An Experimental Comparison of Critical Peak and Hourly Pricing: The PowerCentsDC Program*

by

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Abstract

This paper reports on the results of a dynamic pricing experiment that compares the performance of three popular pricing programs–hourly pricing, critical peak pricing, and critical peak-pricing with a rebate–for a representative sample from the population of households in the District of Columbia. The sampled households differ in terms of their income levels, electricity-using appliance holdings and whether they own a smart thermostat. Using a nonparametric conditional mean estimation framework that allows for customer-specific fixed effects and hour-of-sample fixed effects, I find that customers on all of the dynamic pricing programs substantially reduce their electricity consumption during high-priced periods. The hourly average treatment effects associated with each of these dynamic pricing plans are larger in absolute value for households with all-electric heating and households with smart thermostats. Low-income households have significantly larger hourly average treatment effects than higher income households on the same dynamic-pricing tariff. The results of these experiments are also used to investigate two hypotheses about differences in the customer-level demand response to the three dynamic pricing tariffs. Specifically, I find that for roughly the same marginal price during a critical peak period, critical peak pricing yields a larger hourly average demand reduction than critical peak pricing with a rebate. I also find that the demand reduction associated with higher hourly prices is very similar to the predicted demand reduction associated with the same price increase under critical peak pricing.

1. Introduction

The widespread adoption of dynamic pricing programs for retail electricity in the United States is rapidly becoming feasible. A number of jurisdictions are installing or have installed interval meters for a large fraction or all of their customers. With this technology in place, the only remaining barrier is whether state regulators will require customers to pay for their electricity according to retail prices that vary with hourly system conditions.

Despite the substantial potential benefits to final electricity consumers from dynamic pricing of retail electricity, state regulators face enormous political risk from implementing even voluntary dynamic pricing programs. Consumer groups often oppose the implementation of dynamic pricing programs by arguing that households are unlikely to adjust their consumption in response to prices that vary with hourly system conditions so that the shift to dynamic pricing will only require these customers to pay higher retail prices.

Recently, electric retailers in several jurisdictions have received complaints about the accuracy of recently installed interval meters. For example, a number of Pacific Gas and Electric (PG&E) customers in Kern County have complained that their interval meters recorded substantially higher consumption that they believed had actually occurred. PG&E responded that the higher recorded consumption was the result of an increase in usage due to unusually hot weather.[1] Nevertheless, a number of Kern county customers remain unconvinced and have detailed records demonstrating that their alleged electricity consumption with the interval meter is substantially larger than their historical consumption for the same time period in previous

[1] "Smart meters need independent testing," December 4, 2009, http://articles.sfgate.com/2009-12-04/opinion/17182554_1_smartmeters-pg-e-pacific-gas

years. Ultimately, PG&E admitted that a significant number of their meters did not communicate energy usage back to PG&E, failed to work, or were installed improperly.[1]

To overcome the political resistance to both interval meters and dynamic pricing, state regulators must design programs that yield tangible benefits to final consumers while exposing them to limited bill volatility. This paper reports on the results of a dynamic pricing experiment for the District of Columbia that uses hourly data on household-level electricity consumption for random sample of households from July 2008 to March 2009 to compare the relative performance of several popular dynamic pricing programs across several types of residential customers. This experiment is used to examine three hypotheses about the design of dynamic pricing programs.

The first is concerned with the extent to which retailers to need to pre-commit on day-ahead basis to sustained periods of high retail prices during the following day in order to obtain sizeable hourly demand reductions as opposed to set hourly retail prices that pass through the day-ahead hourly wholesale price. Specifically, if customers have a "cost to take action" to reduce their demand, then clustering periods of high hourly retail prices may result in a larger hourly average price response than a dynamic pricing tariff that that passes through the hourly wholesale price in the hourly retail price charged to final consumers. The critical peak pricing (CPP) tariff addresses the cost of taking action by pre-committing to a CPP event that can last up to 4 to 6 hours, during which retail prices are set at very high level. Comparing the household-level hourly average price response under a retail pricing plan that passes through the wholesale price in the hourly retail price to the hourly average price response achieved under a CPP tariff

[1]Finney, Michael "PG&E Acknowledges SmartMeter Problems," April 26, 2010, http://abclocal.go.com/kgo/story?section=news/7_on_your_side&id=7406652.

can determine whether there is a significant "cost-of-taking-action" with hourly pricing.

The second hypothesis investigates whether there is a difference in a customer's price response under a pure CPP tariff versus a CPP with rebate (CPR) tariff that sets roughly the same marginal price of electricity during a CPP event. The CPR tariff is popular with customers because it pays a rebate that depends on the amount a customer's hourly consumption is below a pre-specified reference level during a CPP event day. However, different from CPP pricing, if the customer's hourly consumption is not below the reference level, the customer pays for his consumption during a CPP event at the standard fixed retail price. In contrast, a customer on the CPP tariff pays for all of his consumption at the high CPP period price during a CPP event. Therefore, the CPR tariff provides a customer with the option to forgo taking actions to reduce demand during a CPP period, with the only consequence being that the customer pays for this consumption according to the standard fixed retail price of electricity. My hypothesis is that this "option to quit" may reduce the magnitude of the average demand reduction during CPP events for customers on a CPR tariff versus customers on a CPP tariff with the same marginal price during a CPP event.

The third hypothesis assesses the impact of automated technology on the ability of customers to achieve demand reductions in response to high-priced hours or CPP events. Smart thermostats were offered to customers in the experimental group with central air-conditioning and the ability to set their thermostat. The hypothesis examined is the extent to which the demand reduction achieved under each of the pricing programs was altered by the existence of a smart thermostat that could automatically change the household's usage of electricity for air conditioning or heating in response to a high hourly prices or a CPP event.

The results of the experiment find precisely estimated demand reductions in response to

high hourly prices and CPP periods across all customer types, although it appears that all-electric customers (those with electric heating) have larger percentage reductions in their consumption during high-priced periods. The estimated hourly average price responses for all dynamic pricing tariffs tend to be larger in absolute value during the summer months versus the winter months. In addition, for the same dynamic pricing tariff, low income consumers have larger in absolute value percentage demand reductions during CPP periods.

In terms of the three hypotheses described above, these results are broadly consistent with there being "no cost-of-taking action" associated with hourly pricing versus critical peak pricing, in part because periods of high hourly prices tend to be clustered during the day, typically during the same hours of the day that CPP periods occur. I also find a clear "option-to-quit" effect associated with CPR pricing versus CPP pricing. Even though both the CPR tariff and the CPP tariff face consumers with roughly the same marginal price during a CPP event (when a rebate is being paid for the CPR tariff), the percentage demand reduction during a CPP event is roughly ½ to 1/4 the magnitude of the demand reduction during a CPP event for the same type of customer on the CPP tariff. Finally, I find that for all types of customers, having a smart thermostat yields a larger percentage demand reduction in response to high hourly prices and CPP events. This boost to the percentage demand reduction is the greatest for all-electric customers and customers on CPP tariffs.

Taken together, these results suggest that the hourly pricing or CPP tariffs will yield the largest demand reductions in response to high hourly wholesale prices. These results also warn against the implementation of CPR tariffs. Although these tariffs achieve substantial percentage demand reductions for low-income customers, because the experiment did not subject low-income customers to CPP or hourly pricing, I am unable to determine whether the "option to

quit" effect also applies to them.

The remainder of the paper proceeds as follows. Section 2 describes the major analytical challenges associated with designing dynamic pricing programs. The results of the District of Columbia experiment will be used to gain a deeper understanding of a number of these challenges. Section 3 describes the details of the experimental design and data collection process. Section 4 presents the general treatment effects estimation framework and the results of estimating these models for three dynamic pricing plans and four customer types. Section 5 describes how the estimation results can be used to design dynamic pricing schemes.

2. The Challenges Faced in Designing Dynamic Pricing Programs

The major challenge with implementing widespread dynamic pricing for the household sector is designing a tariff that delivers tangible benefits to electricity consumers without subjecting them to unacceptable levels of price risk. A tariff that simply passes through hourly wholesale prices in the hourly retail price paid by the household may not yield as stable, predictable and sizeable demand response as alternative dynamic-pricing tariffs. Because of the political constraints faced by state regulators, dynamic pricing plans are typically offered on a voluntary basis. Wolak (2007) discusses the political economy behind the state regulator's logic for implementing dynamic pricing on a voluntary basis. Because how onerous a dynamic-pricing plan is perceived to be determines how many customers are willing to switch to it from the default fixed-price tariff, understanding household behavior under a variety of dynamic pricing planning can contribute valuable input to achieving widespread adoption of dynamic pricing.

