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The Effect on Electricity Consumption of the Commonwealth Edison Customer Applications Program: Phase 2 Final Analysis

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This is an EPRI Technical Update report. A Technical Update report is intended as an informal report of continuing research, a meeting, or a topical study. It is not a final EPRI technical report.

NOTE

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Product Description

This report describes the final Phase 2 analysis of the effects on residential customers' energy consumption patterns of Commonwealth Edison's (ComEd's) Customer Application Program (CAP).

Background

This report presents the findings of a pilot, implemented by Commonwealth Edison, to improve the understanding of how advanced metering infrastructure (AMI) can be used to influence residential electricity consumption. It is part of a series of Electric Power Research Institute (EPRI) studies to help the power industry exploit technological advances and induce changes regarding when and how consumers use electricity in order to increase reliability, reduce costs, and promote sustainable economic growth.

Objectives

The final report will interest those concerned with the efficacy with which smart grid technologies facilitate DR. AMI-enabled pricing structures and technologies can yield system-wide distribution benefits when they provide, at lower cost, services comparable to those that could otherwise be provided only by supply-side resources. These benefits include reduced costs of generation and transmission, lower distribution capital and operating costs, and reduced siting and environmental costs associated with supply-side technologies. DR might also provide flexibility that could help planners ensure reliable delivery with limited resources. Smart grid technologies might facilitate DR by giving customers information to help them make effective consumption decisions and offer automated ways to make those decisions. The ComEd project provides data to assess the extent to which smart grid technologies actually do induce DR.

Approach

This report describes the findings from EPRI's analysis of ComEd's CAP. It updates and expands on the interim findings from the Phase 1 analysis by using a full year's worth of data on electricity usage and prices for participants, as well as data collected as part of a survey of participants in the pilot. The additional data were used to update tests of several hypotheses and to test additional ones that could not be addressed using the limited data available for the Phase 1 analysis.

Results

This analysis determines the extent to which residential customers' consumption of electricity is affected by various combinations of dynamic rates, enabling technologies, and other inducements. The CAP implemented 27 experimental treatments to test for impacts singularly and in combination. The Phase 1 analysis (EPRI report 1022703) was based on data from the first three months of the pilot (June through August 2010) and was considered preliminary.

This Phase 2 report confirms that none of the treatments resulted in any significant change in average customer usage, even when customers paid an additional $1.74/kWh for electricity. However, an important subset of customers facing dynamic rates—about 10%—responded to elevated event-day prices by reducing usage. These event-responders exhibited load reductions in excess of 20% for critical peak pricing and around 14% for peak-time rebate and day-ahead real-time pricing. It also appears that event load reductions were undertaken by some customers on the other rates tested, despite there being no financial advantage to doing so. This might be the result of ComEd's education and event notification to CAP participants that raised awareness of supply cost on certain days of the year.

Applications, Value, and Use

Utilities recognize the need to provide better information to customers about the cost of supply and the time-specific usage levels. Customers are becoming aware of new technologies that make modifying usage easier to accomplish, reducing electricity costs. Many regulators are pressing utilities to fully use a range of DR solutions and offer customers choices in how they purchase electricity. AMI and smart metering can play an important role in meeting these needs, but only if the benefits enabled are well defined and widely accepted. The findings described in this report make a substantial contribution toward defining the benefits attributable to AMI.

Keywords

Advanced metering infrastructure
Demand response–enabling technologies
Dynamic pricing
Inclining block and time-of-use rates
In-home displays
Opt-in and opt-out program recruitment

Abstract

This report presents the findings of a pilot, implemented by Commonwealth Edison, to improve the understanding of how AMI metering influences residential electricity consumption. The Customer Application Program (CAP) is notable for its novel design and scale, and its extensive scope. Participants were engaged using the first large-scale application to an electricity pilot of automatic, *opt-out* subscription. The CAP involved approximately 8,000 residences of a population of 130,000 AMI-metered customers in the greater Chicago area, randomly assigned to a variety of treatments. The treatments span five diverse rate structures and several different enabling technologies constructed to test effects individually, and in combination. Additional treatments involve alternative levels of education and free verses subsidized provision of enabling technologies.

Several analyses were undertaken to identify statistically significant impacts attributable to the treatments. Most treatments exhibited no statistically significant differences in the overall average usage compared to the control group. However, important and significant findings emerged from the more comprehensive analyses that were undertaken. First, the results present the possibility that event notification contributes to reductions in event-hour usage, even in the absence of event-based pricing. This raises the prospect that customer education and event notification could play a role in obtaining customer demand management. This issue merits additional research, as the findings from this study were not widespread across rate treatments. Second, a subset of dynamic rate (DA-RTP, CPP, PTR) customers, referred to as event-responders and which comprise 9-12 percent of all participants, were identified that reduced load by 20 percent or more during event hours. The largest and most consistent usage reductions, in the dynamic rate subset, came from CPP customers. This level of response comports with the findings of other pilots that involve similar treatments, but was masked by the large number of the treatment non-responders.[1] An *opt-out* recruitment strategy by itself does not appear to encourage a greater treatment response level than *opt-in* pilots report.

[1] For a summary of the load reduction impacts of rate technology pilots see: Faruqui, A., Hledic, R., Sergici, S. Rethinking Prices: January 2010. The Changing Architecture of Demand Response in America. Public Utilities Fortnightly.

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Section 1: Introduction

This report describes the findings of the Electric Power Research Institute's (EPRI) evaluation of the impacts of the Commonwealth Edison (ComEd) Customer Application Program (CAP). EPRI conducted an independent and comprehensive assessment of the impacts and implications of the CAP pilot as part of its Smart Grid Demonstration project. The evaluation involves quantifying how CAP customers modified their electricity usage levels and patterns in response to pilot applications (treatments in the experimental sciences vernacular), which are comprised of different rate structures, enabling technologies, and other influences enacted through the pilot. This Phase 2 report extends the analyses conducted in Phase 1, which focused on the CAP impacts over the summer months of 2010, using a full year of load data and the results of a survey administered to CAP participants.[2] For the sake of comprehension, CAP design, method, and data requirements presented in the Phase 1 report are reproduced herein.

Description of the CAP Pilot Applications

The CAP pilot was designed to produce information that would allow analysts to quantify the impact of price structures, enabling technologies, pricing plans, and educational strategies that are facilitated by advanced metering infrastructure (AMI). AMI allows ComEd to record customers' electricity consumption on an hourly basis and provide customers with readily available and timely access to information on their electricity usage online. The pilot was designed to reveal the extent to which customers change their pattern and level of electricity consumption when AMI-enabled pricing and technologies are deployed.

The CAP pilot involves five rate treatments (or applications) that differ in the temporal character of the prices that participating customers pay for electricity, and the enabling technology applications that deliver information to customers.

For the CPP, DA-RTP, PTR, and TOU rates, the peak period is defined as 1:00 - 5:00 p.m. weekdays.

The rate applications differ structurally from the flat rate that most ComEd residential customers pay today, but in different ways. Specifically, the pilot's rates change:

[2] The main Phase 1 report (EPRI 1022703) and a separate volume appendix (EPRI 1022761) are available at EPRI.com. *The Effect on Electricity Consumption of the Commonwealth Edison Customer Application Program Pilot: Phase 1*. EPRI, Palo Alto, CA: 2011. 1022703. *The Effect on Electricity Consumption of the Commonwealth Edison Customer Application Program Pilot: Phase 1, Appendices*. EPRI, Palo Alto, CA: 2011. 1022761.

- Hourly and daily, conveyed through a new hourly price schedule issued each day (day-ahead real-time pricing (RTP)).
- By combining DA-RTP with event-specific prices whereby the price of electricity increases by $1.74 per kWh (critical peak pricing (CPP)) or the customer is eligible for credits of $1.74 per kWh for load reduced during the event (peak-time rebate (PTR))
- Diurnally, according to a fixed time-of-use (TOU) schedule
- According to the level of each customer's monthly consumption (inclining block rate, (IBR)).

A control group of AMI-metered flat-rate customers serves as the basis for comparison of usage behavior with the treatment customers who pay the CAP rates. Participants in the control group pay the applicable ComEd standard tariff rate, which distinguishes according to building type (single or multi-family) and electric or non-electric space heating.

