Residential Customers Response to Critical Peak Events of Electricity: Green Mountain Power Experience

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ABSTRACT

The paper analyzes the impact of Vermont's Green Mountain Power's (GMP) emergency Demand Response (DR) programs on residential customers' electricity consumption during a two-year pilot study program in 2012–2013. We examined potential peak load reductions, monthly electricity consumption, and persistence of responses with the help of difference-in-difference approaches. We created a panel dataset combining hourly electricity load, critical peak event information, and weather variables. The final sample of 2,107 single-home residents in the Central Vermont area were separated into four treatment groups and a control group resulting in 23 million hourly load observations during the period of the study.

Our analysis shows that incentive-based demand response programs have statistically significant impacts on reducing peak load. Specifically, Critical Peak Rebate (CPR) rates reduced peak load usage 6% to 7.7% and Critical Peak Pricing (CPP) rates reduced peak load between 6.8% and 10.3% during critical peak events. Moreover, on average, In-Home Display (IHD)-equipped participants' monthly energy consumption was 2.0% to 5.3% lower than the monthly energy usage of non-IHD customers. However, none of the pricing rate and IHD treatments induced a persistent response across multiple critical events and none of the treatment groups exhibited a consistent response to critical peak events. Based on our evaluation of GMP's DR programs during 2012 and 2013, neither critical peak pricing nor rebates are themselves sufficient to substitute for new capacity to meet resource adequacy requirements.

1. Introduction

The limited and costly electricity storage system makes meeting dynamic electricity demand, especially during peak periods, challenging and economically inefficient. A large amount of generating capacity has to be kept in reserve to supply electricity during high demand periods. At the same time, transmission and distribution systems need to be able to accommodate peak electricity demands, resulting in high reliability costs. Demand response programs, usually through peak pricing and incentive-based approaches, can reduce peak electricity demand by encouraging customers shift their consumption. A Federal Electric Regulatory Commission (FERC) report estimates that DR programs were responsible for potential peak load reductions of 66,351 MW in 2012, a 25% increase from 2010 (FERC, 2012). Besides increasing electric grid reliability, DR programs also benefit utility companies by minimizing the need to build new infrastructure, thereby saving huge capital costs. This paper analyzes the impact of emergency DR programs on the electricity consumption behaviors of residential customers of Rutland, VT during a two-year pilot study in 2012-2013.

Relevant literatures have examined the impact of different types of DR programs in residential customers' electricity usage. With the start of electricity restructuring and advancements in technology, various electric entities have explored the option of implementing

DR programs in their territory. Albadi and El-Saadany (2008), Cappers et al. (2010), Faruqui et al. (2010), and Lave, Lester, and Spees (2007) provided overviews on the scope of demand response programs and also provide empirical evidence of demand response programs in the US electricity market. Herter et al. (2007), utilizing a subset of data from the California Statewide Pricing Pilot of 2003-04, looked at the impact of critical peak pricing on residential customers' behavior in hourly electric consumption. Similarly, Herter and Wayland (2010) found that residential customers, on average, reduce 5.1% of the load due to high electricity prices during the scheduled critical events. A few studies have also looked at the impact of smart meters in electricity consumption. Houde et al. (2013) found that a continuous feedback system initially helps to reduce energy consumption by 5.7 %; however the impact fades away few weeks after the installation.

This paper's primary interest is to predict the impact of different treatment rates and information systems on real-time electricity usage. We created a panel dataset combining hourly electricity load, critical peak event information, and weather variables. We used a difference-in-difference regression approach starting with randomized control treatment (RCT) analysis followed by randomized encouragement design (RED). The paper also conducts persistence analysis to analyze customers' responses within different time periods of the critical peak event, specifically within critical peak event hours and event-to-event analysis. Furthermore, the paper also estimates the impact of real time electricity feedback system on energy consumption.

Our study provides a detailed analysis spanning over two years combined with customer-specific characteristics information. Most of the emergency demand response pilot studies are conducted in regions with a hotter climate; this study provides an insight to electricity usage patterns for customers that face a relatively mild summer. The study is also carefully designed to control for heterogeneity in electricity consumption that may arise due to participants living in different residence types and climate zones.

