Demand Response: The Stick is Mightier than the Carrot

Yingjuan Du, Itron, Inc., San Diego, CA
Priya Sathe, Itron, Inc., San Diego, CA
Dave Hanna, Itron, Inc., San Diego, CA
Jean Shelton, Itron Inc., San Diego, CA

ABSTRACT

We Energies' 2009-2011 demand response portfolio was comprised of two programs designed to reduce peak load, Peak Time Rebates (PTR), and Critical Peak Pricing (CPP). The PTR program is based on a reward or carrot system. PTR participants receive a rebate for energy reduction during event hours. The CPP program is based on a cost or stick system. CPP participants pay a higher price for energy consumption during event hours. This paper presents the unique opportunity to evaluate how these two sets of program participants respond in diametrically opposite ways to similar conditions.

Daily time-of-use data were collected for both PTR and CPP participant households. Similar econometric models were used to evaluate the two programs. The PTR program was found to reduce consumption by 15% during event hours while the CPP program led to a reduction of 18%. The patterns of the savings, however, differ substantially. For PTR participants, the program impact decreased on consecutive event days, as the summer progressed, and when the temperature was really hot. For CPP participants, the impact increased on consecutive event days, as the summer progressed, and did not vary with weather conditions. This pattern of results is of interest to policy maker and program planners designing programs to provide energy savings during hot, later summer events. The findings are also consistent with the belief that PTR participants may tire of the carrots (rebates) while the CPP participants, stimulated by the stick (high prices), learn to respond more effectively through participating in the events.

Introduction

Increasing capacity constraints during hot summer periods are leading to an increase in the number of utilities offering residential demand response programs. Before utilities can rely on the energy savings from these programs they need to know how program design may influence program impacts. There are two main types of demand response programs. Programs can be reward based, providing incentives to the participants who reduce energy usage; alternatively programs can be cost based, punishing participants for using too much energy during events. These two types of programs can lead to very different participants' behaviors.

We Energies' 2009-2011 demand response portfolio was comprised of two programs designed to reduce peak load, Peak Time Rebates (PTR), and Critical Peak Pricing (CPP). The PTR program is based on a reward or carrot system. PTR program participants receive a rebate for energy reduction during event hours. The CPP program is based on a cost or stick system. CPP program participants pay a higher price for energy consumption during event hours. The main goal of the evaluation was to estimate the impact of these two demand response programs. This paper presents the unique opportunity to evaluate how these two sets of program participants respond in diametrically different ways to similar conditions.

The rest of the paper is organized as following. The next section introduces the WE Energy PTR and CPP programs in details; the third section presents the estimated impacts from the PTR and CPP programs; the fourth section compares the impacts of PTR and CPP programs; and the fifth section concludes the paper.

PTR and CPP Programs

We Energies' 2009-2011 demand response portfolio was comprised of two programs designed to reduce peak load, PTR and CPP.

PTR is a no-risk program that allows the customer to keep the same rate they have when they enroll into the program, but gives them the opportunity to obtain a rebate for each kilowatt-hour reduction that they make in their energy consumption at designated times (referred to as events) during the summer. This program is only offered to residential customers in areas within We Energies' service territory where the billing metering technology has the capacity for collecting interval load data.

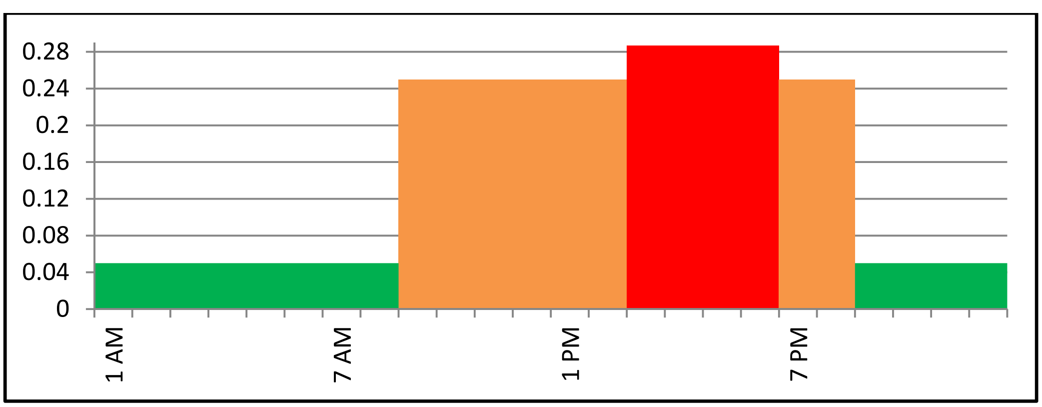
The customers in this program are on a flat rate, at $0.12611 per kWh. For settlement and evaluation purposes only, we will talk about there being three time-of-use (TOU) periods: on-peak, off-peak, and mid-peak. On-peak hours are the hours when energy demand for the system is high, from 2 p.m. to 6 p.m. weekdays. Off-peak hours are the hours when energy demand for the system is low, 8 p.m. to 8 a.m. on weekdays, and all day on weekends and selected holidays. The remaining hours are mid-peak hours, 8 a.m. to 2 p.m. and 6 p.m. to 8 p.m. on weekdays. Only on event days during on-peak hours, does a peak period price come into play. For each kWh saved during the event hours, the participants receive $0.47/kWh rebates.