2.1. The Fixed Cost of Taking Action

A common complaint about retail tariffs that pass through the hourly wholesale price in

the retail price is that these dynamic pricing tariffs require customers to monitor hourly retail prices in order to decide whether to reduce demand during a given hour of the day. The customer must assess whether the pattern of hourly prices is sufficient to justify taking action to reduce demand. For example, assuming that there is a fixed cost to taking action to reduce demand and that the wholesale price increase lasts only one hour implies that a very large price spike is necessary to cause the customer to take action.

Taking the example of a residential customer with a 2.5 kilowatt-hour (KWh) demand in that hour and $5 fixed cost of taking action to reduce demand by 20 percent, implies that a hourly price spike of at least $10,000 per megawatt-hour (MWh), or 1,000 cents/KWh. is needed to produce sufficient cost savings from reducing demand by 0.5 KWh, 20 percent of 2.5 KWh, to overcome the $5 cost of taking action. This logic implies that if customers face a fixed cost of taking action to reduce their demand by 20 percent, there may be many high-priced hours that the customer decides do not produce sufficient electricity cost saving to pay this $5 cost of taking action.

A larger number of consecutive hours of high prices implies that a lower average hourly price is needed to overcome the fixed cost of taking action. For example, if the duration of the price spike is two hours, then the average price for the two hours must exceed $5,000/MWh for a 0.5 KWh demand reduction during each hour to compensate for the $5 cost of taking action. A three-hour duration price spike only requires an average price greater than $3,333/MWh to compensate for the fixed cost of taking action to reduce demand by 0.5 KWh in each of the three hours.

This logic demonstrates that a dynamic pricing tariff that passes through the hourly wholesale price may result in many hours of high prices when little or no demand reduction

occurs, because these hourly prices are not high enough for a large enough number of consecutive hours to yield savings from the resulting hourly demand reductions to overcome the fixed cost to the household of taking action to reduce demand. Consequently, if households have economically significant costs of taking action to reduce their demand, then the average demand reduction for these households to a given percent hourly price increase should be smaller than the estimated demand reduction associated with the same percentage price increase for dynamic pricing programs where the retailer pre-commits to four to six consecutive hours of high retail prices.

2.2. *The Moral Hazard Problem with CPP Pricing*

The CPP tariff pre-commits households to a sustained period of high retail prices during a CPP event. For consumption during all other hours of the day, month and year, the household pays according to a fixed-price tariff. The disadvantage of a CPP tariff from the perspective of the household is that it creates a moral hazard problem for the retailer that offers the CPP tariff because retailer is typically able to charge a price that is substantially higher than the standard retail rate during a CPP event and thereby earn revenues (less transmission and distribution charges) that are vastly in excess of the cost of providing electricity to the household. Moreover, if the retailer can count on a certain percentage demand reduction from households on the CPP tariff, then it has an incentive to under-procure its expected retail electricity needs in the forward market and rely on declaring CPP events (and the resulting demand reduction from CPP customers) to balance its retail load obligations with its wholesale energy purchases.

The moral hazard problem for retailers with CPP pricing is somewhat addressed by the retailer pre-committing to declaring no more than a small number of CPP events during a pre-specified time period. Although this limits the number of times that the retailer can declare at

CPP event, the basic feature of the CPP tariff remains--it puts the entire burden of managing hourly price risk on the customer. The retailer faces no downside risk associated with declaring a CPP day, regardless of what wholesale electricity prices are during the CPP event. It simply charges the household a much higher implicit wholesale price during the CPP event, so the retailer has no incentive not to use all of the CPP events it is allowed to declare under the pricing plan.

The moral hazard problem for retailers associated with CPP pricing is dealt with through CPP pricing with a rebate (CPR). Under this pricing plan, each household is assigned reference level for their hourly consumption relative to which rebates will be issued during CPP events. If Q(ref) is this reference level and Q(act) is the customer's actual consumption during the hour when a CPP event occurs, the CPR customer receives a rebate equal to max(0,Q(ref)-Q(act))*p(rebate), where p(rebate) is the cents per KWh rebate paid during CPP events. This rebate mechanism pays the household the difference between Q(ref) and Q(act) times the rebate price if Q(ref) is below Q(act) and zero otherwise. The CPP with rebate mechanism addresses the moral hazard problem of the retailers with respect to CPP pricing because the retailer now faces revenue risk associated with declaring a CPP event. If it declares a CPP event is has an obligation to pay rebates to households for their hourly consumption reduction below Q(ref). If customers are able to achieve an actual level of consumption far below Q(ref), then the retailer is obligated to make substantial rebate payments. Therefore, under a CPR tariff, the retailer has a strong incentive to only declare CPP events when it believes that the amount of rebate payments that it will make can be recovered from the wholesale energy cost saving that declaring a CPP event will achieve. In this sense, the CPR tariff shares the risk of managing wholesale price risk between the retailer and household, rather than simply passing it through to retail customers.

2.3. The Option to Quit with CPR Pricing

Although the CPR tariff addresses the moral hazard problem associated with the retailer declaring CPP events, there are several complications associated with the design and implementation of CPR tariffs. The problem of setting the customer's reference level, Q(ref), is particularly challenging given the tremendous variability in household-level hourly electricity consumption. Determining what the household would have consumed during a given hour in the absence of the CPP event, requires a very accurate model of the household's electricity consumption behavior. Approaches based on functions of household's historical hourly consumption during similar days that are not CPP days suffer from the baseline inflation problems described in Wolak (2006).

Another potential shortcoming of CPR pricing relative to CPP pricing stems from the asymmetric payoff function to the household under CPR pricing versus CPP pricing. In particular, a customer under a CPP tariff faces both an upside and downside from the decision to take action to reduce his consumption during a CPP event. By reducing its consumption, the household avoids having to pay the very high price for electricity during the CPP event. If the household does not take action to reduce its consumption it still pays for all hourly consumption at the high CPP price. In contrast, the CPR tariff gives a household the option to continue to pay according to the standard fixed price tariff if it does not wish to reduce its consumption below Q(ref). Only if the household takes action to reduce its consumption below Q(ref) does it receive the rebate. Different from the CPP tariff, here is no high-price punishment for failing to reduce consumption during CPP events under the CPR tariff. This creates an "option to quit" for CPR customers that does not exist for CPP customers that could reduce the magnitude of the average demand reduction achieved under CPR pricing, even if the two programs face households with

the same marginal price for consuming electricity during a CPP event (assuming that the CPR customer receives a rebate).

The following example illustrates the "option to quit" effect. Suppose that P(CPP) is the price paid by CPP tariff households during a CPP event, P(fixed) is the standard fixed-price tariff paid by CPR customers for all of the electricity they consume, and P(rebate) is the rebate price for CPR customers that manage to reduce their consumption below Q(ref). Suppose that P(CPP) = P(fixed) + P(rebate) so that both the CPP tariff customers and CPR customers face the same marginal price of an additional KWh during a CPP event if the CPR customer is currently consuming at Q(ref) or below. P(fixed) + P(rebate) is the correct marginal price for a CPR customer with Q(act) below Q(ref), because this customer receives P(rebate) and avoids paying P(fixed) if it consumes one less 1 KWh of electricity.

Suppose that before a CPP event is declared (typically the day before the event day), the amount of uncertainty faced by the household about its electricity consumption the next day is reduced to two possible states of the world for both the CPP and CPR households. The first state of the world is one in which is it relatively low-cost for the household to reduce its consumption below Q(ref) and second is one where it is extremely costly for the household to do this, although smaller reductions are possible at lower cost. The difference between the two states of the world could be the result of external factors such as the weather the following day or other factors specific to the household. For example, the weather could be milder than expected or hotter than expected and this impacts the ability of the household to reduce its electricity consumption.

A risk-averse household facing this decision problem and purchasing according to the CPP tariff would still have a strong incentive to reduce their consumption under both states of

the world. However, under the CPR tariff, if the household determines that it is too difficult to reduce its consumption below Q(ref) in the second state of the world, it will face P(fixed) as the marginal cost of consuming electricity. In this second state of the world, the CPR household will consume more electricity than it would under the CPP tariff facing P(CPP), which is much greater than P(fixed). Consequently, the average realized demand reduction (over these two states of the world) of the household under the CPR tariff is likely to be smaller than the average reduction of the household under the CPP tariff. This difference in the average demand reduction is the result of the "option to quit" under the CPR tariff. Consequently, by comparing the average demand reduction of households on the CPP tariff versus customers on a CPR tariff where P(CPP) for the CPP tariff is approximately equal to P(rebate) + P(fixed) for the CPR tariff, the difference in the estimated price responses CPP events under the CPP tariff versus CPR tariff is a measure of the magnitude of the "option to quit" under the CPR tariff.