The rest of the paper follows with a brief background on GMP's pilot study program, its timeline, and rate structures in Section 2. The econometric methods for analysis are discussed briefly in Section 3. Section 4 contains summary statistics, results, and analysis of the pilot study. Section 5 concludes the paper.

2. GMP Pilot Study

Green Mountain Power launched critical peak events during the summers of 2012 and 2013 with the help of two time-based emergency DR programs – critical peak pricing (CPP) and critical peak rebate (CPR) – coupled with the deployment of in-home display (IHD) equipment. Critical peak pricing treatment charges a very high pre-determined electricity price during the critical event period, whereas CPR provides incentives to participants for reducing consumption below their baseline. In-home display technology allows a two-way communication between customers and the electricity grid, showing information on real-time electricity consumption and critical peak events. Customers equipped with the IHD technology can look at their real-time electricity usage and can adjust their consumption pattern.

The Green Mountain Power consumer behavior study consists of 3,735 residential customers selected from randomized sampling of 12,867 customers in the Rutland, VT area. The study dropped two customer groups that were placed in the flat pricing rate during the period of the study. The study employed a randomized control method featuring four treatment groups and a control group. It took a two-step approach to select the eligible customers for randomization. In the first screening phase, GMP made sure that the potential DR participants were in the Rutland area, lived in single-family home, had consistent monthly usage of 50 kWh – 10,000 kWh, and would receive smart meters by summer 2012.

In the second stage, GMP, with the help of Metrix Matrix, contacted selected customers via phone and mail to direct them to a website where they could fill out the eligibility survey. After the completion of the survey, GMP randomly assigned customers to treatment groups and revealed them to customers that it deemed eligible. Metrix Matrix reported that 367 customers declined to participate in the DR study after the treatment rate was revealed to them. The Figure 1 contains the timeline of the study. Similarly, Figure 2 includes a brief description of different treatment groups.

Fall 2011:	Customer recruitment and smart meter installation begins
March 2012:	Smart meter installation completed; CPR customers placed on new rate
August 2012:	CPP customers placed on new rate; IHDs mailed to CPP and CPR customers
2012 Events:	September 14, September 21, September 25, and October 5
Dec 2012:	Survey of participating customers completed
2013 Events:	July 5, July 15, July 16, July 17, July 18, July 19, August 13, August 21, August 22, and August 28

Figure 1: Timeline of the Green Mountain Power's Study

Critical Peak Pricing (CPP): A standard flat-rate tariff of $0.60/kWh during declared critical peak events. For revenue neutrality, customers on the CPP rate pay $0.144/kWh during non-event hours which slightly lower than the flat-rate customers.
CPP with IHD: Same standard flat-rate as CPP customers, but are provided with the IHD device that gives near-real-time feedback on household energy usage and also receives critical peak time notifications from GMP.
Critical Peak Rebate (CPR): An incentive of $0.60/kWh for reducing energy consumption from their baseline during the declared critical peak events. Reduction of energy usage during the peak event is voluntary.
CPR with IHD: Similar rate structure as of CPR group but with the IHD device.
CPR to CPP: Customers are placed in CPR rate structure in the first year and are moved to CPP treatment in the second year. However, the customers are unaware of the second year rate during the time of enrollment or during the first year of the study. We grouped these customers with CPR in first year and CPP in the second year.
CPR to CPP with IHD: Similar rate structure with CPR to CPP group, but customers are given IHD. We placed these customers with CPR-IHD in the first year and in the CPP-IHD in the second year.
Control Groups: Regular rate with no notification of critical peak events.

Figure 2: Rate structures of GMP Pilot Study

3. Theory

3.1 Peak Load Change Analysis

We used difference-in-difference regression approach using two separate models. We started with Randomized Control Treatment (RCT) analysis followed by Randomized Encouragement Design (RED). Although GMP structured the DR study to be randomized, there were customers that declined to participate when approached during the recruitment process and a few other customers dropped out[1] during the period of the pilot study. The paper uses randomized encouragement design (RED) analysis to take into account the participants that declined to participate or dropped out during the study. Besides RED, we also used the local average effect (LATE) method to account for customers who declined to participate or dropped out of the program. In this method, we divided the estimates of RCT analysis by the difference in the fraction of customers who took up the rate between the encouraged group and the non-encouraged group.