The Critical Peak Pricing (CPP) pilot is a pricing event based program, and does not require any enabling technologies. The CPP pilot can help enrolling participants reduce their electricity bill if they can either reduce or shift their electricity consumption during periods of high electricity demand on hot summer afternoons in June through September. This optional program leverages We Energies' existing approved three-part TOU rate tariff by adding a fourth "critical peak" period for customers who so elect.

The critical peak period is called during on-peak hours, and may be called by We Energies when system conditions are anticipated to reach a trigger point. During the non-event days, the TOU rates are $0.05/kWh for the off-peak periods, $0.25/kWh for the mid-peak periods, and $0.287/kWh for the on-peak periods. Please refer to Figure 1 for the summer non-event day TOU rates. When an event is called, the peak period rate increases from $0.287/kWh to $0.88/kWh.

The decision to call a PTR and/or CPP event is typically made the day prior to the event. Customers are notified by some combination of e-mail, automated phone dialer, media announcements, and website icon. The program targets all residential single family and multifamily homes that pay for electric service.

Figure 1. Summer Time Non-Event Day TOU Rates



Impact Estimation

Data

During the summer of 2010, We Energies' called 17 PTR events and 14 CPP events. Daily TOU data for 804 premises were gathered to estimate the impact of the PTR program and 235 premises for CPP program. For the PTR program, data were retained in the analysis only for those premises that have valid data for at least 15 out of 17 events, and 500 qualified premises entered the analysis. As for CPP program, data were retained for the premises that have valid data for at least 12 out of 14 events, and 111 premises were qualified. Table 1 gives a summary of the number of sites censored for various reasons.

Table 1. Data Censoring

Data Issue	# of Premises Left for PTR	# of Premises Left for CPP
Number of original sites	804	235
On-peak, off-peak or mid-peak data not available	791	234
Sum of the three TOU usages does not match the daily usage[1]	789	214
Usages too low	782	213
Participated in too few events	500	111

The evaluation team was not able to confirm whether a customer received an event notification or the actual time that the event notification was sent to program participants; thus, it was assumed that all customers were notified regarding the event. All participant usage data from May 1, 2010 through September 10, 2010 were retained in the analysis. Data for weekends and legal holidays were eliminated from the analysis.

Methodology

For each participant, *i*, the following regression model was estimated. Each participant's model was tested for autoregressive errors, AR(1), and the AR(1) error was corrected if the error terms were found to be correlated at 5% significance level.

$$\begin{aligned} touavg = {} & \beta_0 + \beta_1 \times touavg_{MidPeak} + \beta_2 \times touavg_{OffPeak} + \beta_3 \times event \\ & + \beta_4 \times touavg_{MidPeak} \times event + \beta_5 \times touavg_{OffPeak} \times event \\ & + \beta_6 \times CDD_{70} + \beta_7 \times CDD_{84} + \beta_8 \times HDD_{60} + \beta_9 \times CTHI \\ & + \beta_{10} \times CDD_{70} \times event + \beta_{11} \times CDD_{84} \times event + \beta_{12} \times CTHI \times event \\ & + \beta_{13} \times Third + \sum_{d=1}^{4} \beta_{14}^{d} \times day_d + \sum_{m=5}^{8} \beta_{15}^{m} \times month_m \end{aligned}$$

---

[1] The usage data is available through September 15, 2010, the CTHI data is available through September 10, 2010, and the weather data is available through the end of the year.

Where:

$touavg$ is the on-peak average hourly usage for a participant,

$touavg_{MidPeak}$ is the mid-peak average hourly usage for a participant,

$touavg_{OffPeak}$ is the off-peak average hourly usage for a participant,

$event$ is a dummy variable that equals to 1 when there is an event, and 0 otherwise,

$CTHI$ is the composite temperature humidity index,

$Third$ is a dummy variable that equals to 1 when it is the third or fourth consecutive event day, and 0 otherwise.

$day_d, d = 1, \ldots, 4$ are dummy variables for Monday, Tuesday, Wednesday, and Thursday. Friday was taken out to avoid perfect multicollinearity, and

$month_m, m = 5, \ldots, 8$ are dummy variables for May, June, July, and August. September was taken out to avoid perfect multicollinearity.

For each participant: (1) the predicted usages for the event hours, as if the event was not called, were calculated using the regressions results, which is called the econometric baseline; and (2) the actual usages for the event hours obtained from the original data were also obtained from the original data. Impacts were calculated for each participant as the difference between the econometric baseline estimates and the actual usages for the events.