2.4. Automated Response

The declining cost and size of computing and communications technologies and the increasing availability of wireless networks in the household has the prospect of allowing customers to combine these technologies with dynamic pricing tariffs to achieve larger and more predictable demand reductions in response to hourly retail price signals. Technologies such as smart thermostats can also be programmed to reduce electricity consumption for heating and cooling automatically in response to high hourly prices. These thermostats can also be programmed to display hourly prices, the existence of CPP event, and other information that can help a household better manage its electricity consumption. In addition, dynamic pricing information can be sent to a home computer and a wireless network can be used to adjust the electricity consumption of appliances throughout the home automatically according to

programmed algorithms that depend on dynamic prices, weather conditions and other factors that determine the household's hourly demand for electricity. Wolak (2007) discusses these technologies and how they might be used in combination with dynamic pricing programs to benefit consumers with interval meters that record their consumption on an hourly basis.

All of these technologies involve up-front costs that must be justified by the cost savings achieved from the increased price-responsiveness they provide. Returning to the above example of the residential customer with a demand of 2.5 KWh and a demand reduction during a CPP event of 20%, suppose that a smart thermostat that automatically responds to CPP events increases the average impact of a CPP event by 10%, so that the customer's response to a CPP event is now 30%. If electricity costs the customer 70 cents/KWh during a CPP event, then the additional 10% reduction in demand, or 0.25 KWh, during each of the 4 hours of the CPP event yields an additional savings of 70 cents per CPP event due to the existence of the smart thermostat. If the customer experiences 10 CPP events per year, then this implies that owning the smart thermostat saves the customer $7 per year. If we assume that the thermostat lasts 10 years and saves the customer $7 in electricity costs each year and customer's risk-adjusted interest rate for this type of investment is 5 percent, then the present value of this annual savings for 10 years is roughly $50. Therefore, if the smart thermostat has up-front costs less than $50, the discounted present value of energy savings from being on the CPP tariff with this smart thermostat justifies this up-front investment.

This example shows that the economic benefits a household receives from automated response technology depends on both the magnitude of demand reduction achieved with the technology as well the structure of dynamic pricing tariff that it is combined with. One set of challenges associated with implementing dynamic pricing is determining which automated

technologies are economic for which dynamic pricing programs.

3. The PowerCentsDC Program

The Smart Meter Pilot Project, Inc. (SMPPI), which was formed as a non-profit organization through a merger settlement approved by the Public Service Commission of the District of Columbia in 2002, initiated the PowerCentsDC program to investigate the impact of a variety of dynamic pricing programs and smart meter and smart thermostat technologies on the household-level consumption of electricity. Starting in July 2008, 1,245 customers—857 treatment and 388 control customers—participated in an experiment designed to assess the price-responsiveness of households to three types of dynamic pricing programs: (1) Critical Peak Pricing (CPP), (2) Critical Peak pricing with a rebate (CPR) and (3) Hourly Pricing (HP).

Random samples of treatment participants were chosen from all eight wards of the District of Columbia from four types of customers: (1) R-regular household customers, (2) AE--all electric (households with electric heating) (3) RAD—regular limited income, and (4) RAD-AE—all electric (households with electric heating) limited income customers. Customers were selected from the four groups to replicate the proportion that they appear in the general population. Treatment customers in the R and AE groups were then randomly assigned to the three types of pricing programs—CPP, CPR, and HP. Figure 1 shows the location of the sample households throughout the 8 wards of the District of Columbia. Treatment customers assigned to each pricing plan and were not told about the existence of the other two pricing plans. The program design only allowed low income participants to be subjected to the CPR treatment. Treatment customers were recruited through direct mail and notified that they "have been selected as a participant." In order to ensure that CPP and HP pricing treatment customers remained on their pricing plan for the duration of the experiment, each treatment customer was

promised a $100 payment, with $50 paid up front and $50 paid at the end of the experiment period. No payment was made to any CPR customers because their bill could not increase as a result of participating in the experiment.

The control group was also randomly selected from the eight wards of the District of Columbia. Control participants were not made aware of the PowerCentsDC program and did not receive any information about the program, CPP events, or hourly prices. Interval meters were installed on the premises of all customers in the treatment and control groups. The meters record electricity use hourly and transmit it every day to the data center using a wireless communications link. The smart meters also have an LCD display so that customers can read the meter locally. A random sample of customers in the treatment group was offered the option to have a smart thermostat that contains a wireless receiver inside. These thermostats can be remotely programmed on behalf of the customer to use less air conditioning or electric heating during CPP events or periods of high hourly prices. Customers can override this automatic adjustment or change the settings. The thermostats also have a small display that shows the current price of electricity faced by the customer and his estimated bill to date. Figure 2 displays a picture of the meter and thermostat.

Table 1 provides a breakdown of the participants by income level, all electric versus regular customers, and by control versus the three dynamic-pricing programs. Both treatment and control customers received their standard monthly billing statements. All treatment customers also received a detailed Electric Usage Report in their monthly bill detailing their rate code and the breakdown of CPP period payments for CPP customers, and CPP period rebates for CPR customers and average hourly prices during the month on weekdays and weekends for HP customers. Figures 3(a) to 3(c) give sample electric usage reports for CPR, CPP, and HP

programs, respectively.

For both the CPP and CPR pricing programs, customers were subject to at most 12 CPP events during the summer months (June 1 to September 30) and 3 CPP events during the winter months (November 1 to February 28). The critical peak hours occur between 2 pm to 6 pm in the summer and between 6 am and 8 am and 6 pm and 8 pm during the winter months. Critical peak events were called based on a day-ahead temperature forecast above a pre-specified threshold during the summer months and below a minimum temperature threshold during the winter months. The summer 2008 threshold was 90 degrees and the winter 2008-2009 threshold was 18 degrees.

At the time of their enrollment in the experiment, treatment customers stated their preferences for how they would like to be notified of CPP events—by phone, e-mail, or text messages on their cell phone. Notifications were delivered no later than 5 pm the day before a CPP event. Some participants asked for two modes of notification in order to avoid the problem of failing to check their voice mail, e-mail or text messages in time to respond to a CPP event or an HP warning. Based on feedback from program participants during the experiment, customers were generally satisfied that they had been adequately notified of CPP events and HP warnings.

All control customers, but the RAD-AE customers, paid for their electricity according to increasing block price schedules with two blocks or tiers. The RAD-AE customers have three pricing tiers. Table 2 lists the price schedules faced by the four types of control customers: R, AE, RAD, and RAD-AE. The CPP treatment customers paid according to increasing-block schedules with two tiers that had slightly lower tier prices than the corresponding control cents/KWh and 78 cents/KWh, for their consumption during critical peak events. Table 3 lists the increasing block schedules for these customers and the CPP event prices for these customers.

The CPR customers pay according to the same increasing block prices as control customers, but they receive rebates for the amount their actual consumption, Q(act), is less than their reference level, Q(ref), during critical peak periods. Otherwise CPR customers receive no rebate. The rebate is computed as max(0,Q(ref)-Q(act))*P(rebate). If there are no CPP periods within a month or the customer is unable to reduce its consumption below Q(ref) during any of the CPP periods that occur in that month the customer's bill is computed the same way as the bill of a control customer. Because of concerns that a CPR household might be able to manipulate its reference level in the manner discussed in Wolak (2006) for the Anaheim CPR pricing experiment, customers were not told how their reference level, Q(ref), was computed each month. Each customer's monthly reference level was computed as the average of the three highest non-event consumption amounts on non-holiday weekdays during CPP periods of that billing month.

Table 4 lists the CPR rebate prices, P(rebate), for each of the four customer types. The rebate prices for the R and AE customers were selected to yield very similar marginal prices during a CPP event for CPP customers and CPR customers. For example, the Summer Tier 1 CPR rebate price from Table 4 is 63.9 cents/KWh and the Tier 1 block price for the CPR customer from Table 2 is 12.9 cents/KWh, which implies a marginal price for a CPR customer receiving a rebate during a summer CPP event of 76.8 cents/KWh. The Summer Tier 1 CPP price from Table 3 is 77.1 cents/KWh. For both R and AE customers and all pricing tiers, rebate prices were chosen to come as close as possible to satisfying the equation P(CPP) = P(rebate) + P(tier), where P(CPP) is the CPP event price for CPP customers and P(tier) is the tier fixed price for CPR customers.

For RAD and RAD-AE customers the rebate amount was set at a slightly higher rate to

encourage the participation of low-income customers in the pricing experiment. CPR was the only dynamic pricing tariff offered to low-income treatment group customers.