RCT Analysis. In a randomized control treatment study, eligible groups of customers are randomly assigned to various treatment and control groups. The difference-in-difference regression model for RCT analysis is presented in equation (1).

$$(1) \quad y_{it} = \beta_i + \beta_1 Temp_t + \beta_2 \sum_j DT_{ji} + \beta_3^{DB} DB_t + \beta_3^{DE} DE_t + \beta_3^{DA} DA_t + \sum_j \beta_{4j}^{DB} DT_{ji} * DB_t + \sum_j \beta_{4j}^{DE} DT_{ji} * DE_t + \sum_j \beta_{4j}^{DA} DT_{ji} * DA_t + \varepsilon_{it}$$

where i, j, and t indices for household, treatment groups, and hour number respectively. y is the residents' hourly electricity consumption. $Temp$ includes three weather related hourly variables – heat index[2], cooling degree hours[3], and cumulative cooling degree hours[4]. DT indicates the variable that represents different treatment rates of the emergency DR study. DB, DE, and DA are three binary variables denoting hours surrounding critical peak event – before, during, and after the event, respectively. The indicator variables are for the six-hour period leading up to the start of an event, the five-hour event period, and the six-hour period following the conclusion of the event. ε is the error term.

The treatment parameter β_2 gives the mean difference in hourly load consumption between treatment group j and control with no-notification group. Similarly, coefficient β_3 estimates the impact of critical peak events in hourly load consumption. The primary interest of this paper is to estimate β_4, which gives the mean differences of hourly loads between various treatment groups with the control-no-notification group during the critical events.

[1] Most of customers that dropped out are from CPP treatment group. CPR participants can simply opt-out of the study by ignoring the critical peak events.

[2] Heat index is "apparent temperature" or the temperature after taking into account of the humidity. It is calculated with the formula of $HI = c_1 + c_2T + c_3R + c_4T * R + c_5T^2 + c_6R^2 + c_7T^2 * R + c_8T * R^2 + c_9T^2 * R^2$ where T is temperature and R is the relative humidity with c_1= -42.397, c_2 = 2.049, c_3= 10.143, c_4= -0.2247, c_5= -6.838*10^{-3}, c_6= -5.482*10^{-2}, c_7= 1.228*10^{-3}, c_8= 8.528*10^{-4}, and c_9= -1.99*10^{-6}

[3] Cooling degree hours are a measure of how much (in degrees) is the outside temperature higher than the base temperature, here 65 degree F. Mathematically, cooling degree hours = maximum(temperature – 65, 0).

[4] Cumulative cooling degree (CCD) is the sum of total cooling degrees in a day.

RED analysis[5]**.** For RED analysis, even though participants were randomly assigned to different groups, we treated all customers as if they were encouraged to take one of the treatments. In our analysis, all customers who were recruited into a particular treatment are treated as if they were "encouraged" to adopt the treatment. Since the vast majority of customers who exited the study did so during the initial survey contact (before actually being put on their rate and/or information treatment) we grouped those customers together with the few customers who dropped out after actually being put on their rate and/or information treatment.

The RED analysis for customers in CPP and CPP with IHD groups proceeded in two stages. The first stage regression predicted the proportion of customers in each treatment groups who adopted the treatment. The second stage is similar to RCT analysis except for the indicators used to denote critical event hours. Instead of a binary variable, we used the predicted values calculated in the first stage, equation (2).

(2) $T_{Aj} * DE = \sigma_j + \sigma_1 (T_{Ej} * DE) + \sigma_2 \, DE + e_{it}$

(3) $y_{it} = \beta_i + \beta_1 \, Temp_t + \beta_2 \sum_j DT_{ji} + \beta_3^{DB} DB_i + \beta_3^{DE} \widehat{DE}_i + \beta_3^{DA} \, DA_i + \sum_j \beta_{4j}^{DB} DT_{ji} * DB_i + \sum_j \beta_{4j}^{DE} DT_{ji} * \widehat{DE}_{ki} + \sum_j \beta_{4j}^{DA} \, DT_{ji} * DA_t + \varepsilon_{it}$

where, in equation (3), T_{Aj} is the binary variable that indicates the set of customers in the accepted group. Similarly, the dummy variable T_{Ej} indictates participants that are in the encouraged group[6]. $\widehat{DE}$ is the predicted value from calculated from the first stage regression.