Goodness-of-Fit of the Econometric Model

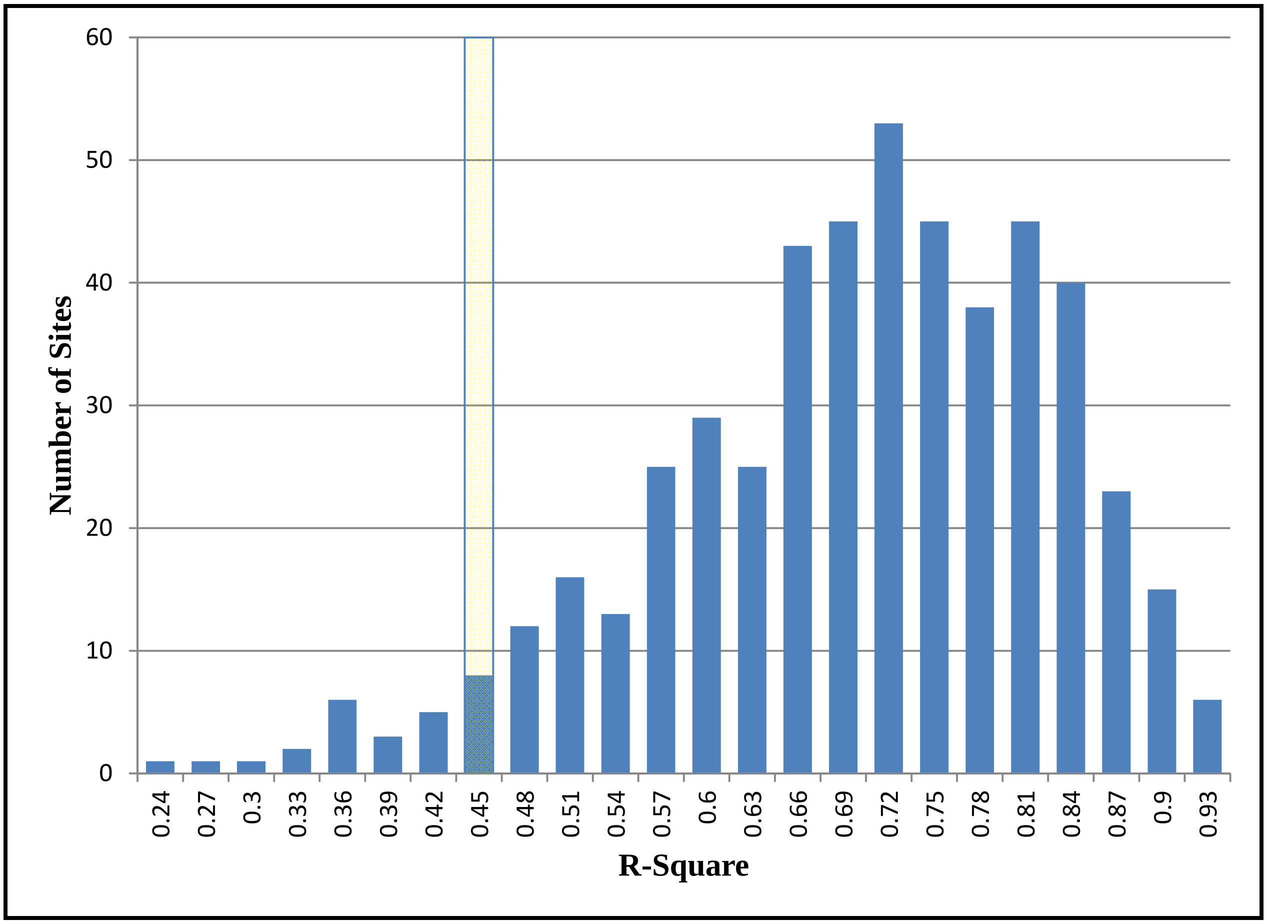
The analysis was done at the site or participant level; therefore, each site has its own set of estimations and predictions. Across the five hundred regressions analyzed for the PTR program, the average r-square is 0.69. On average, 69% of the variance of the on-peak hourly kWh usage was explained by the models. Figure 2 plots the distribution of the r-squares associated with the PTR analyses. From the figure, it can be seen that the lowest r-square is 0.23 and the distribution is skewed to the right with a long tail on the left. For those sites with low r-squares, the model could explain only a small part of the variance of the on-peak usage, and the prediction from the model might be poor. Therefore, when constructing the econometric baselines and calculating the impacts, the sites with r-squares lower than 5 percentile of the r-squares[2] were excluded to ensure the prediction quality.[3] By excluding these sites, the results do not change substantially. The results for the whole sample are available in the appendices. After excluding the sites with low r-squares, the average r-square became 0.71, and the standard deviation of the r-square was 0.11.

---

2 The 5 percentile of r-squares is 0.4518, as shown in Figure 2 as the light yellow bar.

3 Twenty five participants were excluded to ensure the quality of the prediction. However, this would not affect the results very much. For example, by including these 25 participants, the overall average load impact would be 15.3%, while by excluding these 25 participants, the number would be 14.9%.

