. Peak Time Rebate. See Critical Peak Rebate.

TOU. Time of use. A form of electricity pricing that is differentiated according to when electricity is consumed.

RTP. Real-time Pricing. A form of pricing that varies hourly, either in real-time, hour-ahead or forecast on a day-ahead basis.

[23] *Guidelines for Designing Effective Energy Information Feedback Pilots: Research Protocols, op. cit.*, p. 1-1.

[24] *Ibid*., p. 2-1.

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