3.2 Persistence Analysis

The paper analyzed the change in customers' electricity usage as more critical events are called. The persistence analysis shows how customers behave in the long-term. The analysis specifically looked at two different time horizons – within a critical event period and across critical events. The study of participants' responses at different time horizons along the critical peak events is important for planning purposes.

Equation (4) estimates the within-event persistence analysis where we look at the hourly electricity consumption during the critical peak event.

(4) $y_{it} = \alpha_i + \alpha_1 HI_t + \alpha_2 \, DE * H_t * HI_t + DE * \sum_j \alpha_{3j} DT_{ji} * H_t * HI_t + \varepsilon_{it}$

where HI indicates the heat index, H is the hour of the day. The coefficient α_2 estimates the temperature-controlled hourly change in electricity consumption in each hour within the critical peak event. Similarly, α_3 predicts the hourly change in customers' electric load by treatment groups across the event period.

The paper uses equation (5) to determine event-to-event persistence effects on the hourly load consumption. The response of participants, as a function of number of events called, is important to analyze to determine whether the behavior is consistent across the events.

(5) $y_{it} = \mu_i + \mu_1 \, HI_t + \mu_2 \sum_k DE_{ki} + \sum_k \mu_{3k} \, DE_{ki} * HI_t + \sum_j \sum_k \mu_{4k} \, DT_{ji} * DE_{ki} * HI_t + \varepsilon_{it}$

[5] RED analysis is only performed for participants that face CPP rates. CPR customers pay a fixed normal electricity rate during the peak events and only get financial incentives if they decrease the consumption. Even if CPR customers that are not excited about participating in the program, they might still be a part of the program and not respond during the peak events since the participation is voluntary.

[6] Please note that the majority customers declined to participate during the recruitment process, not during the period of the study, thus the set of customers in both encouraged and accepted groups remain same for all the critical events of the first year study.

In equation (5), k denotes critical peak events. The parameter μ_3 estimates the temperature controlled hourly load change in different critical peak events, whereas μ_4 estimates the impact in hourly electricity consumption by each treatment group.

4. Results and Analysis

4.1 Summary Statistics

The final sample of the two-year study consists of 23 million hourly observations of 2,107 unique customers, divided into four treatment groups and a control group. Table 1 gives summary statistics of different treatment groups during year 2012 and 2013. The average hourly load of participating customers during first year of the study is 0.82 kW, with the standard deviation of 0.88 kW. The average hourly weekday consumption is 0.81 kW, with the standard deviation of 0.86 kW. During the critical peak event hours of first year, the average hourly load consumption across the participants is 0.68 kW.

Table 1: Descriptive statistics, and summary of treatments[7]

Groups	**Year 2012**			**Year 2013**		
	Customers (N)	***Mean (kWh)***	***SD (kWh)***	***Customers (N)***	***Mean (kWh)***	***SD (kWh)***
a) All Hours						
CPR	809	0.84	0.91	433	0.80	0.87
CPR-IHD	332	0.79	0.85	233	0.79	0.86
CPP	445	0.81	0.85	603	0.80	0.85
CPP-IHD	167	0.79	0.86	307	0.79	0.95
CTRL	354	0.81	0.87	353	0.81	0.88
Total	*2107*	*0.82*	*0.88*	*1929*	*0.80*	*0.88*
b) Critical Peak Event Hours						
CPR	809	0.69	0.76	433	1.20	1.20
CPR-IHD	332	0.65	0.75	233	1.13	1.11
CPP	445	0.66	0.71	603	1.14	1.14
CPP-IHD	167	0.61	0.67	307	1.06	0.98
CTRL	354	0.72	0.78	353	1.20	1.16
Total	*2107*	*0.68*	*0.74*	*1929*	*1.15*	*1.14*

[7] Please note that CPR-CPP group customers were in CPR rate structure in year 1 and were unaware of the change in their rate structure in the second year. So, we include them with CPR group in first year analysis. Similarly, CPR-CPP-IHD customers are in the CPR-IHD category. Number of participants in four treatment rates – CPR, CPR-IHD, CPP, and CPP-IHD are 809, 332, 445, and 167 respectively. The reason of higher number of participants in CPR and CPR-IHD groups than the other two is due to the inclusion of CPR-CPP and CPR-CPP-IHD group customers in CPR and CPR-IHD during the first year.