Figure 2: PTR - Histogram of the R-Squares

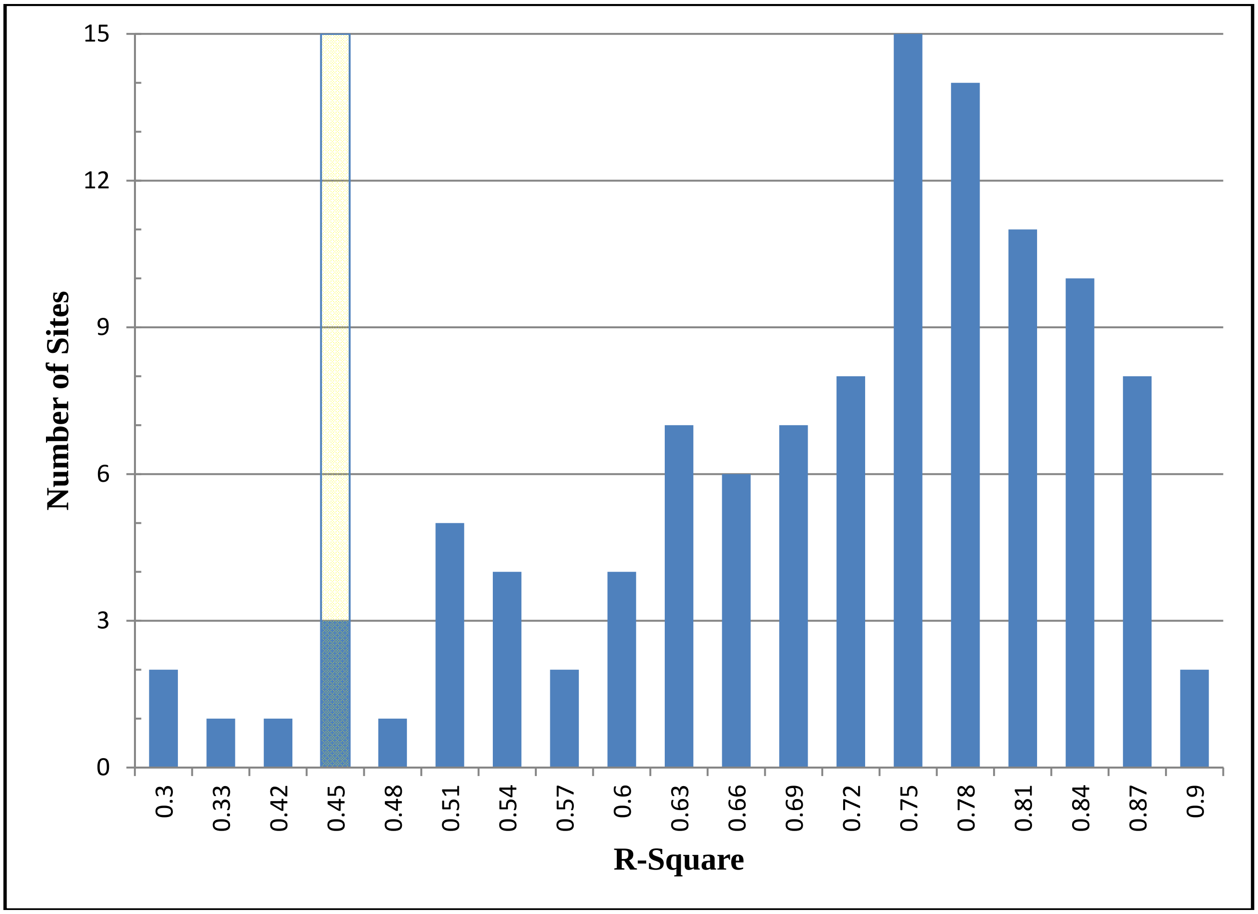


Similarly, Figure 3, below, plots the distribution of the r-squares for the 111 CPP regression models. The average r-square is 0.71, the lowest r-square is 0.29, and the distribution is skewed to the right with a long tail on the left. When constructing the econometric baselines and calculating the impacts for the CPP program, the sites with r-squares in the lowest 5 percentile[4] were excluded to ensure the prediction quality. By excluding these sites, the impact results did not change substantially. The results for the whole sample are available in the appendices. After excluding the sites with low r-squares, the average r-square increased to 0.73, and the standard deviation of the r-square was 0.11.

---

4 The 5 percentile of r-squares is 0.4499, as shown in Figure 3 as the light yellow bar.

Figure 3: CPP – Histogram of the R-Squares



Percentage Impact and Price Elasticity

Table 2 presents the difference between the econometric baseline and the actual demand on event days for the PTR program. The average percent impacts are the hourly kWh savings as a percentage of the baseline usages. As shown in the table, these impacts are all positive, ranging from 8% for the event on August 10, 2010 to 25% for the event on June 18, 2010, suggesting that during the event hours, the participants saved 8% to 25% of the kWh usages they would have consumed were there no event. Overall, the percentage impact is 15%. The average econometric baseline usage is 3.2 kWh per hour. Therefore, the estimated hourly saving from each participant is 3.2×15% = 0.48 kWh/hour. By applying this number to all 804 participants and all 17 events, it can be calculated that the overall saving is 0.48×804×17×4 = 26,243 kWh.