CAP also involves different enabling technology applications to deliver information to customers. All participants were invited to sign up for eWeb service that provides access to detailed information about the participants billing data. Selected participants also have access to basic or advanced in-home displays (IHD), to a web-based information system, and to the means for regulating their household thermostat at times when load relief is needed. The simple IHD continuously displays information, extracted directly from the AMI meter, about household electricity usage, including both the current rate of energy usage and a historical comparison. Previous pilots that have deployed this technology report a wide range of customer responses, from no change to a 5 percent or greater overall reduction in electric consumption.[3]

The advanced IHD incorporates electricity usage information into a device that serves a variety of roles including internet access. The maintained hypothesis is that consumers with these devices are more likely to pay attention to usage information more often and readily and therefore respond to a greater extent.[4] An additional enabling technology application provides customers with a programmable and controllable thermostat to facilitate adjusting load to price changes.

Other treatments the CAP provides include additional applications involving: more education; a bill protection guarantee which ensures that participants will pay no more under the pilot than they would in the absence of it; and a requirement for partial payment for some enabling technologies.

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[3] *Guidelines for Designing Effective Energy Information Feedback Pilots: Research Protocols.* EPRI, Palo Alto, CA: 2010. 1020855.

[4] A hypothesis is a concise and specific statement of impact constructed to serve as the basis for measuring the level of observed impact.

Structure of the Design

A randomized design was used to select which customers (approximately 8,000 in the AMI footprint of about 130,000) would participate in the CAP and to assign them to an application, or to the control group. The use of a randomized design comports with accepted social science protocols for isolating and attributing significant impacts to treatments in experiment settings.[5] Furthermore, it defines a methodology for estimating the significance of impacts, which are differences from those of the control group measured as one of the following: total energy consumed during the pilot, peak-period load or maximum demand, particularly on event days, and other measures of usage.

A unique and important feature of the CAP is that it employs an *opt-out* recruitment design whereby customers chosen randomly to participate were automatically enrolled in the CAP and informed of their rate, technology, or other treatment (or combination thereof) prior to the commencement of the pilot (April-May 2010). The customers enrolled remain in the program unless they take action to opt out. ComEd adopted a systematic and comprehensive set of protocols designed to manage the customer experience in ways that were expected to reduce opt-outs and increase satisfaction with the pilot experience.

ComEd employed the *opt-out* pilot design for both practical and research purposes. ComEd designed the CAP over two years, but implemented it in very short order in 2010. The experience from other similarly constructed pilots suggested that recruiting volunteers would require several months, result in high costs, or both, to achieve the participation level required to produce statistically significant results. Conversely, an *opt-out* deployment could be accomplished in relatively short order, and possibly at a lower cost.

The traditional *opt-in* recruitment process results in all participants being volunteers. Tests can still be conducted to determine application impact differences and their significance. However, extending the result to the population as a whole is not straightforward, because it requires establishing what distinguishes volunteers, identifying them in the general population, and forecasting the likely enrollees in a full-scale rollout of the applications. In contrast, because CAP *opt-out* customers are representative of the general population, the pilot results can be used to make inferences about the full population impacts, as long as the dropout rate is low.

Objectives of the Analysis

The primary objective of the Phase 2 evaluation of the CAP is to determine how customers' patterns of energy consumption are affected by rate structures and prices, various behavioral factors (e.g., education and interaction with web-based information), and various enabling technology applications (e.g., basic and advanced in-home displays and programmable controllable thermostats). An

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[5] EPRI 1020855.

additional objective is to estimate how the entire ComEd residential population would respond to similar pricing, behavioral factors, and technologies.

EPRI has conducted the CAP evaluation in two stages. The first stage, which comprised the Phase 1 report, involved evaluating data from June through August of 2010.[6] The primary goal of that study was to estimate and report the 2010 summer months' load changes associated with the various price applications or treatments, with special attention paid to Day-Ahead Real-Time Pricing (DA-RTP), Critical Peak Pricing (CPP), and Peak-Time Rebate (PTR), all of which feature prices that vary each hour.[7] The CAP pilot imposed higher PTR and CPP payouts and rates, respectively, six times during the period covered by the Phase 1 analysis. Analysis of an additional event, which occurred in late September 2010, is included in this report.

The analysis described in this report applies to the entire year's data, supplemented with survey data collected to characterize participants' household and demographic circumstances, as well as their perceptions of various aspects of their CAP experience.

The Approach to the Analysis

Several analytical and statistical methods were used to conduct the components of this comprehensive evaluation of the CAP. Some are appropriate to examine differences in behavior among groups of customers (e.g., various treatment and control groups). Other methods facilitate an examination of the data at the individual customer level.

Since the experimental design of the pilot embodied a series of treatment and control groups, a logical first step is to apply methods of analysis of variance (ANOVA) to test for differences in the average electricity consumption of various types (e.g. average daily consumption, average hourly peak-period consumption, etc.) between treatment and control groups.

ANOVA tests identify significant aggregate differences in electricity consumption among treatment and control groups. Other methods are needed to sort out and separately quantify the various ways in which customers in the several dynamic pricing treatments (CPP, PTR and DA-RTP), respond to price level, differences in peak and off-peak prices, and other price structure effects. Several regression models are specified to estimate the effects on peak load during event and non-event days. Formal customer demand models are also specified to determine the extent to which event-day load impacts and customer price responsiveness square with economic theory.

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[6] The Effect on Electricity Consumption of the Commonwealth Edison Customer Application Program Pilot: Phase 1. EPRI, Palo Alto, CA: 2011. 1022703.

[7] Although CPP events, PTR events, and high RTP prices also occurred in September 2010, billing data for that month were not available early enough for the Phase 1 analysis.

Finally, several of the hypotheses require the identification of factors that affect some specific, discrete customer choices (e.g., decisions to *opt-out* of the pilot). Such issues are investigated by specification and estimation of several logistic discrete choice models.

Section 2: Research Agenda

This report describes the findings of EPRI's comprehensive evaluation of Commonwealth Edison's (ComEd) Customer Application Program (CAP) pilot. The evaluation involves the characterization and quantification of how CAP participants responded to the behavioral influences (applications) that were administered under experimental protocols throughout the pilot period from June 2010 to May 2011. Those applications reflect different rate structures, enabling technologies, and educational strategies.

Imposing rigor on the CAP pilot design, through randomized assignment of customers to applications and a control group, facilitates conducting statistical tests to establish whether observed differences among applications are significant or are instead the result of factors other than the applications. This rigor furthers the CAP goal of quantifying to a high degree of credibility how AMI technology can be used to further the efficient use of electricity by households.

Based on the design of the CAP pilot, 46 hypotheses were constructed describing the extent to which, or manner in which customers change their pattern and level of electricity consumption when they are exposed to the applications. Some hypotheses involve comparisons of the relative effects (and significance) of the applications themselves. Others seek to verify the effectiveness of processes and administrative features that were designed specifically for this pilot. The data collected during the pilot are used to perform statistical tests of these hypotheses and other analyses. The pilot includes additional characterizations and quantifications of load impacts to provide additional insight, as well as the estimation of electricity demand models at the aggregate and individual customer level.

Widely Deployed Applications

The CAP pilot involves five rate applications (i.e., treatments in experimental design) that differ in the temporal character of the prices that participating customers pay for electricity. These rates differ structurally from the flat rate that most ComEd residential customers pay today. Two of the treatments involve rate schedules that are set prior to the beginning of the pilot period, as follows:

- Under the time-of-use (TOU) rate schedule, prices ($/kWh) differ between the peak and off-peak periods of weekdays.

- Under the inclining block rate (IBR) schedule, prices ($/kWh) during each billing month vary according to the cumulative level of the individual customer's energy consumption.

The TOU and IBR rate schedules and price levels are established in advance and are in effect throughout the pilot period (June 2010- May 2011).[8] The IBR block sizes, which delineate the price changes as consumption increases in a billing month, were established individually for each participant based on historical consumption to achieve the revenue neutrality feature.[9] As a consequence, selection of customers in the AMI footprint to participate in IBR was conditioned on the availability of five years of billing records for the customer. As discussed in Section 5, this resulted in larger than average customers participating in the IBR application.