During the summer months of 2008, only six CPP events were declared based on the maximum temperature threshold. Table 5 lists the critical peak days during the summer months and actual maximum daily temperature and time of the maximum temperature on the CPP day. For all but the first CPP day on August 4, the realized maximum temperature on all of the summer CPP days was larger than the 90 degrees threshold. For all but the first CPP day, the maximum temperature for the day occurred during the 2 pm to 6 pm CPP event period. Table 6 lists the minimum realized daily temperature for the winter CPP days and the hour of the day when the minimum temperature occurred. The last column of the table lists the mean temperature during the wintertime critical peak period. Except for the January 16 CPP event, the realized average temperature during the CPP period was significantly higher than the 18 degrees threshold. These results suggest that maximum temperatures for the day are more straightforward to forecast on a day-ahead basis than minimum temperatures for the day.

Hourly pricing customers paid according to the day-ahead prices that tracked prices set in the PJM day-ahead wholesale electricity market for the District of Columbia. These prices were weighted across hours of the day so that the wholesale price implicit in the hourly retail price was higher in the high-priced hours of the day and lower in the low-priced hours of the day than the PJM day-ahead prices. This was done to increase the attractiveness to HP customers of reducing their hourly demand in response to these prices. The hourly prices were posted on the PowerCentsDC project website for HP participants to access and are also available by calling a toll-free number. The prices are also displayed in real-time on the smart thermostats.

HP participants were also notified on a day-ahead basis by phone, e-mail, or text message

when hourly prices were "high" as determined by a preset threshold. The threshold for high hourly prices was set to be 23 cent/KWh during the summer months. Because of the massive slowdown in economic activity after September 2008, the threshold was revised downward to 15 cents/KWh for the winter months. These "high price" hour notifications were sent to customers before 5 pm of the day before these prices were in effect. Different from the CPP event notification, customers were told which hours of the following day the hourly price exceeded the threshold. Notifications were given for 38 hours during the sample period. Figure 4 displays the time path of hourly prices from July 2008 to February of 2009.

4. Experiment Estimation Results

This section presents the analysis of household-level behavior under the three dynamic pricing plans for the entire sample period and the summer and winter months separately for the R and AE customers. For these customers, I recover hourly average treatments effects for a CPP event for CPP customers and CPR customers combined and separately and an hourly average treatment effect for an HP warning for HP tariff customers. For RAD and RAD-AE customers, I estimate hourly average treatment effects associated with a CPP event for CPR tariff for the entire sample period and the summer and winter months separately. Finally, for each of these customer types and pricing plans, I also estimate the change in the magnitude of the average treatment effect associated with the customer having a smart thermostat.

Define the following notation:

y(i,h) = the natural logarithm of the consumption in KWh of customer i during hour h

Hour(h) = indicator variable for hour-of-sample h=1,…,24*D, where D is the total number of days in the sample period

Treat(i,j) = indicator variable for whether customer i is in treatment group j (j=CPP, CPR, or HP)

CPP(h) = indicator variable for whether hour-of-sample h is a critical peak event hour

THERM(i) = indicator variable for whether customer i has a smart thermostat

From these variables construct the following interactions:

CPP_PER(i,h) = CPP(h)*Treat(i,j)=CPP or CPR) = indicator variable for whether customer i is in the treatment group and is either a CPP or CPR customer and hour h is during a CPP event,

HP_PER(i,h) = HP(h)*Treat(i,j=HP) = indicator variable for whether customer i is in the treatment group and is an HP customer and hour h is during a HP warning hour,

CPP_PER(i,h)*THERM(i) = indicator variable for whether customer i has a smart thermostat and is in the treatment group and either a CPP or CPR customer and hour h is during a CPP event,

HP_PER(i,h)*THERM(i) = indicator variable for whether customer i has a smart thermostat and is in the treatment group and an HP customer and hour h is during an HP warning hour,

CPM_K(i,h) = CPP(h)*Treat(i,K) for customer type K=R,AE and dynamic pricing tariff M = P (for CPP) or R (for CPR).

For example, CPP_AE(i,h) is an indicator variable for whether hour h is a CPP event given that customer i is an AE customer.

The basic average treatment effects model takes the following form:

$$y(i,h) = \alpha(CPP\_PER(i,h)) + \beta(HP\_PER(i,h)) + \lambda_h + \delta_i + \varepsilon_{ih,} \quad (1)$$

where δ_i is a customer-specific fixed-effect that controls for persistent differences across customers in their hourly consumption, λ_h is an hour-of-sample fixed effect for hour-of-sample h which accounts for differences in y(i,h) across hours in the sample period for a given household, and ε_{ih} is an unobserved mean zero stochastic disturbance that is uncorrelated with any of the regressors in this model, including the two sets of fixed-effect. This model assumes the same

hourly average treatment effect associated with the CPP event for CPP customer and a CPR customer and a separate hourly average treatment effect for a HP warning.

The second model allows for different hourly average treatment effects associated with a CPP day for CPP customers and CPR customers:

$$y(i,h) = \alpha_1(CPP\_M(i,h)) + \alpha_2(CPR\_M(i,h)) + \beta(HP\_PER(i,h)) + \lambda_h + \delta_i + \varepsilon_{ih}, \quad (2)$$

where α_1 is the hourly average treatment effect associated with a CPP day for CPP customer of type M = R or AE and α_2 is the hourly average treatment effect associated with a CPP day for CPR customer of type M = R or AE. The third model estimated allows for a different treatment effect for each dynamic pricing plan depending on whether the household has a smart thermostat. It the following form:

$$y(i,h) = \alpha_1(CPP\_M(i,h)) + \alpha_2(CPR\_M(i,h)) + \beta(HP\_PER(i,h)) + \gamma_1(HP\_PER(i,h)*THERM(i))$$
$$+ \gamma_2(CPP\_M(i,h)*THERM(i)) + \gamma_3(CPR\_M(i,h)*THERM(i)) + \lambda_h + \delta_i + \varepsilon_{ih} \quad (3)$$

for M = R or AE. RAD and RAD-AE customers are only subjected to the CPA tariff so, only the following model is estimated for these customers:

$$y(i,h) = \alpha_1(CPP\_PER(i,h)) + \gamma_1(CPP\_PER(i,h)*THERM(i)) + \lambda_h + \delta_i + \varepsilon_{ih}, \quad (4)$$

so α_1 is the hourly average treatment effect associated with a CPP day for CPA customer.

Tables 6.1 to 6.3 present the estimates of models (1)-(3) for R customers for the full sample period of July 21, 2008 to March 17, 2009. To guard against arbitrary forms of both heteroscedasticity and autocorrelation in the ε_{ih}, all of the standard errors presented in the remainder of the paper are computed using the heteroscedasticity and autocorrelation-consistent covariance matrix for two-way panel data models presented in Arrellano (1987).

The model (1) results demonstrate sizeable and precisely estimated average treatment effects associated with both HP warnings and CPP events for both CPP and CPR customers.

The hourly average treatment effect of a CPP event for both CPP and CPR customers is 9 percent and hourly average treatment effect for an HP warning is 3 percent. Table 6.2 breaks out the average treatment effect of a CPP event separately for CPP and CPR customers. These results reveal a much larger hourly average treatment effect for a CPP event for a CPP customer versus CPR customer, 13 percent versus 5.3 percent, respectively. For these estimates, the hourly average treatment effect for an HP warning is still 3 percent. Table 6.3 includes interactions with the smart thermostat indicator variable for each of the regressors in Table 6.2 to quantify the change in the hourly average treatment effect if the customer has a smart thermostat. These results show that the existence of a smart thermostat increases the size of the hourly average treatment effect for all three customer types, but by far the largest increase is for CPP customers. There is an 11 percentage point increase in the size of the hourly average treatment average treatment effect for an R-customer on a CPP tariff having a smart thermostat.

The results in Tables 6.1 to 6.3 illustrate a number of points that also apply to AE-customers. First, all dynamic pricing tariffs result in sizeable and precisely estimated hourly average treatment effects. Second, the treatment effect of a CPP event for CPP customer is typically more than 2 to 3 times the absolute value of the treatment effect of a CPP event for CPR customer. Third, the treatment effect associated with a HP warning is roughly 1/3 to ¼ of the absolute value of the hourly average treatment effect of a CPP event for CPP customer. Fourth, the existence of the smart thermostat increases the absolute value of the hourly average treatment effect associated with all dynamic pricing plans and the increase in the treatment effect is largest for CPP customers.

The second result is consistent with the existence of sizeable "option to quit" associated with the CPR tariff versus the CPP tariff. The third result is roughly consistent with there being

little or no "cost of taking action" because the price during a CPP event is roughly 70 to 75 cents per KWh and lowest hourly price at which an HP warning is issued is 23 cents/KWh in the summer and 15 cents/KWh in the winter, which are both roughly 1/3 to ¼ of 70 to 75 cents/KWh. Therefore, the ratio of the hourly average treatment effect of a CPP event for a CPP customer to the hourly average treatment effect of an HP warning for an HP customer appears to be roughly consistent with the ratio of the hourly price faced by a CPP customer during a CPP event versus a HP customer during an HP warning. In future research I plan to explore the issue of the equality of the two demand responses for CPP customers and HP customers by estimating a demand system using hourly pricing data for both sets of customers and the three dynamic pricing tariffs.