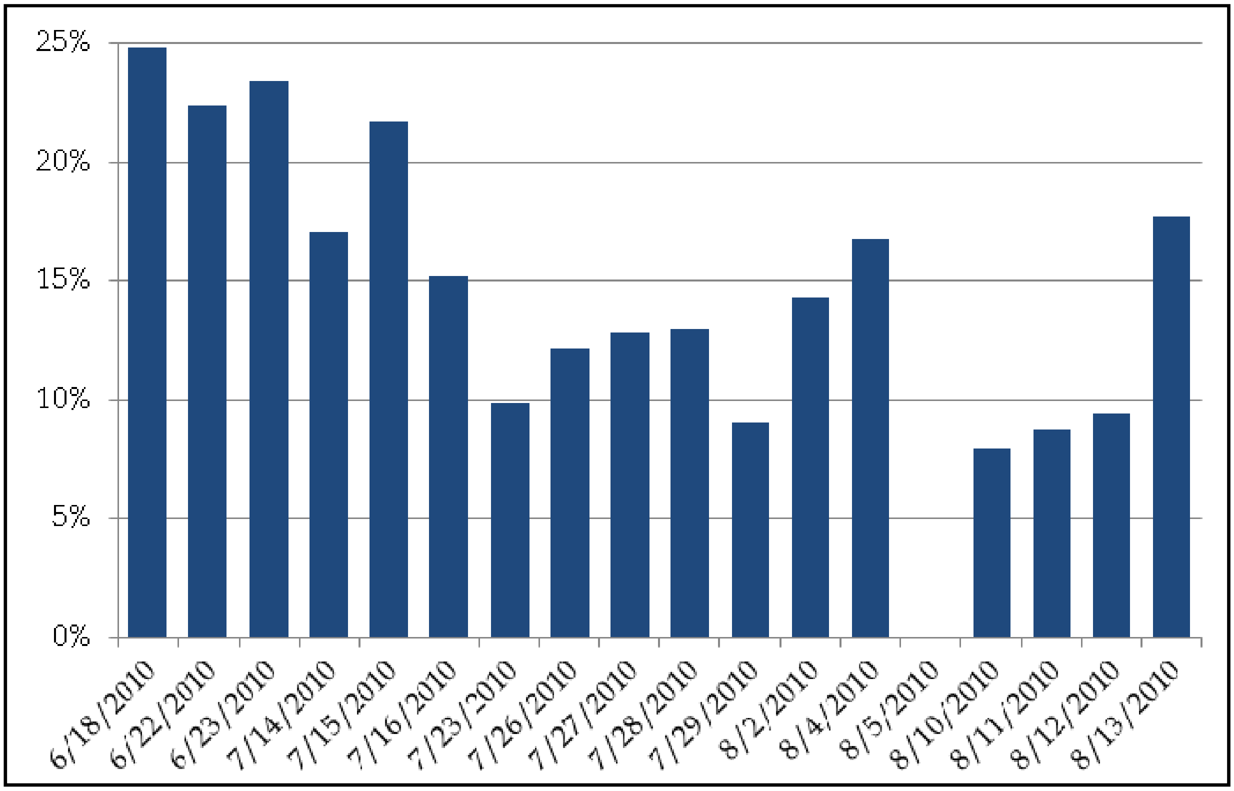
Table 2: PTR - Difference between Econometric Baseline and the Actual Demand for Event Hours

Event Date	# of Sites	High Temperature	Realized Demand	Econometric Baseline Demand	Average Hourly Impact	% Impact
6/18/2010	459	89	2.132	2.836	0.704	25%
6/22/2010	430	87	2.302	2.967	0.664	22%
6/23/2010	464	87	2.338	3.053	0.714	23%
7/14/2010	466	84	2.672	3.220	0.548	17%
7/15/2010	465	85	2.609	3.333	0.724	22%
7/16/2010	473	90	2.795	3.295	0.499	15%
7/23/2010	440	88	2.811	3.119	0.307	10%
7/26/2010	473	80	2.449	2.789	0.339	12%
7/27/2010	474	86	2.928	3.360	0.431	13%
7/28/2010	475	85	2.889	3.319	0.430	13%
7/29/2010	472	79	2.419	2.660	0.241	9%
8/2/2010	474	82	2.723	3.177	0.454	14%
8/4/2010	465	84	2.576	3.095	0.520	17%
8/10/2010	459	84	3.039	3.300	0.261	8%
8/11/2010	463	90	3.134	3.434	0.299	9%
8/12/2010	472	88	3.280	3.622	0.342	9%
8/13/2010	466	83	2.939	3.571	0.632	18%
Average		85	2.710	3.186	0.476	15%

* Price elasticity is defined as the percentage change in demand over the percentage change in price.

Table 2, above, shows some interesting patterns of the impacts. Please refer to Figure 4 for a better view. First, the percentage impacts are high in June and low in July and August. The average percentage impact is 23.5% in June, 13.8% in July, and 12.5% in August, displaying a clear downward trend as time went by.

Figure 4: PTR Percentage Impact



Secondly, even though temperature has been incorporated when constructing the econometrics baseline, the percentage impacts are still lower when temperature is higher. For example, on August 11th, the high temperature was 90oF, and the average percentage impact was 9%.

Finally, the percentage impact is smaller for third and fourth consecutive event days. For example, We Energy called PTR events on July 14 through July 16, hence July 16 is the third consecutive event day and the percentage impact drops from 17% and 22% of the two previous events to 15%. Also, July 29 is the fourth consecutive event day; the percentage impact dropped from about 13% to 9%.