In each of the other three rate treatments, prices change daily to correspond to ComEd's forecasted supply conditions. A unique feature of the CAP dynamic rate treatments is that all customers in those treatment cells pay hourly prices patterned after day-ahead real-time prices. For two groups of CAP customers, however, the hourly rates differ for the period 1:00 to 5:00 p.m. on event days, which are the days when ComEd invokes its option to add a pre-determined and very high $1.74/kWh price to the DA-RTP prices during event hours. The characteristics of these three dynamic rate treatments are as follows:

Under the real-time pricing rate with day-ahead notice (DA-RTP), customers are charged hourly prices that reflect hourly wholesale market prices.[10]

Under the CPP rate, customers are charged higher prices (an additional $1.74 per kWh) during peak periods on event days (see sidebar). On non-event days, CPP customers face DA-RTP prices.[11]

Under the PTR treatment, customers are paid high rebates, or credits ($1.74 per kWh) for peak-period load reductions on event days.[12] Otherwise, PTR customers face DA-RTP prices.

<u>CAP Events</u>

The CPP and PTR rates employed in the CAP allow ComEd to raise prices above the prevailing DA-RTP prices. When ComEd foresees supply conditions that might jeopardize its ability to serve all loads reliably, it invokes a price overcall, which is referred to as an *event*. The tariff stipulates that events must:

- apply only to weekdays
- be declared (and all CAP customer so notified) a day in advance
- be in effect for four consecutive hours, 1:00 p.m. – 5:00 p.m.

The CAP made provision for six events to be invoked during June – August 2010, with an additional event called in September 2010.

[8] The price schedules specify the prices for kWh consumption, which include forecast generation costs and established T&D costs. Adjustments to these prices are made monthly to reflect actual energy supply costs and other surcharges. These adjustments are not posted in advance; but because they are generally less than 5 percent, they do not materially change the prices that customers act upon.

[9] Revenue neutrality is a property of a rate that assures that the customer pays the same amount under the CAP rate application as it would have under the standard ComEd tariff if the CAP energy usage is the same as the historical average. In the case of the IBR, revenue neutrality is imposed on a customer-specific basis.

[10] To maintain bill neutrality with the flat rate, the DA-RTP prices are adjusted each day so that the average matches the customer's preexisting flat rate.

[11] To maintain revenue neutrality, CPP prices are actually slightly lower than DA-RTP prices in non-event hours, so even if the customer does not reduce load during event hours it should pay no more, over the year, than it would have paid under the applicable conventional residential tariff.

[12] Load reductions are measured relative to a baseline load calculated for each PTR customer based on usage on prior non-event days.

CPP and PTR are different ways to expose customers to inducements to modify their usage behavior, beyond what the prevailing RTP price might have produced, during events. PTR offers a payment to reduce usage (a carrot), while CPP raises the price for the energy consumer, in effect penalizing usage (the stick).[13] Testing these pricing structures side-by-side, under rigorous experimental protocols, may clarify which produces the largest event-period load change.

A randomly selected control group of AMI-metered customers who pay the applicable conventional tariff rate serves as the basis for comparison of usage behavior with the treatment customers who face the CAP rates.[14]

CAP also involves deploying enabling technology applications that deliver current usage information to customers. These applications involve basic or advanced in-home displays (IHD), and the means (a programmable communicating thermostat (PCT)) for regulating their household thermostat at times when load relief is needed.[15] In addition, some of these applications were bifurcated to impose additional treatments such as requiring that the customer pay for part of the cost of the IHD device.

All customers were provided access to a web-based information system that portrays usage data in several ways, so the effect of this system cannot be separately established using ANOVA tests. However, the effect of a customer establishing an account with this system is evaluated as part of one of the CAP hypotheses.

Limited Applications

CAP also provides some differences in the level of educational information provided to customers regarding the use of the enabling technologies. Another treatment involves offering some customers a bill protection guarantee up-front.[16] Like the IHD partial payment requirement, this application was only applied on a limited basis.

A unique and important feature of the CAP is that it employed an *opt-out* recruitment design whereby customers were: a) chosen randomly from the larger population of AMI-enabled customers to participate in one of the treatment cells or as a control; b) enrolled automatically in the CAP; and c) informed

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[13] The very high CPP prices and PTR credits on event days are intended to reflect the capacity cost of peaking generation that may be avoided by consumers' load reductions during event periods.

[14] ComEd has four residential rates that differentiate single-family from multi-family homes and distinguish residences with electric space heat from those without electric space heat. Energy prices vary among these categories, but only slightly in relative terms.

[15] Some pilots install PCT so that the utility can adjust the temperature during events. The CAP just provided the device to the customer and left it to each participant to decide how to use it

[16] The CAP implementation plan provides bill protection to all participants, but the majority of customers are not aware of it during the course of the pilot. Two cells are notified of bill protection (D1 and L1), and ComEd only notified other customers in attempt to prevent them from opting out of the pilot.

subsequently of their rate and technology treatments at the commencement of the pilot. Customers remained in the pilot unless they took steps to *opt-out*. An *opt-out* approach was intended to lead to greater participation compared to an *opt-in* design whereby customers are recruited to participate.

ComEd adopted a systematic and comprehensive set of protocols designed to manage the customers' experience in ways that were expected to reduce opt-outs and increase satisfaction with the pilot experience. Many of the hypotheses test the extent to which these protocols were successful both in sustaining enrollment and in inducing price response.

A detailed description of the CAP design is available in the EPRI Methods report.[17] It describes how the CAP was designed, how the sample sizes were derived, and details the processes developed to support the implementation of the pilot. Section 3 provides more detail on the experimental design and its implications for testing application impacts.

Objectives of the Program Evaluation

Three primary objectives were established for the evaluation of the CAP pilot:

1. To determine how the applications influenced the level and pattern of energy consumption, particularly:
   - changes in overall energy consumption,
   - reductions in peak demand, and
   - load shifts from peak to off-peak periods
2. To identify the key drivers of customer attrition over the course of the pilot as a function of bill impacts, customer characteristics, and so forth.
3. To identify the key drivers of customers' acceptance of technology as a function of the price charged for the technology, variations in tariffs, customer characteristics, and so forth.

As established above, the CAP evaluation has been conducted in two phases. In Phase 1, the three objectives above were examined, to the extent possible, using available data from the three summer months, June through August 2010. Special attention was given to identifying load changes associated with DA-RTP, CPP, and PTR. Each of these price structures features prices that differ each day.

This Phase 2 analysis utilizes the entire year's data, as well as data obtained from a customer survey administered at the end of the pilot term (May 2011) to accomplish the evaluation objectives.

[17] *The ComEd Customer Applications Program – Objectives, Research Design, and Implementation Details*. EPRI, Palo Alto, CA: 2010. Product ID: 1022266.

The Evaluation Methods

Several analytical and statistical methods were drawn upon to conduct the components of the CAP evaluation. Some are appropriate to examine differences in behavior among customers by group. Others facilitate an examination of the data at the individual customer level in order to examine changes in electricity consumption in greater detail.

Since the experimental design of the pilot embodies a series of treatment and control groups, a logical first step is to apply methods of ANOVA to test differences in the average electricity consumption (e.g., average daily consumption, average hourly peak-period consumption, etc.) between treatment and control groups.

While these ANOVA tests highlight any aggregate differences in electricity consumption among treatment and control groups, other methods are needed to understand the various ways in which customers in the several dynamic pricing treatments (CPP, PTR and DA-RTP), two of which include large price differences on event days, may respond to prices or differences in peak and off-peak prices. Several regression models are specified to estimate differential effects on peak period consumption on event and non-event days. Formal customer demand models are also specified to determine the extent to which event-day load impacts and customer price responsiveness square with economic theory.

Finally, several of the hypotheses require the identification of factors that affect some specific, discrete customer choices (e.g., the decision to *opt-out* of the pilot). These issues are investigated by specification and estimation of appropriate logistic choice models.

Each of these research methods is summarized below and described in more detail in Section 5, which presents results of the analyses.

Analysis of Variance (ANOVA)

Many of the hypotheses are addressed using ANOVA or analysis of covariance (ANCOVA). These are formal statistical protocols that compare differences between the mean values of measured outcomes (e.g., differences in overall energy consumption or peak-period usage) associated with the applications. For example, ANOVA may be used to assess the significance of the difference in average summer peak-period usage between customers receiving an individual application (e.g., receiving the CPP treatment) and a control group during the pilot period. ANOVA analyses are typically conducted using commercial software such as SAS and Stata that provide established routines for conducting the analyses and produce summary statistics. In practice, these methods can be implemented by means of equivalent regression methods using indicator (dummy) variables for the treatment groups, which allow simultaneous testing of a number of treatments, as described in Section 5 below.