Tables 7.1 to 7.3 reproduce the results in Table 6.1 to 6.3 for the summer sample period. These results allow the same quantitative and qualitative conclusions to be drawn as the results presented in Tables 6.1.to 6.3. Tables 8.1 to 8.3 reproduce the Tables 6.1 to 6.3 results for the winter time period. For this time sample period, the average treatment effects are smaller in absolute value and less precisely estimated. Only the CPP tariff appears to have a substantial and precisely estimated hourly average treatment effect and precisely estimated increase in the absolute value of the hourly average treatment effect associated with a smart thermostat. The smaller in absolute value and less precise hourly average treatment effects for the winter sample versus the summer sample holds for the other three customer types. This can be attributed to the fact that there were a much smaller number of CPP events and HP warnings during the winter sample period versus the summer sample period, or simply the fact that customers have less ability or desire to reduce their electricity consumption during the winter versus the summer. Ongoing additional data collection efforts over a longer time period could resolve this issue.

Tables 9.1 to 9.3 present the estimates of models (1) to (3) for the AE customers for the full sample period. These results show sizeable and very precisely estimated hourly average treatment effects for all dynamic pricing tariffs. For example, the hourly average treatment effect of an HP warning is 17.5 percent and the average treatment effect of CPP event for both CPP and CPR customers is 16.1 percent. Consistent with the same modeling results for R customers, the hourly average treatment effect of CPP event for CPP customers is almost 3 times the value of the hourly average treatment effect of CPP event for a CPR customer, 24.5 percent versus 8.46 percent, respectively. These results provide further evidence for the existence of a sizeable "option to quit" associated with CPR tariff. A comparison of the hourly average treatment effect of an HP warning to the hourly average treatment effect of a CPP event for CPP customer provides even stronger evidence of no "cost of taking action" associated with hourly pricing. The HP warning hourly average treatment effect is roughly 70 percent of the CPP event hourly average treatment effect for CPP customers. The impact of a smart thermostat for AE customers is also consistent with the impact of a smart thermostat for R customers, although the absolute value and precision of the estimated increase in the absolute value of the hourly average treatment effects are larger for AE customers. Once again, the largest increase in the absolute value of the hourly average treatment effect associated with a smart meter is for CPP customers.

Table 10.1 to 10.3 and 11.1 to 11.3 present estimates of the same models as Tables 9.1 to 9.3 for the summer and winter samples, respectively. Similar to the R customer results, the average treatment effects for the summer months are similar to those for the full sample, except for the HP customers. The HP customers have significantly smaller hourly average treatment effects for an HP warning during the summer months relative to the full sample. Different from the R customer results, the winter sample hourly average treatment effects estimation results are

larger in absolute value and generally more precisely estimated, particularly for the HP customers. This result is consistent with the fact that AE customers use electricity for heating and therefore many have greater opportunities relative to R customers to reduce their electricity consumption during CPP periods and HP warning periods during the winter months.

Tables 12.1 to 12.3 estimate model (4) for the RAD customers for the full sample and the summer sample and winter sample, separately. Because they are low-income, RAD customers were only allowed to be treated with the CPR dynamic pricing tariff. For all three samples, the hourly average treatment effect associated with a CPP event for CPR customers is substantially larger than the hourly average treatment effect associated with a CPP event for an R or AE customer paying according to a CPR tariff. This increase in the magnitude of the hourly average treatment could be partially explained by the larger rebate paid to RAD customers on the CPR tariff versus R or AE customers on the CPR tariff. However, the RAD hourly average treatment effect is almost twice the hourly average treatment effect of a CPP event for R or AE customers on the CPR tariff, even though the RAD customer rebate price is approximately 30 to 38 percent higher than the rebate price for R or AE CPR customers. This result is consistent with other factors besides the larger rebate price explaining the much larger hourly average treatment effect of a CPP event for RAD customers on the CPR tariff. For the full sample, results, I also find that RAD customers with a smart thermostat have a noticeably larger in absolute value hourly average treatment effect.

Tables 13.1 to 13.3 estimate model (4) for the RAD-AE customers for the three samples. These low-income consumers also have a substantially higher hourly average treatment effect associated with a CPP event for customers on the CPR tariff than regular AE customers. For example, for the full sample RAD-AE customer results the average treatment effect is 12

percent, whereas for the full sample of AE customers shown in Table 9.2, the hourly average treatment effect of a CPP event for customers on the CPR tariff is 8.5 percent. For the same reasons as described above for the RAD households, this increase in the hourly average treatment effect for RAD-AE versus AE customers on the CPR tariff does not appear to be completely explained by ratio of the rebate prices set for these two types of customers. These results are also consistent with a smart meter increasing the absolute value of the magnitude of the treatment effect for a CPP day for RAD-AE customers on a CPR tariff. However, none of these parameter estimates are very precisely estimated. This result is likely to be due to the fact that there is less than 20 RAD-AE customers in the treatment group and a very small number of them have a smart thermostat, so that it is very difficult to precisely estimate the impact of a smart thermostat given the available data. The larger in absolute value average treatment effect from a CPP event for RAD and RAD-AE customers on CPR tariffs versus R and AE customers on these same tariffs is very encouraging for the prospect of dynamic pricing benefitting low-income consumers.

5. Implications of Experimental Results for the Design of Dynamic Pricing Programs

The results of the PowerCentsDC Program experiment demonstrates that all three dynamic pricing programs provide stable, predictable and sizeable demand reductions in response to CPP events and HP warnings for both R and AE customers. For low-income R and AE customers on the CPR tariff, a CPP event yields a larger hourly average treatment effect than the same tariff yields for R and AE customers. For all four types of customers and all dynamic pricing programs, having a smart thermostat predicts an increase in the absolute value of the treatment effect. Smart thermostats appear to implement the largest increase in the absolute

value of the hourly average treatment effect for customers on CPP tariffs, particularly AE customers.

These experimental results also provide clear answer to several of the major challenges associated with the design of dynamic pricing programs. First, there does not appear to be an economically significant "cost of taking action" to reduce demand associated with hourly pricing. The ratio of the hourly average treatment effect associated with an HP warning to the hourly average treatment effect of CPP event for CPP customers appears to be completely explained by the ratio of average price paid by HP customers during an HP warning period relative to the average price paid by CPP customers during a CPP event. One explanation for this result is shown in the graph of the hourly prices in Figure 4. Hours with high prices tends to be clustered within the day and during the same time intervals covered by CPP events. This is particularly the case during the summer months. For example, a number of the CPP events during sample period contained at least two HP warning periods.

The experimental results also confirm the existence of a substantial "option to quit" associated with the CPR tariff for both R and AE customers. For the full sample, summer sample, and winter sample results, despite the fact the marginal prices for the CPP period for the CPP tariff and CPR tariff (assuming a rebate was being paid) were approximately equal, the hourly average treatment effect associated with a CPP event for the CPR tariff was ½ to 1/3 the size of the hourly average treatment associated with a CPP event for the CPP tariff for the same customer type. These results suggest a substantial shortcoming to the CPR tariff in achieving the goal of a stable, predictable and sizeable demand reduction at least cost.

The experimental results demonstrated that the presence of a smart thermostat increased the absolute value of the hourly average treatment effect for all customer types and pricing plans.

However, the CPP tariff was shown to experience the highest boost to the hourly average treatment effect from a smart thermostat. Although further information must be collected on the costs of installing and operating smart thermostats in order to evaluate the discounted present value of the costs saving from installing a smart thermostat, one conclusion is possible from these results. The greatest cost savings will come from combining a smart thermostat with CPP pricing.

A final encouraging result from the experiment is that the average hourly treatment effect associated with low-income customers was consistently larger than the average hourly treatment effect associated the same dynamic pricing tariff for higher income customers. Combining this result with results for the three pricing programs for R and AE customers suggests that an HP or CPP pricing plan for low-income consumers that mitigates the bill risk concerns of these tariffs for low-income households could produce larger hourly average treatment effects. For example, an HP or CPP plan that provides low-income households with a monthly credit on their electricity bill, that if unused in one month rolls over to the next month, could yield average hourly treatment effects larger than those achieved for R and AE customers.

References

Arrellano, M. (1987) "Computing Robust Standard Errors for Within-Groups Estimators," *Oxford Bulletin of Economics and Statistics*, 49, 431-434.

Wolak, F.A. (2006) "Residential Customer Response to Real-Time Pricing: The Anaheim Critical-Peak Pricing Experiment, available a.