The average hourly electricity consumptions across treatment groups during the first year's critical peak event hours range from 0.61 kW to 0.72 kW. The descriptive statistics suggest that, during the critical peak hours, the average hourly consumption for all treatment groups is lower than that of the control group. Among four treatment rates, participants in the CPP rate with in-home-display technology have the minimum average hourly consumption of 0.61 kW whereas only the control group customers have a maximum hourly usage of 0.72 kW.

The distinction of hourly load usage among treatment groups is more apparent in Figure 3 where we plot hourly average kW consumption, as well as load profile differences between treatment and control groups, across 2013 event days. The figure also gives the difference in hourly load usage between the IHD and control groups around the x-axis. The shaded part in the figure indicates the five-hour critical event. The customers in rate and technology treatment groups are responding during the declared critical peak events. Treatment group customers' electricity consumption is lower than that of the control group customers. The response of customers with the information treatment is greater than the customers that do not possess the technology. Similarly, there is a distinction between IHD and non-IHD customers' electricity consumption before the start of the critical peak events. As preemptive measure, customers with IHD technology reduced consumption, as compared with the control group customers, before the start of the events. However, the average hourly load shows that treatment group customers without IHD technology also consume more electricity during the same period.

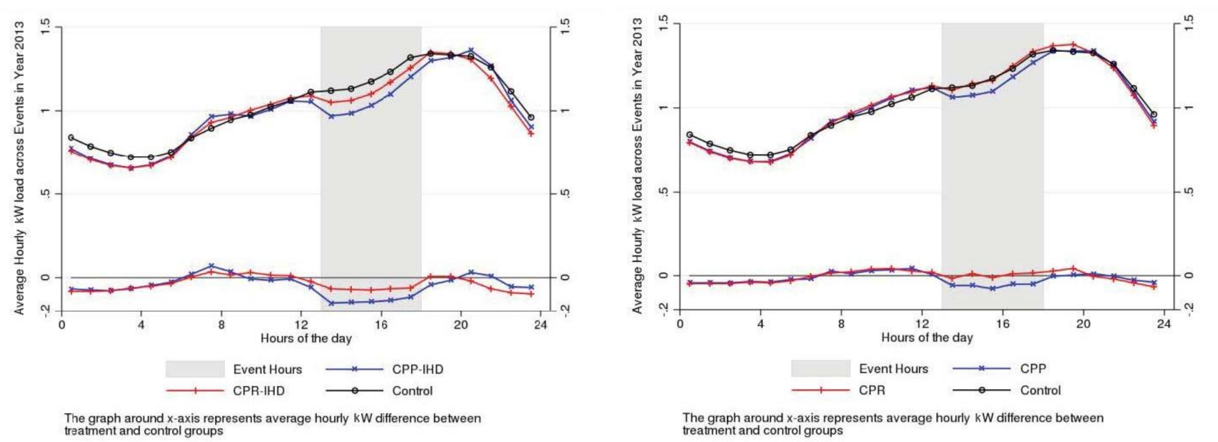

Figure 3: Average hourly load of treatment and no-notification control groups during critical peak events of 2013

4.2 Peak Load Analysis

This section presents the regression results analyzing the customers' behavior in response to the critical peak events. We start by estimating the potential peak load reduction at different time periods surrounding the critical event period with the help of RCT approach. Then, we conducted RED analysis to incorporate CPP customers that declined to participate in the pilot study. All the models include customer-level fixed effects. Standard errors are robust and clustered at the customer-level to control for the serial correlation.

The regression results in Table 2 show the impact of different treatments on customers' hourly load usage during the critical peak period. The pilot study participants of Rutland, VT decreased their usage by 0.034 kW per hour on average as compared with control with no-notification customers during the five-hour critical peak event period. Similarly, during the six-hours prior to the events called and twenty-four hours after the event, the hourly consumption of electricity was higher as compared with the control with no-notification group customers. On average, treatment group participants increased electricity usage by 0.069 kW and 0.147 kW than the control group participants during the pre- and post-event periods respectively.