Regression Analysis of Rate Impacts

The ANOVA analyses were designed to test for the various hypothesized treatment effects at an aggregate level by comparing to a control group. A separate series of regression analyses were employed to measure the event-day load impacts of the various rate treatments. No control group customers were used in these latter models. Rather, non-event day usage is used as a control for event-day usage, controlling for weather, day of week, and month differences. These regression models are applied to panels of customers (e.g., all CPP customers, retaining customer-level data), aggregations of customer data (e.g., CPP customers who reduced load on event days, adding loads across customers), or customer-level data (e.g., estimating a separate model for each customer). For example, the customer-level models are used to identify those customers who appear to respond to prices (CPP and DA-RTP) or financial incentives (PTR) in a statistically significant way.[18] Regression analysis is then applied to average-customer load data for the subsets of responders to estimate hourly load impacts and metrics such as the elasticity of substitution, a measure of the degree of peak to off-peak load shifting.

Customer Demand Analysis

The regression analyses described above rely on models that are largely empirical in construction. The estimated relationships reflect the data, but not necessary in a way that is consistent with the tenets of consumer behavior as implied by economic theory. To impose behavioral structure, theoretically motivated electricity demand models were estimated based on data for various groups of customers. Two such models often used to measure price responsiveness under hourly pricing conditions are the nested constant elasticity of substitution (NCES) and the Generalized Leontief (GL) models.

The most important indicator of demand response that can be derived from these estimated models is known as the elasticity of substitution, which is often denoted by the symbol σ. In our case, σ is a measure of load shifting and is defined as the percentage change in the ratio of peak to off-peak electricity use caused by a 1 percent change in the ratio of off-peak to peak electricity prices. The theoretical underpinnings of these demand models, as well as the empirical specifications, are provided in Appendix A of the Phase 1 report.[19]

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[18] Dynamic or event-based rate structures, in which prices vary across days or episodically across a season, permit analysis at the individual customer level because the observations on their energy usage for many days on which prices are relatively low may be used to establish implicit reference loads from which changes in usage on high-price days may be measured.

[19] EPRI. April 2011. The Effect of Electricity Consumption of the Commonwealth Edison Customer Applications Program Pilot: Phase 1, Appendices. EPRI 1022761.

As is discussed in that appendix, the GL model is flexible in that elasticities of substitution for any customer or group of customers can differ by day, which allows them to vary by the price level on that day. In contrast, the elasticities of substitution for the NCES model are assumed to be constant for any individual customer or group of customers, regardless of the nominal level of prices. The GL model's flexibility with regard to elasticities, which comes at the cost of increased analytical and estimation complexity, facilitates testing the extent to which consumers' willingness to shift load differs based on the absolute level of prices, rather than imposing the same responsiveness on the estimates. In Section 5 below, where findings are presented, the NCES and GL estimates of elasticities of substitution are presented for event-responders under the CPP and PTR rate treatments. Event-responders are customers who were identified in customer-level regressions as exhibiting consumption behavior during event periods that is consistent with reducing load in response to the substantially higher price (or availability of PTR credit) during event hours.

Analysis of the Inclining Block Rate

Because of sampling issues described in Section 4, it was not possible to compare directly IBR customers with other treatment or control cells in order to estimate usage changes due to IBR.[20] Instead, the analysis of IBR customers is based on comparing monthly usage before and after the introduction of the IBR rate. In these regressions, the dependent variable is the natural log of monthly usage while the independent variables are cooling degree-days (CDDs), heating degree-days (HDDs), and a dummy variable that indicates the months in which the customer faced the IBR rate rather than a flat rate.

The Logit Choice Models

Formal choice models are used to test hypotheses where the feature being observed is not measured continuously, such as with energy usage or hourly prices, but rather as a state or condition outcome. For example, individual customers either *opted out* of the pilot or they did not, a dichotomous outcome. In this study, these models are used to model the customer's decision to *opt-out* of CAP or to acquire/adopt enabling technology.

Logit models are regression-based models that are functionally similar to commonly used Ordinary Least Squares (OLS) regression models.[21] However, they differ from other regression models in that they account explicitly for the fact that the outcome is the result of a dichotomous choice. For this reason, the left-hand-side variable in the model takes on only values of one or zero,

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[20] Had these data issues not been apparent, such comparisons would have still been difficult because the rates are not comparable. Prices in the IBR rates differ depending on the amount of electricity purchased during a particular billing cycle, and not by the time of day as in the CPP, PTR, and DA-RTP rate structures. Some of the issues in modeling these different rate structures are discussed in Appendix B of the Phase 1 report.

[21] For an excellent and complete discussion of the logit model and other models of discrete choices, see W. Greene, *Econometric Analysis*. 5th edition, Englewood Cliffs, NJ: Prentice Hall, Inc., 2003, Chapter 21.

depending on whether the customer chooses to take some action or not (e.g., yes/no, buy/not buy), and the right-hand-side (or explanatory) variables are customer characteristics (e.g., electric space heating vs. non-electric space heating) and descriptions of the treatments (i.e., rate type) to which the customer has been exposed.

Section 3: Structure of the Analysis

Experimental Design

The experimental design for the CAP pilot is illustrated in **Error! Reference ource not found.**. This figure shows a matrix of cells for the treatment (or applications) and control groups that characterize the structure of the CAP pilot. The number of participants in each treatment or control group is given in each cell. Participation quotas for each of the treatments (cells) were established based upon considerations of statistical significance.[22]

Participants for each treatment cell were selected randomly from the AMI footprint. This area includes approximately 100,000 residential customers along the I-290 corridor region of Chicago (Bellwood, Berwyn, Broadview, Forest Park, Hillside, Maywood, Melrose Park, Oak Park, and River Forest) and about 29,000 customers in the nearby Humboldt Park neighborhood of Chicago. These areas were selected for their apparent representativeness of all ComEd residential customers. In early 2010, new advanced metering equipment was installed in all homes in these two areas.

The matrix in Figure 3-1 also provides the structure for the construction and analysis of the important hypotheses to be tested, many of which suppose that there are differences in usage patterns between customers in various treatment cells compared with customers in control cells (e.g., reductions in peak demand on event days by CPP customers compared with customers who face a flat rate). Cells in different rows generally represent alternative rate treatments, while cells in different columns represent alternative types of enabling technologies. One set of analyses involves statistical tests of differences in the behavior among customer groups in specific cells (applications) of this matrix.

Dual treatments are embedded in some cells or applications: D1, L1, L5, and L6. These dual treatments are indicated by the two separate sample counts in these cells. For example, cells D1 and L1 are bifurcated to test the effect of offering bill protection to customers: in some cases, customers are aware that they will be made whole at the end of the pilot, while in other cases the customers are not aware of this provision. Furthermore, cells L5 and L6 involve different levels of incentives to adopt the enabling technology: in some cases, the technology is free;

[22] EPRI 1022266.

while in other cases the customer is offered the opportunity to purchase the technology at less than the full cost.

Cells F1 (flat rate, existing meter, and no education) and F3 (flat rate, new meter, and basic education) are designed as control groups (i.e., base cases) against which other applications or treatment groups (i.e., change cases) can be compared to determine usage changes due to the treatment.