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Table 1: Program Participants

Active Participants	By Usage
Rate Code	**Count**
All Electric	215
Not All Electric	642
Total	**857**

Active Participants	By Income Level
Income Level	**Count**
Low-Income	118
Non Low-Income	739
Total	**857**

Active Participants	By Rate Code
Rate Code	**Count**
Control	388
CPP	236
CPR	387
HP	234
Total	**1245**

Table 2: Increasing Block Prices for Control Group and CPR Customers

Price Plan	Summary	Tier 1 Size (kWh)	Tier 1 Price per kWh	Tier 2 kWh	Tier 2 Price	Tier 3 kWh	Tier 3 Price
R	Applies to most residential customers	0-400	12.9¢	401+	14.7¢	–	–
AE	Customers with electric heating	0-400	12.8¢	401+	14.7¢	–	–
RAD	Limited income customers	0-400	5.4¢	401+	14.8¢	–	–
RAD-AE	Limited income with electric heating	0-400	5.4¢	401-700	12.3¢	701+	14.6¢

Table 3: Block Prices and CPP Event Prices for CPP Customers

Price Plan	Summer Tier 1	Summer Tier 2	Summer Tier 1 Critical Peak	Summer Tier 2 Critical Peak	Winter Tier 1	Winter Tier 2	Winter Tier 1 Critical Peak	Winter Tier 2 Critical Peak
R	12.3¢	14.1¢	77.1¢	78.9¢	11.7¢	12.6¢	72.2¢	73.1¢
AE	12.3¢	14.2¢	75.1¢	76.9¢	11.6¢	12.1¢	70.2¢	70.7¢

Table 4: Rebate Prices for CPR Customers

Price Plan	Summer Tier 1 Critical Peak	Summer Tier 2 Critical Peak	Summer Tier 3 Critical Peak	Winter Tier 1 Critical Peak	WInter Tier 2 Critical Peak	WInter Tier 3 Critical Peak
R	-63.9¢	-62.1¢	–	-63.9¢	-62.1¢	–
AE	-64.9¢	-63.1¢	–	-64.9¢	63.1¢	–
RAD	-82.1¢	-79.0¢	–	-82.1¢	-79.0¢	–
RAD-AE	-88.0¢	-89.0¢	-85.0¢	-62.0¢	-61.4¢	-60.4¢

Table 5.1: Summertime Critical Peak Days and Actual Maximum Daily Temperatures

Critical Peak Day	Actual Max Temp (°F)	Time of High Temp
Tuesday, August 5	86	1:00 pm
Wednesday, August 6	94	4:00 pm
Monday, August 18	93	4:00 pm
Tuesday, August 19	94	4:00 pm
Wednesday, September 3	95	3:00 pm
Friday, September 4	95	4:00 pm

Note: CPP period is from 2 pm to 6 pm.

Table 5.2: Wintertime Critical Peak Days and Actual Minimum Daily Temperatures

Critical Peak Day	Actual Min Temp (°F)	Time of Low Temp	Mean Temp during Critical Peak (°F)
Thursday, January 15	17.1	12:00 am	22.9
Friday, January 16	10.9	12:00 am	12.5
Wednesday, February 4	23.0	12:00 am	28.0

Note: CPP period is from 6 am to 8 am and 6 pm to 8 pm

Table 6.1: Model 1 Results for R Customers (Full Sample)

Parameter	Estimate	Std. Error	t Value
HP_PER	-0.03003	0.01110	-2.70
CPP_PER	-0.09087	0.00731	-12.43

Table 6.2: Model 2 Results for R Customers (Full Sample)

Parameter	Estimate	Std. Error	t Value
HP_PER	-0.03010	0.01110	-2.71
CPP_R	-0.13030	0.00939	-13.88
CPR_R	-0.05315	0.00923	-5.76

Table 6.3: Model 3 Results for R Customers (Full Sample)

Parameter	**Estimate**	**Std. Error**	**t Value**
HP_PER	-0.04788	0.01262	-3.80
CPP_R	-0.10636	0.01034	-10.29
CPR_R	-0.05021	0.01059	-4.74
HP_PER*THERM	-0.01799	0.01285	-1.40
CPP_R*THERM	-0.11060	0.02001	-5.53
CPR_R*THERM	-0.00996	0.01771	-0.56

Standard Errors computed using heterosceasticity and autorcorrelation consistent covariance matrix from Arrellano (1987).

Table 7.1: Model 1 Results for R Customers (Summer Sample)

Parameter	Estimate	Std. Error	t Value
HP_PER	-0.02574	0.01312	-1.96
CPP_PER	-0.08892	0.00810	-10.98

Table 7.2: Model 2 Results for R Customers (Summer Sample)

Parameter	Estimate	Std. Error	t Value
HP_PER	-0.02576	0.01312	-1.96
CPP_R	-0.12529	0.01031	-12.15
CPR_R	-0.05349	0.01021	-5.24

Table 7.3: Model 3 Results for R Customers (Summer Sample)

Parameter	**Estimate**	**Std. Error**	**t Value**
HP_PER	-0.05149	0.01488	-3.46
CPP_R	-0.09653	0.01131	-8.54
CPR_R	-0.04819	0.01169	-4.12
HP*THERM	-0.03819	0.02679	-1.42
CPP_R*THERM	-0.13592	0.02197	-6.19
CPR_R*THERM	-0.01801	0.01947	-0.93

Standard Errors computed using heterosceasticity and autorcorrelation consistent covariance matrix from Arrellano (1987).

Table 8.1: Model 1 Results for R Customers (Winter Sample)

Parameter	Estimate	Std. Error	t Value
HP_PER	-0.00753	0.01817	-0.41
CPP_PER	-0.05542	0.01453	-3.81

Table 8.2: Model 2 Results for R Customers (Winter Sample)

Parameter	Estimate	Std. Error	t Value
HP_PER	-0.00753	0.01817	-0.41
CPP_R	-0.08600	0.01919	-4.48
CPR_R	-0.02815	0.01834	-1.54

Table 8.3: Model 3 Results for R Customers (Winter Sample)

Parameter	Estimate	Std. Error	t Value
HP_PER	-0.01427	0.02072	-0.69
CPP_R	-0.05617	0.02146	-2.62
CPR_R	-0.03274	0.02113	-1.55
HP*THERM	-0.02564	0.03789	-0.68
CPP_R*THERM	-0.12609	0.04059	-3.11
CPR_R*THERM	0.01561	0.03575	0.44

Standard Errors computed using heterosceasticity and autorcorrelation consistent covariance matrix from Arrellano (1987).

Table 9.1: Model 1 Results for AE Customers (Full Sample)

Parameter	Estimate	Std. Error	t Value
HP_PER	-0.17501	0.02350	-7.45
CPP _PER	-0.16162	0.01433	-11.28

Table 9.2: Model 2 Results for AE Customers (Full Sample)

Parameter	Estimate	Std. Error	t Value
HP_PER	-0.17514	0.02350	-7.45
CPP_AE	-0.24578	0.01841	-13.35
CPR_AE	-0.08462	0.01781	-4.75

Table 9.3: Model 3 Results for AE Customers (Full Sample)

Parameter	Estimate	Std. Error	t Value
HP_PER	-0.16161	0.02657	-6.08
CPP_AE	-0.17026	0.02248	-7.57
CPR_AE	-0.07833	0.02071	-3.78
HP*THERM	-0.05260	0.04824	-1.09
CPP_AE*THERM	-0.19146	0.03269	-5.86
CPR_AE*THERM	-0.01949	0.03266	-0.60

Standard Errors computed using heterosceasticity and autorcorrelation consistent covariance matrix from Arrellano (1987).

Table 10.1: Model 1 Results for AE Customers (Summer Sample)

Parameter	Estimate	Std. Error	t Value
HP_PER	-0.05787	0.02686	-2.15
CPP_PER	-0.12629	0.01439	-8.78

Table 10.2: Model 2 Results for AE Customers (Summer Sample)

Parameter	Estimate	Std. Error	t Value
HP_PER	-0.05799	0.02686	-2.16
CPP_AE	-0.22356	0.01841	-12.14
CPR_AE	-0.03644	0.01788	-2.04

Table 10.3: Model 3 Results for AE Customers (Summer Sample)

Parameter	**Estimate**	**Std. Error**	**t Value**
HP_PER	-0.05069	0.03054	-1.66
CPP_AE	-0.13325	0.02240	-5.95
CPR_AE	-0.01901	0.02073	-0.92
HP*THERM	-0.02749	0.05417	-0.51
CPP_AE*THERM	-0.23122	0.03265	-7.08
CPR_AE*THERM	-0.05452	0.03284	-1.66

Standard Errors computed using heterosceasticity and autorcorrelation consistent covariance matrix from Arrellano (1987).