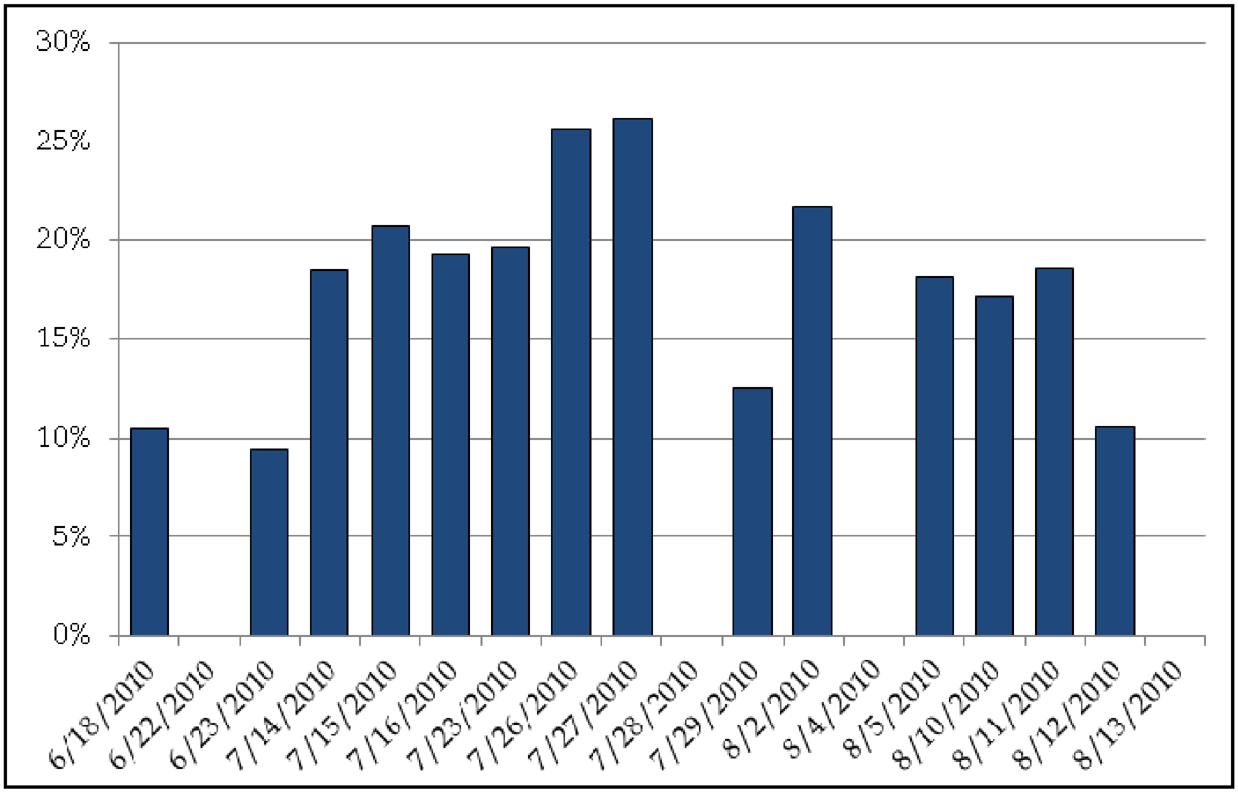
Table 3 presents the difference between the econometric baseline and the actual demand on event days for CPP program. The percent impacts are the hourly kWh savings as a percentage of the baseline usages. As shown in the table, the average percentage impacts are all positive, ranging from 9% for the event on June 23, 2010 to 26% for the event on June 26, 2010. During the event hours, the participants saved 9% to 26% of the kWh usages they would have consumed were there not the event. For the CPP program, the estimated average percentage impact is 18%. The average econometric baseline usage is 2.7 kWh per hour. Therefore, the estimated hourly saving from each participant is 2.7×18% = 0.486 kWh/hour. Applying this number to all 235 participants and all 14 events, it can be calculated that the program saving is 0.486×235×14×4 = 6,396 kWh.

Table 3: CPP - Difference between Econometric Baseline and the Actual Demand for Event Hours

Event Date	# of Sites	On-Peak High Temperature	Average Hourly On-Peak Event Day Demand (kWh/hour)	Econometric Baseline Average Hourly Demand (kWh/hour)	Estimated Average Hourly Impact (kWh/hour)	% Impact
6/18/2010	70	89	1.975	2.207	0.232	11%
6/23/2010	78	87	2.426	2.680	0.254	9%
7/14/2010	109	84	2.087	2.563	0.476	19%
7/15/2010	109	85	2.062	2.600	0.538	21%
7/16/2010	111	90	2.338	2.898	0.560	19%
7/23/2010	105	88	2.252	2.805	0.553	20%
7/26/2010	111	80	1.883	2.532	0.649	26%
7/27/2010	111	86	2.142	2.903	0.761	26%
7/29/2010	110	79	1.993	2.279	0.286	13%
8/2/2010	111	82	1.968	2.517	0.549	22%
8/5/2010	111	81	1.815	2.216	0.401	18%
8/10/2010	110	84	2.150	2.596	0.446	17%
8/11/2010	110	90	2.243	2.757	0.514	19%
8/12/2010	111	88	2.297	2.569	0.272	11%
Average		85	2.113	2.588	0.474	18%

Figure 5 graphs the percentage impact for CPP events. Unlike what has been found in PTR results, for CPP events the percentage impacts are low in June, and high in July and August. The average percentage impacts are 10%, 20%, and 17% for June, July, and August, respectively. Also, for the CPP program, there is no clear relationship between temperature and the percentage impacts, nor is there any effect from consecutive events.