In contrast to all of the treatment cells and to control group F3, customers in groups F1 and F2 were selected from ComEd's load research sample, where these samples were intended to be representative of residential customers located throughout the ComEd service area.[23]

		Enabling Technology Type					
		None	**Removed**	**Enhanced Web (eWeb)**	**eWeb+ Basic IHD (BIHD)**	**eWeb+ Advanced IHD (AIHD)**	**eWeb+PCT /IHD (AIHD/PCT)**
Flat Rate Type N = 1,650	**Flat Rate Existing Meter No Education**	Control F1 N=450					
	Flat Rate Existing Meter Education			Application F2 N=225			
	Flat Rate AMI Meter Basic AMI Education			Control F3 N=225			
	Flat Rate AMI Meter Education		Application F4 N=0	Application F5 N=225	**Application F6 N=300**	Application F7 N=225	
Energy Efficiency Rate Type N = 750	**IBR Rate AMI Meter Education**			Application E1 N=225	**Application E2 N=300**	Application E3 N=225	
Demand Response Rate Type N = 3,525	**CPP/DA-RTP Rate AMI Meter Education**			**Application D1 N(a)=525 N(b)=225**	**Application D2 N=525**	**Application D3 N=525**	**Application D4 N=525**
	PTR/DA-RTP Rate AMI Meter Education			Application D5 N=225	**Application D6 N=525**	Application D7 N=225	Application D8 N=225
Load Shifting Rate Type N = 2,625	**DA-RTP Rate AMI Meter Education**			Application L1 N(a)=225 N(b)=225	**Application L2 N=525**	Application L3 N=225	
	TOU Rate AMI Meter Education			Application L4 N=225	**Application L5 N(a)=525 N(b)=225**	Application L6 N(a)=225 N(b)=225	
N = 8,550		N = 450	N = 0	N = 2,550	N = 2,925	N = 1,875	N = 750

Primary Application   Not Used

Figure 3-1
Applications by Rate Type and Enabling Technology

[23] As explained in Chapter Section 4: below, however, the load research sample does not appear to be representative of the residential customers located in the CAP service area.

Hypotheses about Impacts

EPRI and ComEd established a set of working hypotheses to guide the CAP analysis. They are described in detail elsewhere.[24] The purpose of the hypotheses was to construct concise statements of what quantifiable effects might be expected from the CAP applications and could be subjected to logical or statistical tests of veracity.

Some of the hypotheses refer specifically to the results of the applications, for example:

- **H3a**: The basic in-home display (BIHD) will have a higher implementation rate than other enabling technology
- **H2e**: The CPP rate delivers the best combination of energy efficiency, demand response, and load shifting benefits.
- **H2c**: The CPP rate causes the greatest reduction in peak load during the summer.
- **H3d**: The advanced in-home display (AIHD)/PCT solution will achieve greater energy efficiency, demand response, and load-shifting benefits than other enabling technology.

Because they refer directly to differences among the average loads of the customers facing certain applications, which represent different rates and enabling technologies, these hypotheses can be tested using ANOVA tests of significance. Statements about the inference can be drawn regarding the significance of measured differences, and hence whether the hypothesis can be accepted or rejected as being representative of the CAP population's behavior during the pilot.

Other hypotheses refer to the success or outcome of process and other implementation actions that were intended to achieve greater behavioral changes, for example:

- **H3f**: Customers who received and activated a BIHD will experience greater satisfaction than customers who have received and activated other enabling technology
- **H7b**: An *opt-out* strategy will result in a higher enrollment percentage than an *opt-in* strategy.
- **H7h**: Customers whose rate comparison shows a monthly gain will have a drop-out rate that is less than customers who experience a monthly loss.
- **H7r**: Customers who contact the customer support center will experience greater energy efficiency, demand response, and load-shifting benefits than customers who do not.

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[24] EPRI 1022266.

Testing the verity of statements such as these requires combining data collected or measurements calculated as part of the CAP implementation. Such data include customer bills, logs of participant access to the eWeb or contacts with the customer service assistance center, and information on customer premise characteristics, demographics, perceptions, expectations, and opinions.

The goal of the CAP analyses is to address all of these hypotheses. Figure 3-2 describes those that were included in both the Phase 1 and Phase 2 analyses. They were singled out for preliminary analysis because either they were statements about the directly measured effects of the various treatments, or they involve other influences that could be measured readily and might have a marginal influence on the application effect. All price and major enabling technology effects were tested in Phase 1 and are updated in this report. The next section describes the methods that were undertaken to test the veracity of these statements, the results of which are reported in Section 5.

Hypotheses Addressed in Phase 1 and Phase 2

- Rate Type: H2a, H2b, H2c, H2d, H2e
- Enabling Technology: H3a, H3d, H3e
- Enabling Technology Acquisition: H4a, H4b, H4d
- Bill Protection: H5a, H5b
- Customer Education: H6a, H6b, H6c
- Customer Experience-Notifications: H7n, H7o
- Customer Experience-Customer Support: H7r, H7s, H7t, H7u, H7v

Figure 3-2
Hypotheses Tested in Phase 1 and Phase 2

Figure 3-3 lists hypotheses that could not be evaluated in Phase 1 because they required customer information not collected until the end of the CAP, but are included in the Phase 2 analysis. Also appearing in Figure 3-3 are hypotheses that will be evaluated in a supplemental addendum to this Phase 2 report in January 2012.

Hypotheses Addressed in Phase 2 Only

- Rate Type: H2f
- Enabling Technology: H3b, H3c, H3f
- Bill Protection: H5c
- Customer Experience-Observable Steps: H7a

Hypotheses Addressed in Phase 2 Addendum

- Customer Experience-Opt-Out Enrollment: H7b, H7c, H7d, H7e
- Customer Experience-Comparisons: H7f, H7g, H7h, H7i, H7j, H7k, H7l, H7m

Figure 3-3
Hypotheses Tested in Phase 2 and Phase 2 Addendum

Figure 3-4 lists hypotheses that will not be evaluated for various reasons that are described in Section 5.

Hypotheses that cannot be Evaluated due to Design Issues

- Meter Type: H1 (*Meter type has no effect on electricity usage behaviors.*)
  - Sample design issues
- Enabling Technology Acquisition: H4c (*The adoption rate of purchased enabling technology will exceed free enabling technology*.)
  - Insufficient treatment participation
- Customer Experience-Comparisons: H7l, H7m (*Customers receiving normative comparisons and whose normative comparisons show them having higher electricity consumption than their neighbors will experience greater effects.)*
  - *Insufficient OPower data*
- Customer Experience-Notifications: H7p, H7q (*Customers who view hourly prices online or who sign up multiple family members to receive notifications will experience greater effects.*)
  - Insufficient data
- Customer Experience-Customer Support: H7w (*Customer satisfaction with customer support center will exceed satisfaction levels of ComEd's customer care center.)*
  - Satisfaction with the customer support and care centers unknown

Figure 3-4
Hypotheses Slated for Testing, but not Addressed in Phase 1 or Phase 2

Section 4: Data Collection

The data to support the Phase 2 analyses undertaken in this evaluation came from several sources, as described below. In collecting and examining the requisite date, EPRI discovered that the customer composition for a few of the applications did not comport with that of the general population of ComEd customers, raising challenges to testing hypotheses using such data.[25]

The Data

The data available for this Phase 2 analysis includes the following:

- Hourly interval load data for each treatment and control participant;
- Monthly billing data (kWh, per unit energy prices, total cost, rebates paid) for each participating customer;
- Initial and post-pilot survey data for those participants who responded;
- Hourly prices faced by the CPP, PTR and DA-RTP customers;
- Days on which CPP and PTR events were declared;
- Enabling technology device installation and usage information; and
- Customer interaction data on all touch-point contacts from ComEd to the sample participants; and by the participants to the program website or ComEd customer support center.

This Phase 2 report uses data for the entire study year ending May 2011.[26] As conveyed in Section 3, tests for some hypotheses and the results of an extended evaluation will appear in a supplementary EPRI report to be published in January 2012.

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[25] See Appendix C of the Phase 1 report in EPRI 1022761 for additional details about data and data issues.

[26] CAP participants were enrolled starting late April through early June 2010 based on their billing cycle change. Each experienced 12 monthly billing periods on the pilot application(s), ending with the twelfth billing month, either April or May 2011. Due to reduced availability of load data for May, the Phase 2 analyses generally used data through April 2011.

Some Issues with the Data

A study of this complexity presents challenges in implementation. The compromises needed to implement the study into the field can affect the way the data can be used. A careful examination of the data often reveals some issues that need to be resolved (for example, missing data or design specification issues) prior to conducting the analysis, generally in a way that does not affect the veracity of the analysis' findings. In some instances, however, program implementation can cause data shortcomings that complicate analysis, and thereby render inappropriate the use of the conventional statistical models. In some cases, the shortcomings are such that some elements of the hypothesis testing must be abandoned altogether.

A few anomalies or incongruencies in the CAP data have affected the way in which the analyses have been conducted. As is evident in the discussion below, strategies have been developed to restructure some hypothesis tests to mitigate the effects of these data issues. In a couple of cases, tests of hypotheses had to be abandoned. Because these abandoned hypotheses involved impacts that were of secondary interest, there is little consequence for the overall value of the evaluation.