Table 11.1: Model 1 Results for AE Customers (Winter Sample)

Parameter	Estimate	Std. Error	t Value
HP_PER	-0.32245	0.03670	-8.79
CPP_PER	-0.04279	0.03048	-1.40

Table 11.2: Model 2 Results for AE Customers (Winter Sample)

Parameter	Estimate	Std. Error	t Value
HP_PER	-0.32251	0.03670	-8.79
CPP_AE	-0.21594	0.03957	-5.46
CPR_AE	0.02163	0.03772	0.57

Table 11.3: Model 3 Results for AE Customers (Winter Sample)

Parameter	**Estimate**	**Std. Error**	**t Value**
HP_PER	-0.29384	0.04112	-7.15
CPP_AE	-0.14696	0.04896	-3.00
CPR_AE	-0.04459	0.04431	-1.01
HP*THERM	-0.11975	0.07743	-1.55
CPP_AE*THERM	0.07566	0.07033	1.08
CPR_AE*THERM	-0.06764	0.06859	-0.99

Standard Errors computed using heterosceasticity and autorcorrelation consistent covariance matrix from Arrellano (1987).

Table 12.1: Model 4 Results for RAD Customers (Full Sample)

Parameter	Estimate	Std. Error	t Value
CPR_PER	-0.13609	0.01768	-7.70
CPR_PER*THERM	-0.04193	0.02039	-2.10

Table 12.2: Model 4 Results for RAD Customers (Summer Sample)

Parameter	Estimate	Std. Error	t Value
CPP_PER	-0.10009	0.01840	-5.44
CPP_PER*THERM	-0.04727	0.04841	-0.98

Table 12.3: Model 4 Results for RAD Customers (Wiuter Sample)

Parameter	Estimate	Std. Error	t Value
CPP_PER	-0.13171	0.03451	-3.82
CPP_PER*THERM	-0.05261	0.08962	-0.59

Standard Errors computed using heterosceasticity and autorcorrelation consistent covariance matrix from Arrellano (1987).

Table 13.1: Model 4 Results for RAD-AE Customers (Full Sample)

Parameter	Estimate	Std. Error	t Value
CPP_PER	-0.1204	0.06173	-1.96
CPP_PER*THERM	-0.0227	0.01595	-1.36

Table 13.2: Model 4 Results for RAD-AE Customers (Summer Sample)

Parameter	Estimate	Std. Error	t Value
CPP_PER	-0.14308	0.10514	-1.36
CPP_PER*THERM	-0.05561	0.05523	-1.01

Table 13.3: Model 4 Results for RAD-AE Customers (Winter Sample)

Parameter	Estimate	Std. Error	t Value
CPP_PER	-0.07944	0.04695	-1.69
CPP_PER*THERM	-0.07661	0.12336	-0.62

Standard Errors computed using heterosceasticity and autorcorrelation consistent covariance matrix from Arrellano (1987).

Figure 1: Distribution of PowerCentsDC Program Participants (District and Ward Boundaries in Orange)

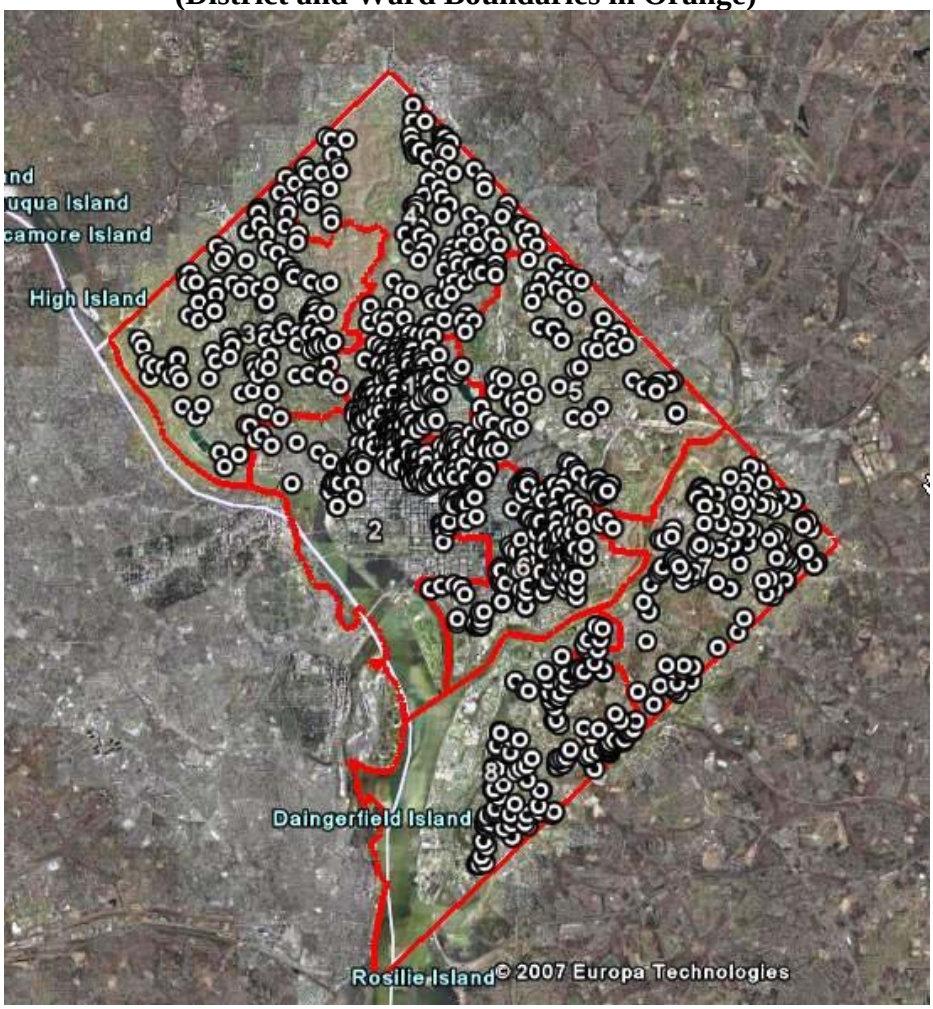

Figure 2: Interval Meter and Smart Thermostat

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Figure 3(a): Electric Usage Report for CPR Customer

PowerCentsDC

Electric Usage Report

Account

Rate Information

Rate code: **CPR-R**
Critical Peak Rebate (CPR) - Residential

Price Definitions

CPR Reduction
Rebate for reduced usage during critical peak periods.

- 6am - 8am & 6pm - 8pm (Nov - Feb)
- 2pm - 6pm (Jun - Sep)

Above 400 KWH
Price for usage in excess of 400 KWH

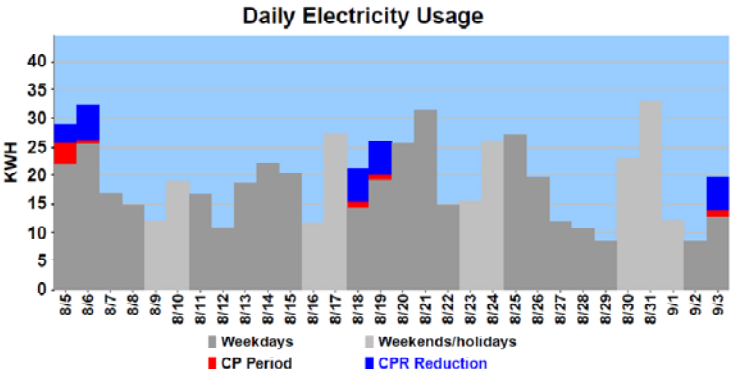
31 to 400 KWH
Price for usage 31 KWH up to 400 KWH.

Minimum charge
Up to first 30 kWh.

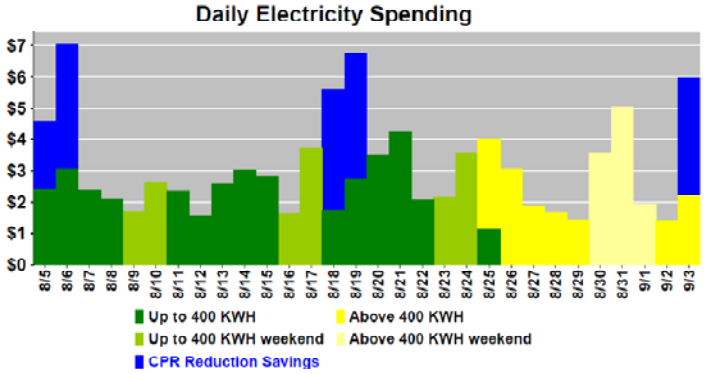
Critical peak periods during August 5, 2008 - September 3, 2008

August 05, 06, 18, 19, September 03

Services for August 5, 2008 to September 3, 2008



To reduce your next electric bill, reduce usage during critical peak periods (2pm to 6pm).