Figure 5: CPP Percentage Impacts



Section IV. Comparison between PTR and CPP

A regression model was estimated, to examine which factors affect the impacts. The model is as following.

$$
\begin{aligned}
Impact = {} & \beta_0 + \beta_1 \times Second + \beta_2 \times Third + \beta_3 \times CTHI + \beta_4 \times CDD_{70} + \beta_5 \times CDD_{84} \\
& + \sum Day\ Dummy + \sum Month\ Dummy + \sum Site\ Dummy
\end{aligned}
$$

Where:

$Impact$ is the difference between the econometric baseline usage and the actual usage,

$Second$ is a dummy variable that equals to 1 if it was the second consecutive event, and 0 otherwise, and

$Third$ is a dummy variable that equals to 1 if it was the third/fourth consecutive event, and 0 otherwise.

Table 4, below, presents the regression results for PTR and CPP.[5] In the first part of Table 4, it can be seen that while the dummy *Second* is not significant, the dummy *Third* is negative and statistically significant at the 5% level, showing that the impact of the PTR program is smaller when it was the third or fourth consecutive event. This result is consistent with participants tiring of the program when it is called consecutively on repeated hot days.

---

5 Note that the estimation of site dummies are omitted to save spaces.

The second observation from Table 4 is that CTHI is positive and statistically significant at the 1% level, showing that when the weather is hotter or more humid, the impact from the PTR program is larger. The hotter, humid weather increases the econometric estimate of baseline usage, and since the impact is defined as the difference between baseline usage and the actual usage, the positive effect of CTHI on the impact implies the baseline usage went up more than actual usage during an event during hotter, humid days. This result, however, should be viewed together with the estimation for CDD_84. The coefficient of CDD_84 is negative and statistically significant at the 1% level. When the weather became really hot, the impact from the PTR program decreased. Combine the effects from CTHI and CDD_84, as temperature increases, the estimated impact increases and then as temperature meets and exceeds 84 degrees, the impact increases more slowly.[6]

The third observation is that both dummy variables *Month7* and *Month8* are negative and significant at 1% significance level, showing that the impact from the PTR program decreased in these months. With all other things constant, the impact for July is lower than the impact for June by 0.15 kWh, and the impact for August is lower than the impact for July by 0.12 kWh.[7]

Table 4: Influential Factors Affecting Program Impacts

Variable	PTR			CPP		
	Parameter Estimate	Standard Error	t Value	Parameter Estimate	Standard Error	t Value
Second	-0.040	0.043	-0.94	0.326	0.153	2.13
Third	-0.089	0.042	-2.14	0.182	0.218	0.83
CTHI	0.047	0.016	2.88	0.053	0.044	1.22
CDD_70	0.009	0.014	0.69	-0.027	0.028	-0.95
CDD_84	-0.072	0.024	-3.02	-0.069	0.068	-1.01
June	-0.151	0.036	-4.24	0.196	0.113	1.73
August	-0.272	0.063	-4.31	0.327	0.175	1.87
Day2	-0.001	0.052	-0.01	0.010	0.109	0.09
Day3	0.026	0.051	0.51	-0.046	0.187	-0.25
Day4	0.037	0.054	0.70	-0.102	0.089	-1.14
Day5	-0.019	0.062	-0.31	0.101	0.187	0.54
# Observations	8,302			1,399		
R-Square	0.454			0.395		

From the second part of Table 4, it can be seen that in the CPP model only three variables are statistically significant using a 10% level, including *Second*, *Month7*, and *Month8*. None of the weather relative variables (CTHI, CDD_70, or CDD_84) and none of the day dummies are significant, indicating that the CPP participants respond to the event calls relatively consistently across different weather conditions and day of week. This may be because there is a penalty for not responding to a CPP event in the form of a higher electricity bill. Given the structure of the program, CPP participants may have been more serious about saving, and for all events, they tried their best to save energy regardless of the weather.

6 When regressing CTHI on CDD_84, the result shows that CTHI = 10.5+0.63*CDD_84.

7 When using *Month6* and *Month8* dummies in the regression, the *Month8* dummy is significant at 5% significance level, showing that the difference between July and August is significantly different from zero.

The estimated coefficient on the dummy variable *Second*[8] within the CPP program is positive and significant at a 5% significance level, showing that the impact from the event was higher if it was the second consecutive event called. The dummy variable, *Third*,[9] on the other hand, is positive but not significant. The positive signs indicate that the participants might have learned from the previous event day to respond to the event calls effectively. The low t-test for *Third* might be because only two events were in this category. Note the sign of the estimated effect of a second and third consecutive event in the CPP program is the opposite of the effect of consecutive events in the PTR program. In the PTR program, consecutive events led to a lower impact while in the CPP program consecutive events are associated with a larger impact.