The first data issue is the specification of the time periods for which participant-specific data are available. The date at which a customer's CAP hourly load data first becomes available in the data set depends on the customer's monthly billing cycle. Some customers began service in late April 2010 while the last commenced service in early June 2010. As a result, fully time-corresponding data for all customers were not available until June 11, 2010. For many analyses, especially statistical tests involving ANOVA, all customers should have data for the full time period to which the analysis is applied.

Customers also completed participation in the program on different dates depending on the customer's monthly billing cycles. Incomplete data also resulted from participant's decisions to *opt-out* (only about 2%) and customers who closed their accounts. In many cases, enabling devices were installed and/or activated on dates different from when the customer was enrolled in CAP. There are also some interruptions in usable data for several hundred participating customers as a result of two major service outages during the summer and one in the non-summer months.

The differences among customers in the time periods of their data are of some concern in conducting ANOVA, since in these types of statistical analyses it is generally assumed that the data from each customer used to construct the application average are from exactly the same time period. If the time periods differ, the ANOVA-style comparisons of average usage between two cells remain valid as long as differences in the data available for customers are randomly distributed across the applications and hence do not affect the comparisons of means. In other words, if there is no systematic correspondence between when a customer was enrolled in CAP and the application to which it was assigned, the ANOVA-style comparisons can be valid.

Fortunately, it is reasonable to presume that the differences in data availability among customers are randomly distributed across the applications. The method by which ComEd selected participants and assigned them to applications was random over customers located in the entire AMI footprint and independent of the customer's monthly bill cycle. Therefore, there is no reason to suspect systematic bias. The outages occurred after the sample was composed and were geographically concentrated, but were not related to the customer's monthly billing cycle or the application to which an affected CAP participant was enrolled. Hence, ANOVA analyses are appropriate using customers with data for all days from June 11 through September 30, 2010 in the summer; and October 2, 2010 through April 27, 2011 for the non-summer analyses.[27] To avoid extreme value bias, customers for which 2 percent or more of the observations were zero for the relevant summer or non-summer time period were excluded from the Phase 2 ANOVA analysis.[28]

Other design and data characteristic issues are more problematic. Five circumstances limited the extent to which some of the pre-specified analyses could be undertaken.

The first had to do with the composition of the two control groups (F1 and F2). They were constructed to represent the ComEd's entire customer population to facilitate making system-wide residential customer population inferences from the CAP findings. Participants in cells F1 and F2 were created by selecting customers at random from customers currently included in ComEd's load research sample. That sample combines two different samples, constructed at different times, each drawn to be representative of the entire residential population. The earlier sample employed stratification by usage level and premise characteristics (single/multi-family, premises with and without electric space heat), while the later sample stratified only by premise characteristics.

Stratification by size is often used in load research where the objective is to estimate the class peak load or a representative load profile. However, in combining the two samples, the resulting sample of customers is not suitably representative of the population in general for the purpose of comparing load to the CAP customers. That is, it appears that high-usage customers are over-

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[27] One exception is August 3, 2010, where the data indicate an outage for customers in only some of the rate treatments, and as such, this date is omitted from the ANOVA analysis. This was likely due to a technical error in data collection rather than an actual outage.

[28] About 1,100 of the approximate 8,000 enrolled customers were excluded through this process. The data available at the time of the Phase 1 report were less complete and therefore resulted in approximately 1,500 exclusions. The ANOVA analysis uses the most restrictive set of customers, whereas other methods discussed in this report use a broader sample that retains customers with incomplete data. The alternative to making these assumptions is to employ a much more complex regression model. For example, we could have used monthly customer data, so the dependent variable would have been the average usage for each customer in each month. The independent variables would control for the share of the month in which the customer was enrolled, had equipment installed, or experienced a service outage. Such a model may also benefit from the introduction of customer fixed effects that control for customer-specific characteristics that do not change during the sample timeframe. This modeling structure is capable of accounting for the data issues described above, but it complicates the analysis and the interpretation of the models results.

represented, relative to what would be expected in the population, both in the load research sample, and in the CAP delivery class segments (e.g., single- or multi-family premises with or without and electric space heat) that comprise F1 and F2.

This outcome can be seen in Figure 4-1, which shows the average hourly kWh usage for the F1 and F2 control groups and the rate application customers. The average hourly electricity usage for the F1 and F2 control groups (the first bar in the left-most graph) is nearly double that of the rate treatments (the other six bars). This distinction is not due to customer response to prices, but rather, it is an artifact of the systematically different characteristics of the F1 and F2 control group customers relative to customers in any of the rate treatment groups.

The control groups, F1 and F2, also have higher peak and all-event hour usage than customers in the five rate treatments (the middle and right-most graphs in Figure 4-1, respectively), providing further indication that the control groups constructed from the load research sample are not representative of customers in the CAP, based on average usage.

The differences are evident, but somewhat less pronounced, when comparing the ratio of peak to off-peak usage as portrayed in Figure 4-2. The figure shows that customers facing TOU rates have relatively lower peak usage shares compared to the other rate treatment groups, although the difference from the flat rate, as described in Section 5 below, is not statistically significant.