The study's primary interest is to predict the impact of different treatment and information rates in real-time electricity usage. The coefficient estimates of interaction variables between critical event hours and treatment groups, β_3 in equation (1), show that customers in different rates responded distinctly. On average, residents on CPR treatments decreased hourly load by 0.045 kW and CPR customers equipped with IHD reduced hourly load by 0.068 kW. The log-linear econometric model suggests that CPR group customers' peak load reduction is 5.5 – 6.8 percent higher than the control group customers. The response of CPP treatments customers is larger than the CPR customers. Customers in the CPP rate reduced hourly electric usage by 0.051 kW during the event period. The maximum hourly load reduction is seen among CPP customers with IHD technology. On average, CPP with IHD customers decreased 0.103 kW of electric load per hour, 8.5 percent more than control group customers, during the critical peak events of the first year of the study. Please note that responses of CPR-IHD and CPP-IHD group customers are only statistically significant among the responses of different treatment groups.

The paper also examines the impact of treatment rates during the periods surrounding the critical events. The results show that there is no statistical significant difference in hourly load usage between treatment and control group customers during both periods – the six-hour window preceding the start of the event and six hours after the end of the event.

Table 2: Regression Results for Randomized Control Treatment Analysis

Treatment Groups	*Only Group*	*Interaction of Group*Events*		
		DB	*DE*	*DA*
		0.069***	-0.034	0.147***
		(0.016)	(0.023)	(0.019)
CPR	0.025	-0.006	-0.045	-0.032
	(0.022)	(0.021)	(0.031)	(0.026)
CPR with IHD	-0.013	0.006	-0.068*	-0.028
	(0.025)	(0.027)	(0.036)	(0.030)
CPP	-0.013	0.033	-0.051	0.002
	(0.023)	(0.022)	(0.031)	(0.026)
CPP with IHD	-0.017	0.024	-0.103***	0.010
	(0.026)	(0.027)	(0.036)	(0.031)
Control with notification	0.011	-0.025	-0.053*	-0.032
	(0.008)	(0.023)	(0.032)	(0.027)

*note: *** p<0.01, ** p<0.05, * p<0.1*

The RED analysis results are presented in Table 3. The analysis, taking CPP customers that declined to participate or dropped out during the study into account, shows that the hourly load reduction by CPP customer is larger than the one predicted by RCT analysis. On average, CPP customers decreased 0.116 kW of electric load per hour, which is 1.12 times larger than predicted by the RCT approach. During the first year of the study, 155 participants in the critical peak treatment rate, of which 113 customers are in the CPP group (25.4 % of the total CPP treatment group) and 37 residents belong to CPP with IHD customers (22.1 % of the CPP-IHD group), declined to participate after the treatment groups were revealed to them. Similarly, during the period of the second year, 37 CPP customers (11.5 %) and 21 CPP-IHD customers (12.2 %) dropped out of the pilot study.

Next, we estimated the impact of the program with the help of local average effect (LATE) to account for customers that declined to participate or dropped out of the program. The accepted percentage for CPP and CPP-IHD groups are 80.75% and 82.89%, respectively. The coefficients of CPP and CPP-IHD customers during critical peak event hours are comparable across three different methods. LATE method suggests that CPP treatment group customers reduced 0.0630 kW as compared with the control group customers during event hours. Similarly, CPP with IHD customers' reduction is 0.125 kW during the same period.

Table 3: Comparing coefficient estimates of CPP and CPP-IHD customers with RCT, RED, and LATE methods

Independent Variables	*RCT Analysis*	*RED Analysis*	*LATE Analysis*
Before Event Hours * CPP	0.033	0.038	0.0406
	(0.022)	-(0.026)	(0.028)
Before Event Hours * CPP - IHD	0.024	0.027	0.0285
	(0.027)	-(0.030)	(0.032)
During Event Hours * CPP	-0.051	-0.058	-0.0632
	(0.031)	-(0.036)	(0.039)
During Event Hours * CPP - IHD	-0.103***	-0.116***	-0.1247
	(0.036)	-(0.040)	(0.043)
After Event Hours * CPP	0.002	0.002	0.0021
	(0.026)	-(0.030)	(0.032)
After Event Hours * CPP - IHD	0.010	0.011	0.0118
	(0.031)	-(0.035)	(0.038)

4.3 Persistence Analysis

The goal of persistence analysis is to estimate customers' electric usage pattern during different time-horizons within the period of the study. Hourly persistence compares the customers' electricity usage during the critical peak events. The responses in residential power consumption during all event hours are statistically significant. The result suggests that treatment-group customers' hourly consumption increased by 0.030 – 0.036 kW with a degree increase in the heat index during event hours as compared with the control group customers. The more important result is the responses of different treatment groups during event hours.