The dummy variable *Month7* and *Month8* are both positive and significant at 10% significance level, showing that CPP program participants responded to the event calls more effectively as time went by. This result is also consistent with the hypothesis that the CPP participants are learning how to respond from the previous event calls. Again, the effect of the month variables in the CPP model differs from the effect of July and August in the PTR model. CPP participants appear to learn from participating and have larger impacts later in the program while PTR participant impacts' appear to decline later in the program.

The regression results in Table 4 and **Error! Reference source not found.Error! Reference source not found.Error! Reference source not found.**Table 5 confirm the observation in Section III that (1) as time goes by, PTR percentage impacts decrease while CPP impacts increase; (2) when temperature is high, the PTR percentage impacts decrease while the CPP impacts remain constant; and (3) PTR percentage impacts decrease for the third and fourth consecutive events while CPP impacts increase. The difference may be because (1) the participants of the two programs are different and (2) the design and/or operation of the two programs are different.

For the participants, PTR participants were on flat rate, and CPP participants were on TOU rate. Although flat rate customers can participate in the CPP program by joining the TOU rate first, they had no previous experience being on TOU rates. It is very likely that the CPP participants self-selected to participate in this more risky program because they were more experienced, and were confident of the ability to save energy during events.

The designs of the two programs are different. The PTR participants were stimulated by the rewards. As time went by, they may have tired of the rewards, and the program impacts decreased. Also, when the temperature became really high and when consecutive events were called, the marginal comfort benefit from using air conditioners may have increased, leading to the decrease of the program impacts. On the other hand, the CPP participants were stimulated by the high cost of the electricity during event hours. As time went by, they learned to respond to the event calls more effectively, and hence increased the program impacts. The CPP program impacts were also higher for the second consecutive events, further supporting the learning hypothesis.

The operations of the two programs are different. It is much easier to calculate the bills for the CPP participants, yet not as easy to calculate the rewards for the PTR participants. Therefore, the CPP participants had better feedback from the program, which in turn helped them to learn to respond to the event calls. For the PTR participants, on the other hand, it took We Energy longer to gather information, to build a model to construct the baseline usages, and to calculate the rewards. Therefore, the PTR participants did not have feedback as updated as CPP participants did, and were not be able to learn to respond to the event calls as effectively.

---

[8] There are three event days for which the dummy variable *Second* equals one: July 15, July 27, and August 11.

[9] There are two event days for which *Third* equals to one, including July 16 and August 12.

Conclusions and Further Study

Table 5: Comparison between PTR and CPP

		PTR	CPP
Program Design			
	No Event Energy Price	Flat Rate at $0.126	TOU Rate at $0.05, $0.25 and $0.287
	Incentives/Costs	$0.47 per kWh Saved	On-Peak Rate Increased by $0.593
Data Used			
	# Sites Used in the Study	500	111
	# Events Called	17	14
Program Impact			
	Program Impact	15%	18%
Factors That Affect the Program Impacts			
	Consecutive Events	Impact Decreased	Impact Increased
	As time went by	Impact Decreased	Impact Increased
	As temperature increased	Impact Decreased	No significant effects

Table 5 compares between PTR and CPP programs. The average hourly on-peak load impact per participant was nearly the same for the We Energy PTR and CPP programs. Participants in both programs also showed little evidence of load shifting to mid or off peak periods. The most significant difference between the two programs has been the number of customers enrolling in the programs. The PTR program has been more successful in attracting participants than the CPP program. This may be more a function of the different populations that have been targeted by each.

However, the study found that the participants of the two programs behaved very differently when events were called. The PTR participants did not save as much energy as time went by, when the weather was too bad, and in consecutive events. Conversely, the CPP participants saved more energy as time went by and in consecutive events, and weather had very little effect on CPP participants' behavior.

The difference is very likely to be caused by the different design of the two programs. PTR provides rewards for participants who reduce their energy usages. As the participants receive more rewards, the marginal utility decreases and the marginal dis-utility of not using air conditioners increases dramatically, especially when weather conditions are bad and/or consecutive events are called. Further, the design of PTR program makes it more difficult to calculate rewards and to provide feedback to the participants, which discounts participants' utilities even further. Therefore, as time goes by with no sufficient feedback from the program, some participants might choose to respond to the events less. The CPP program, on the other hand, punishes participants for using too much energy. The program clearly specifies the energy cost; thus, the participants were able to compare the cost to their marginal utilities and responded to the events more rationally. The design of CPP program makes it much easier to give participants timely feedback and, as a result, after the first month of program as the participants received their June bills, the program impacts increased greatly.

Overall, the study found that demand response programs with higher energy costs like CPP stimulate participants to reduce energy more effectively when weather conditions worsen and when too many events have been called. However, this kind of program is not as successful in attracting participants. The best results can be achieved by providing both kinds of programs and carefully designing the incentive and cost structures.