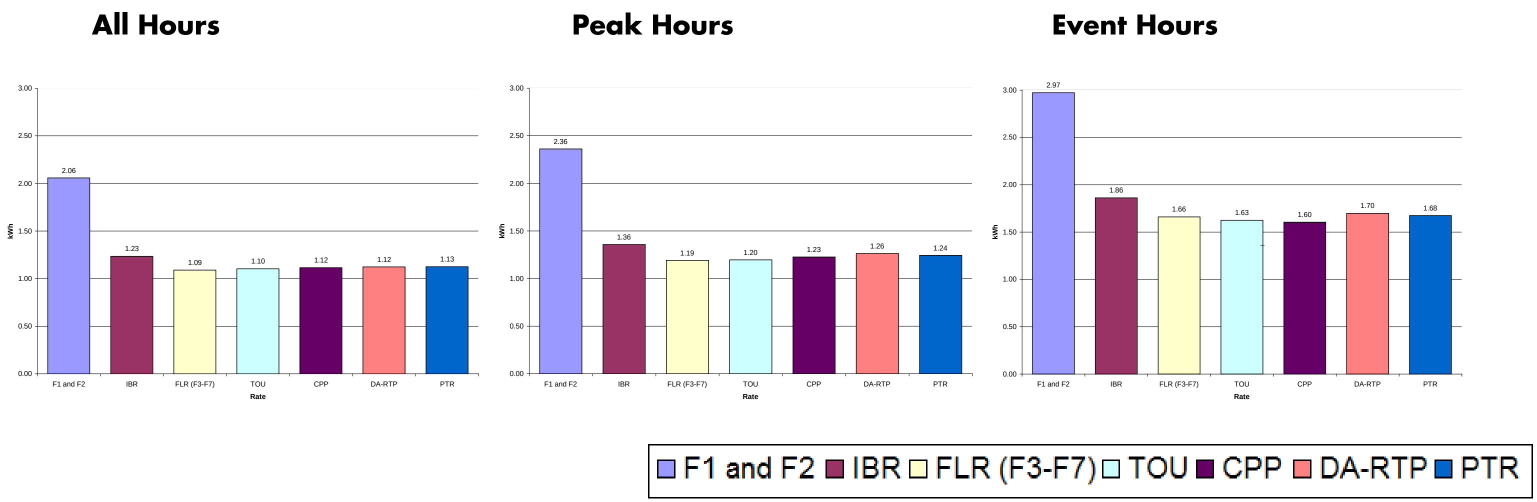


Figure 4-1
Average Usage by Rate Structure, for Various Periods

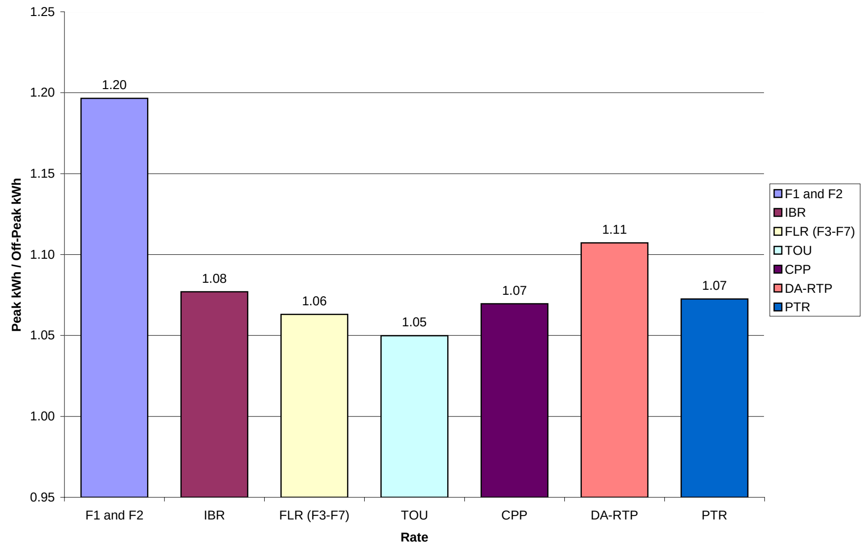


Figure 4-2
Average Peak to Off-Peak Usage Ratio, by Rate

The control groups F1 and F2 were intended to represent customers who did not receive AMI metering, specifically to test whether there was any influence on customer usage solely attributable to installing AMI, as opposed to the AMI-enabled treatments. The bias inherent in the composition of the two control groups precludes testing this hypothesis because the sampling error assumptions that support ANOVA are not met. The result of such a comparison would portray the non-application (control) case as having higher load, and as a result differences between it and the application loads, which would appear as load reductions, would be exaggerated.

The second issue with the data affects the analysis of IBR customers. Selection of customers to be on the IBR rate was restricted to those with at least five years of billing history to create long-term average usage levels from which the break points in the IBR were constructed for each customer. As a result of this restriction, customers in the IBR cells appear to over-represent high usage and under-represent low-usage customers. The likely explanation is that low-usage customers live in multi-family units and in smaller homes and tend to move more frequently than the average ComEd customer. Therefore, those premises are not as likely to have the required five years of billing history and are under-represented in the sampling process.

Figures 4-1 and 4-2 above illustrate this condition. The average hourly kW usage is 10 to 15 percent higher for customers in the IBR treatment than for those in other rate treatments (excluding the F1 and F2 control groups). The presence of obvious bias precludes any direct tests (using ANOVA) of differences in customer energy usage due to the IBR treatment relative to usage by customers in other rate treatments. To provide some indication of the extent to which IBR affected customer usage, we separately analyzed changes in electricity consumption for IBR customers through comparisons of the available monthly billing-level usage data from mid-2009 and mid-2011, before and after the IBR treatment.

A third data issue is that the application cells involving in-home display technology (IHD) applications tend to also under-represent low-usage customers because they exclude customers in multi-family residences above the first floor of a residential building. This exclusion is due to technical limitations on the ability of IHDs to function properly for customers residing above the first floor.[29] The IHD treatment cells therefore include fewer multi-family residences than would be expected through random selection because multi-family residences tend to have relatively low average hourly kW usage, as is evident from Figure 4-3.

The BIHD treatment application cells have average hourly kW usage that is about 3 percent higher (and even higher for AIHD customers) than it is for eWeb customers without IHD.[30] This characteristic of the data in these cells may compromise our efforts to test for the effects of IHDs on customers' electricity use. However, as discussed below, the very low uptake of IHDs in these applications makes detecting any influence, biased or not, difficult using ANOVA, at least at the aggregate level.

[29] The BIHD and AIHD technologies rely on a radio-based signal from the meter to provide energy usage data for display on the device. These radio waves do not radiate much upward past the second floor of many building.

[30] ComEd offers all CAP customer access, through an internet connection, to its eWeb portal. This portal displays billing data and compares customers' usage to that of other customers that are deemed to be comparable in life and premise circumstances. Since all customers have access, the eWeb is not a treatment but a general condition that must be incorporated into the construction of the control reference load for ANOVA analyses.

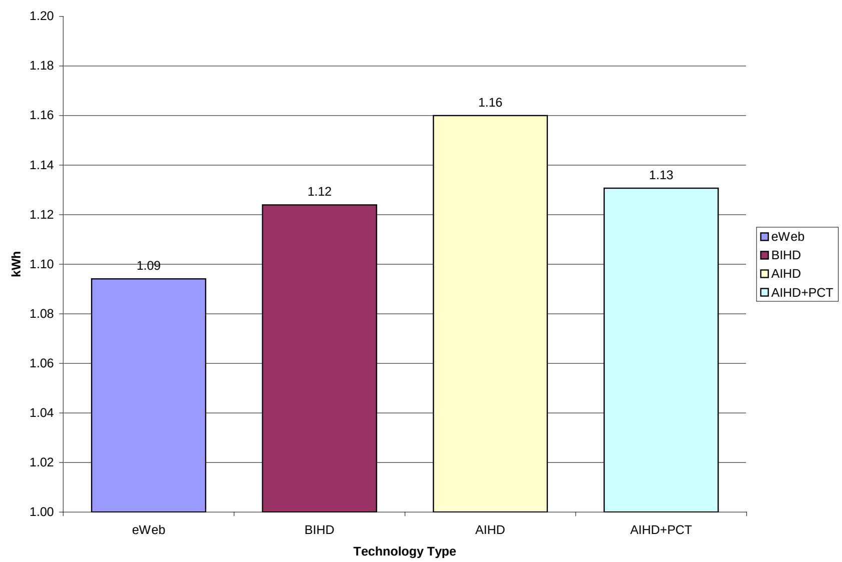


Figure 4-3
Average Hourly Usage, by Technology[31]

Fourth, customer acceptance of PCTs is low; less than 10 percent of those offered the device installed it. As a result, tests of the effects of the PCT enabling technology on customers' response to time-based rates such as CPP and PTR, if they exist at all, are likely obscured. To circumvent this problem we adopt an intention-to-treat design for analysis of energy usage effects of PCTs.[32]

Finally, as shown in Table 4-1, very few customers purchased IHDs (as opposed to those that were offered IHDs at no cost). This precludes comprehensive tests of the effects of the partial payment applications of IHDs. As in the case above, the analysis of the effects of customer purchases was instead analyzed based on an assumption of intention to treat, with the caution that ANOVA may reject the hypotheses that the IHD application is different from those without that device, when in fact that is not true of all customers.

[31] Data for IBR, F1, and F2 customers are excluded from this figure.

[32] Intention to treat is used in cases wherein a treatment was offered to a particular set of customers who largely (or entirely) declined to accept the treatment. Because they were offered a treatment, customers in such a treatment group cannot be considered as completely untreated, nor can they be treated like another untreated group. The intention-to-treat design in effect equates the response of customers that took the treatment but did not use it with those that did not take the treatment: in both cases, the treatment effect is nil. When the treatment uptake is low, as is the case with the PCT application, it is all but assured that there will be no observed treatment effect.

Table 4-1
Acquisition and Implementation of Free and Purchased Technology

	Numbers			Rates	
	Offer	**Acquire**	**Implement**	**Acquire**	**Implement**
For Free					
L5a	525	525	171	100%	33%
L6a	225	Unavailable	27	Unavailable	12%
For Purchase					
L5b	225	5	4	2%	80%
L6b	225	4	4	2%	100%

Section 5: Findings

This section, divided into four sub-sections, presents the findings from the various analyses of the participant responses to the CAP rate and technology treatments in the pilot. The section begins with a presentation of the ANOVA analysis of the aggregate average electricity usage impacts due to the various rates and other treatments. That is followed by the results of regression-based analyses designed to directly estimate the impacts of the CAP rate treatments on participants' load profiles, with particular focus on the peak-period impacts of the dynamic pricing applications of CPP, DA-RTP and PTR. The regression analyses use data at a variety of levels of aggregation, or averaging, including: 1) average load by rate treatment, 2) pooled (fixed-effects) analysis of customer-level loads within rate treatment, 3) individual customer-level analysis to identify "event-responders" for each rate treatment, and 4) average load of event-responders, by rate treatment.

The third sub-section describes the application of formal customer demand models to analyze data for the CPP and PTR event-responders to estimate elasticity of substitution parameters that characterize customers' degree of load shifting between peak and off-peak electricity consumption. Finally, a separate analysis examines the effect of IBR on those customers' overall electricity usage.