We looked at each treatment groups' electricity usages during the critical peak event hours. The treatment indictor variables are interacted with hourly heat index to control for the possible variations in electricity consumption due to the temperature change. The results of different treatment rates show that the responses are consistent across different hours during the event. This result is very encouraging for utility companies because it indicates that customers' electricity usage behavior does not change during the event. We find that, even when we account for weather conditions, customers in all four treatment groups reduced electricity consumption during the event hours. Any variations in persistence of response are small, amounting to 0.001 kW or less. This may suggest that customers are not micro-managing electricity consumption during peak events, but rather are taking actions at a single point in time (such as adjusting thermostat settings) that would ultimately lower their consumption levels during critical peak events.

Figure 4 shows the change in hourly usage due to planned critical events of 2013. Figure 4 presents the mean difference of average electricity consumption between the treatment and control group customers during different 2013 critical event days. The estimates also contain the 95 percent confidence intervals. Please note that events 2 to 6 were called on consecutive days from July 15 to July 19 of 2013. The responses do not show any particular trend. We see that maximum reductions in the second year occurred during the last three event periods. The average temperatures during these three events are very closely related and lie in the range of 80 F. However, treatment group customers used more electricity that control group customers during Event 5. This might be due to the shift in electricity usage from the earlier event day (event 4) to event 5[8]. Customers were unaware of critical peak event 5 during event 4 and may have shifted some of their electricity-intensive work to the next day. And treatment customers may have completed the tasks on next day even though it was another critical peak event day.

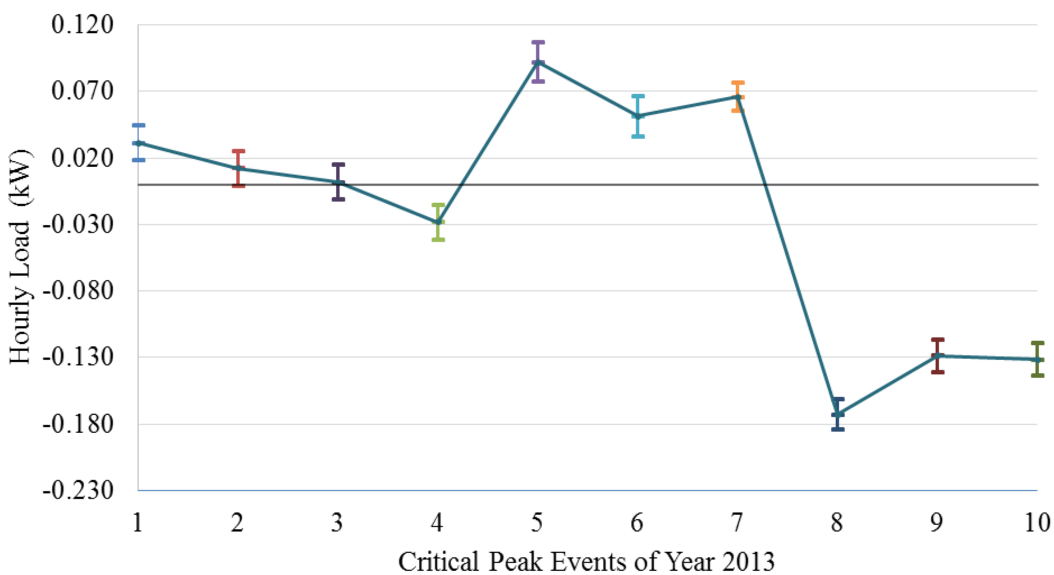

Figure 4: Persistence Analysis – change in hourly electricity consumption (kW) – during critical peak events of 2013

[8] Events 4 and 5 occurred on July 17 and 18 of 2013.