Electric Bill Summary

	Services for Aug 5 to Sep 3			Generation Services		Distribution Services		Transmission Services		Current Charges this period
	Price level	KWH Used	Per KWH	per KWH		per KWH**		per KWH		
	CPP Reduction	-26.95	-$0.66	-$0.66000	-$17.79					-$17.79
Usage	Above 400 KWH	158.81	$0.14	$0.10815	$17.18	$0.02796	$4.44	$0.00413	$0.66	$22.28
	31 to 400 KWH	370.00	$0.12	$0.10815	$40.02	$0.00945	$3.50	$0.00413	$1.53	$45.05
	0 to 30 kWh	30.00	$0.01	*Included in minimum charge*		$0.00945	$0.28	*Included in minimum charge*		$0.28
	Energy charge	**558.81**			**$39.41**		**$8.22**		**$2.19**	**$49.82**
	Customer/Min charge				$3.24		$2.00		$0.12	$5.36
	*Other charges****	558.81			$0.85		$4.59			$5.44
	Total Charges	**559**			**$43.50**		**$14.81**		**$2.31**	**$60.62**

* Totals may not add up due to rounding. ** Average price per KWH *** This may be displayed as multiple lines on the bill.

Figure 3(b): Electric Usage Report for CPP Customer

PowerCentsDC

Electric Usage Report

Account

Rate Information

Rate code: **CPP-R**
Critical Peak Pricing - Residential

Price Definitions

Critical Peak Pricing (CPP)
Price for usage during critical peak periods.

- 6am - 8am & 6pm - 8pm (Nov - Feb)
- 2pm - 6pm (Jun - Sep)

Non-CPP Usage
Price for usage outside of critical peak periods.

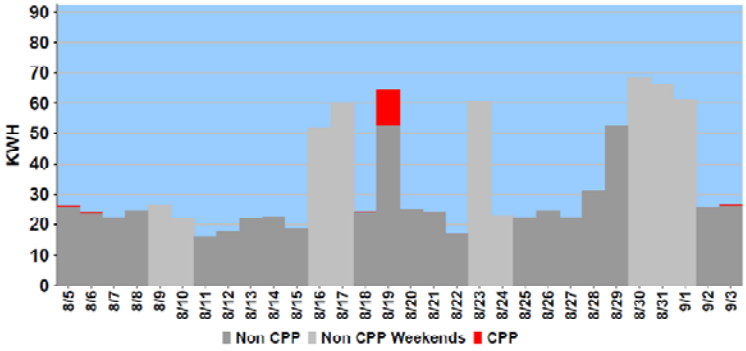
Minimum charge
Up to first 30 kWh.

Critical peak periods during August 5, 2008 - September 3, 2008

August 05, 06, 18, 19, September 03

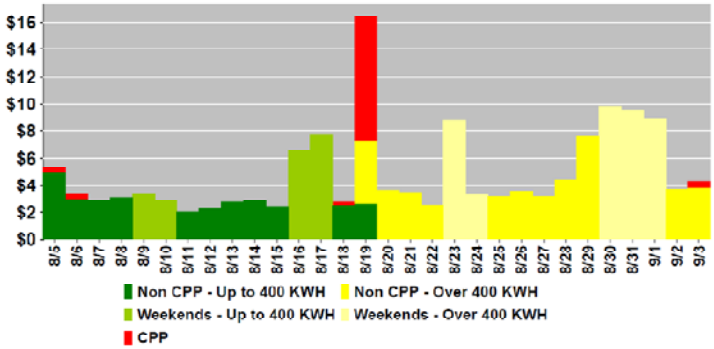
Services for August 5, 2008 to September 3, 2008

Daily Electricity Usage



To reduce your next electric bill, reduce usage during critical peak periods (2pm to 6pm).

Daily Electricity Spending



Electric Bill Summary

Services for Aug 5 to Sep 3				Generation Services		Distribution Services		Transmission Services		Current Charges this period
	Price level	KWH Used	Per KWH	per KWH		per KWH**		per KWH		
Critical Peak		13.98	$0.78	$0.75000	$10.49	$0.02575	$0.36	$0.00429	$0.06	$10.91
Non-CPP	Above 400 kWh	580.07	$0.13	$0.10217	$59.27	$0.02796	$16.22	$0.00413	$2.40	$77.89
	31 to 400 kWh	369.10	$0.12	$0.10217	$37.71	$0.00945	$3.49	$0.00413	$1.52	$42.72
	Non-CPP in first 30	29.48	$0.11	$0.10217	$3.01	$0.00945	$0.28	*Included in minimum charge*		$3.29
	Energy charge	**992.63**			**$110.48**		**$20.35**		**$3.98**	**$134.81**
	Customer/Min charge						**$2.00**		**$0.12**	**$2.12**
	*Other charges****	992.63			$1.52		$8.15			**$9.67**
	Total Charges	**993**			**$112.00**		**$30.50**		**$4.10**	**$146.60**

* Totals may not add up due to rounding. ** Average price per KWH *** This may be displayed as multiple lines on the bill.

Figure 3(c): Electric Usage Report for HP Customer

PowerCentsDC

Electric Usage Report

Services for August 5, 2008 to September 3, 2008

Account

Rate Information

Rate code: **HP-R**
Hourly Pricing - Residential

Price Definitions

High Cost: Hours when the generation price is greater than or equal to $0.23 per KWH

Medium Cost: Hours when the generation price is from $0.11 per KWH to $0.22 per KWH

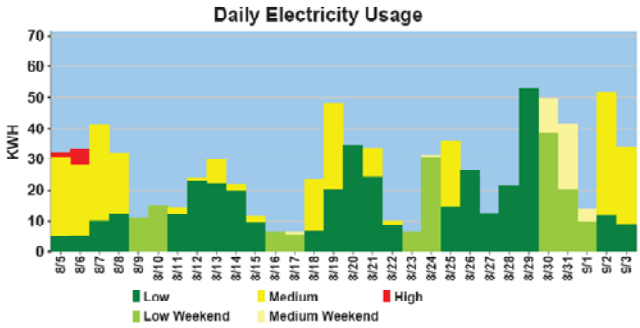
Low Cost: Hours when the generation price is less than or equal to $0.10 cents

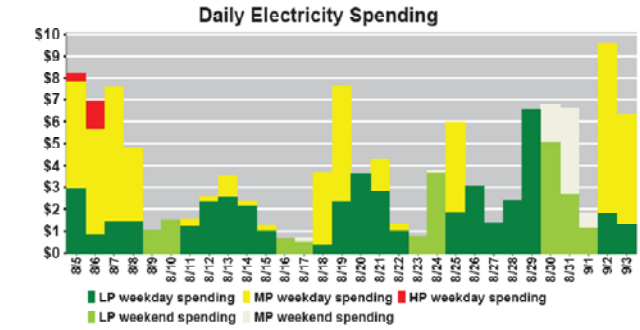
Days with high prices during August 5, 2008 - September 3, 2008

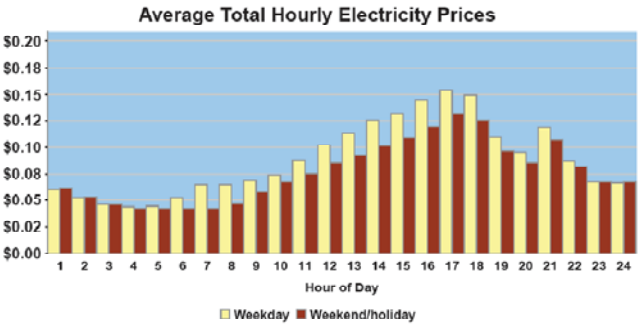
August 05, 06

The total Hourly prices are shown in the chart to the right for the average weekday and weekend/holiday for this billing period.

To reduce your bill, avoid using energy when prices are high. For tips on saving energy or more detail on hourly prices, see www.PowerCentsDC.org.







Electric Bill Summary

	Services for August 5 to September 3			Generation Services	Distribution Services	Transmission Services	Current Charges this period
	Price level	KWH	Per KWH**				
Usage	High	6.85	$0.23 and above	$1.58	$0.06	$0.02	$1.66
	Medium	293.46	$0.11 - $0.22	$48.86	$5.26	$1.11	$55.23
	Low	505.50	$0.10 and below	$39.25	$9.81	$2.08	$51.14
	Energy charge	805.81		$89.69	$15.13	$3.21	$108.03
	Customer/Min charge				$2.00	$0.12	$2.12
	*Other charges**	805.81		$1.23	$6.61		$7.84
	Total Charges	806		$90.92	$23.74	$3.33	$117.99

*This may be displayed as multiple lines on the bill

**For generation prices only

Figure 4: Hourly Prices for PowerCentsDC HP Customers