4.4 Energy Consumption Analysis

We also assessed the impact of IHD technology on customers' electricity consumption. The regressions use month-fixed effects in order to control for the heterogeneity in electricity consumption that may arise due to weather affects. The results show that the impact of feedback technology in monthly electricity consumption is considerable and statistically significant. On average, during the first year, customers with IHD technology decreased monthly electricity usage by 34.6 kWh as compared with the average monthly usage of customers without the continuous feedback system. However, the impact of IHD equipment in 2013 is considerably lower than what was seen in 2012 – the monthly electricity usage customers with the feedback technology is 12.7 kWh lower than the customers that do not possess the equipment. The higher impact seen in for 2012 may have to do with timing of installation of IHD technology. GMP distributed the IHD system during August 2012 right after the hot summer days. The model puts IHD customers in the non-IHD group from March 2012 to July 2012, limiting the analysis for estimating the impact of technology during relatively milder weather.

We believe the results from 2013 give better estimates of the impact of IHD in monthly electricity usage. This is mainly for two reasons – the data is available for the entire year, and customers have had IHD for at least few months and their behavior may be consistent. The log-linear model shows that this decrease in monthly load usage amounts to 2.0 – 5.3 percent reduction as compared with the non-IHD customers. The relevant study by Houde et al. shows the continuous feedback technology reduces electricity usage by 5.7%.

5. Conclusion

We studied Green Mountain Power's customers' electricity consumption patterns in a response to the critical peak events during two-year long pilot study. Critical peak events are called when utility companies anticipate very high electricity demand during the summer. Participants were notified by 6 pm of the day before each critical event day. In total, GMP called four events during the first year and another ten events in the second year. According to the participants' treatment rates, customers either receive payment for lowering electricity usage below their baseline or have an opportunity to reduce their electricity bill by decreasing usage to avoid high pre-determined critical peak pricing. Moreover, we also analyzed the change in total electricity consumption due to the installation of continuous feedback technology.

The analysis of customer-level electricity consumption shows that incentive-based demand response programs have a statistically significant impact in reducing peak load. Regardless of weather, both the CPR and CPP rate groups measurably reduced electricity usage, in the range of 6.0 – 10.3 percent, during the declared critical peak event. The CPR rate reduces peak load usage by 6.0 – 7.7 percent whereas the impact of CPP treatment rate is larger. The decrease in electricity consumption by CPP rate participants is between 6.8 and 10.3 percent during the critical peak events. The results also suggest that participants with IHDs show larger responses during non-event hours than customers facing similar electricity rates but are not equipped with the IHDs.

The results indicate that customers on CPR reduced their average hourly loads by 0.038 to 0.081 kW (6.0 – 7.7 percent), relative to the control group that was not notified of peak events and was not placed on any special rate during the critical peak event hours. Similarly, customers on CPP exhibited larger average hourly load reductions of 0.045 to 0.142 kW (6.8 to 10.3

percent), relative to the control group. Besides RCT analysis, we also conduct RED and LATE analysis for CPP related customers to account for the participants that opted-out of the pilot study.

Customers equipped with In-Home Displays (IHDs) generally exhibited larger reductions during peak events. While CPR customers equipped with IHDs exhibited reductions around 20% larger than CPR customers without the IHD, CPP customers equipped with the IHD exhibited critical peak reductions nearly twice as large, on average, as CPP customers without the IHD. Moreover, we also studied the impact of IHD technology in monthly electricity usage. On average, IHD-equipped participants' monthly energy consumption is 2.0 to 5.3 percent lower than the monthly energy usage of non-IHD customers.

Participants' electricity usage patterns differ across different critical peak event periods. We observed that customer responses were quite persistent during the hours of the critical peak event, indicating that customers take response actions at the beginning of critical peak times or prior to the start of the critical peak period, rather than managing their electricity usage on an hour-to-hour basis during critical peak events. Persistence of customer responses between events, and between 2012 and 2013 was less consistent.

We acknowledge that our study lacks a way to measure the long-term energy efficiency adjustments that customers may make due to the impact of critical peak events and IHD technology. Even though we are able to analyze customers' behavior due to various treatment rates, our study undermines the impact of long-run emergency DR programs. The impact of DR programs increases with the length of the program. Since the short-term electricity demand is more inelastic than long-term demand, customers' peak load reduction in the short-term may not be as significant as in the long run. King and Chatterjee (2003) find that the median price elasticity of electricity demand in short-run and long-run to be -0.2 and -0.90 respectively. A long-term DR program may encourage customers to reduce electricity usage by purchasing energy efficient appliances and we might be able to see large peak load reductions as a result.

6. References

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