Analysis of Variance (ANOVA)

As described in Section 2, the ANOVA analysis was conducted using ordinary least squares (OLS) regressions with indicator variables for each treatment. That is, if a given customer is in a particular treatment group, the indicator variable for that treatment is assigned a value of unity for that customer; the indicator variable is assigned a value of zero otherwise. This approach facilitates simultaneous comparisons across many treatments. The primary OLS regression model used in the ANOVA analysis is as follows:

$$
\begin{aligned}
Usage_i \;=\; & \alpha + \beta_{CPP} \times CPP_i + \beta_{RTP} \times RTP_i + \beta_{PTR} \times PTR_i + \beta_{TOU} \times TOU_i + \beta_{BIHD} \times BIHD_i \\
& + \beta_{AIHD} \times AIHD_i + \beta_{PCT} \times PCT_i + \beta_{Bill\_prot} \times Bill\_prot_i + \beta_{Purch} \times Purch_i \\
& + \beta_{Educ} \times Educ\_Not_i + \beta_{SFSH} \times SFSH_i + \beta_{MFNS} \times MFNS_i + \beta_{MFSH} \times MFSH_i + e_i
\end{aligned}
$$

Equation 5-1

where: i indexes customers, α is the constant term (the effect associated with the specified control group), the βs are estimated parameters (the revealed treatment effects), and e_i is the error term. SFSH denotes single-family residences with space heat, MFNS denotes multi-family residences with no space heat, and MFSH denotes multi-family residences with space heat.[33]

To assess customers' responses to CAP program design and incentives, the ANOVA or ANCOVA analysis focuses on evaluating the 46 hypotheses that were discussed in Chapter 3.[34] In some cases, hypotheses are addressed using metered usage data such as monthly energy consumption or average hourly consumption in peak periods. In other cases, conducting significance tests requires that ordinal or cardinal metrics be generated from information in the CAP system process, measurement, and validation databases (MVDB). For example, the number of times that a customer accessed the CAP website was derived in that way to ascertain if doing so affected the main treatment effect.

ANOVA quantifies the relative effects of different factors on customers' usage of electricity, and indicates their significance. For analytical purposes, customers' usage of electricity is measured in three distinct ways:

- Average overall usage, a reduction in which serves as a measure of electricity conservation
- Average peak-period usage, a reduction in which serves as a measure of demand response, which can be further distinguished by whether the response applies to all days or to event days only
- Peak-to-off-peak usage ratio, a reduction in which serves as a measure of load shifting

Hourly billing data are used to construct the application metrics described above, which are then evaluated using a regression-based test of significance. No weather adjustments are required for ANOVA because all customers experienced the same weather conditions and we evaluate all customers using a consistent period of time (e.g., average usage during the summer months). Subsequent models that examine variations in customer usage across time (either for individual customers or aggregations of customers) include weather adjustment variables.

The different factors that are hypothesized to affect one or more of these measures of electricity usage can be grouped into four major categories, as follows:

- rate structure - CPP, PTR, TOU, DA-RTP, and IBR
- enabling technology - basic and advanced in-home display and PCT

[33] Single-family residences with no space heat do not appear in the equation because such residences are indicated by zero values on all three of the residence types that *are* included in the equation.

[34] The hypotheses themselves will be described in detail in a supplemental addendum to this report to be published in January 2012, as are the model specifications and results of the formal tests.

- other limited deployment applications – education, event notification,[35] bill protection, technology cost sharing
- housing type - included to control for sample selection issues

Housing type variables were added to account for differences in premises due to: whether it is a single-family or multi-family building; and whether the building has electric space heating. These are characteristics used to distinguish residential premises under the conventional ComEd tariff because they are believed to represent differences in electricity usage levels and/or profiles. Adding them as conditioning variables accounts for the effect of these factors, and thereby improves the ability to detect application effects in the regression models.

ANOVA regression results are structured so that the primary application effects can be quantified and their statistical significance ascertained. This is accomplished by measuring treatment effects relative to a baseline, or control group. The model estimates allow us to determine whether the measured difference between the treatment and control group is statistically significant. The statistical significance threshold is the 95 percent confidence level.

Because treatment effects may differ seasonally, separate models are estimated for the summer (June through September) and non-summer (October through April) time periods. Summer results are presented first.

Summer Months ANOVA Results

Table 5-1 contains the estimated coefficients from the summer ANOVA regression models for dependent variables based on four separate measures of electricity usage. The first column lists the CAP treatments. The next four columns correspond to alternative impact measurements: for all summer hours (conservation effect); during summer peak hours (peak usage effect); for summer event hours (event-specific effects); and on the summer peak to off-peak usage ratio (the load shape impact).

The estimated coefficients listed for each impact measure indicate the difference in average hourly use relative to that of control group customers that: 1) pay the conventional ComEd residential rate applicable to a single-family residence without electric space heat, 2) receive only the eWeb application, 3) were provided only basic education, 4) were not notified of events, and 5) received no notification of bill protection. Given this control construct (that establishes baseline usage), the average effects of the individual applications can be quantified and deemed as being statistically significant or not.

To interpret the coefficients, it is convenient to focus initially on the coefficients for multi-family residences (multi-family non-electric space heating (MFNS) and multi-family electric space heating (MFSH)), beginning with the all summer hours impact measure. These variables are included in the equations to control

[35] Full customer education always accompanies event notification in the program design, so the effects of these treatments can only be tested jointly.

for differences in electricity use due to type of residence, and the coefficients on these variables are easy to interpret as conditioning factors.

The coefficients associated with (MFNS) and (MFSH) in the second column of Table 5-1, both of which are negative, indicate that average summer hourly use is lower by 0.682 and 0.695 kWh for multi-family residences with non-electric space heating and electric space heating respectively, compared to the single-family residences without electric space heating. These negative signs are to be expected given that multi-family residences are generally smaller than single-family residences. In all but one case, the MFNS and MFSH coefficients are significantly different, as indicated by the bold type in Table 5-1

Comparing the estimated impact across the four impact measures adds context to the importance of housing type. For multi-family residences (with and without electric space heating), negative signs associated with the other three ANOVA models are expected as well. These table coefficients are in bold, indicating that the effects are statistically different from zero at the 95 percent level of statistical significance. In contrast, none of the impact measure coefficients for single family residences with electric space heat (SFSH) are statistically different from zero at the 95 percent level.

The coefficients associated with the CAP treatments indicate the effect on electricity price structures and prices, technology, bill protection, technology purchase incentive, level of education, and event notification. For example, the value of 0.044 in the first row of the all summer hours impact indicates that in the regression for all hours, CPP customers were found to use an average of 0.044 kWh per hour more than do flat-rate customers. However, because the 0.044 is not in bold, this difference is not statistically significant from zero at the 95 percent level of significance, and therefore the effect should be interpreted as zero. This is the case with most of the treatments.

The rate and technology application differences are not statistically significantly different from zero, with three exceptions. The significant but positive coefficients for DA-RTP, summer peak hours (0.101) and summer peak to off-peak ratio (0.037) are counterintuitive because the positive signs on the coefficients indicate that despite the generally high DA-RTP peak-period prices compared to prices in other hours, customers on DA-RTP have higher peak-period consumption than do customers who pay a flat rate.

The full education and event notification impact for event hours exception is potentially more interesting: The estimated impact is negative and statistically different from zero (-0.223). The implication is that educating customers and notifying them of events can lead to usage reductions during event hours, independent of rate structures and enabling technologies.

Table 5-1
Estimated Coefficients from the Summer ANOVA Models[36]

Variable	Dependent variable = average usage across....			
	All Summer Hours	Summer Peak Hours	Event Hours	Summer P/O Ratio
CPP	0.044	0.059	0.002	0.003
DA-RTP	0.063	**0.101**	0.102	**0.037**
PTR	0.061	0.082	0.080	0.007
TOU	0.069	0.063	0.071	-0.016
BIHD	-0.007	0.005	0.016	0.012
AIHD	0.037	0.059	0.087	0.019
AIHD/PCT	0.014	0.001	0.012	0.003
Bill Protection	0.024	0.041	0.077	0.030
Purchase Tech.	-0.055	-0.056	-0.081	0.001
Educ. / Notif.	-0.077	-0.107	**-0.223**	-0.009
SFSH	0.061	0.083	-0.086	0.032
MFNS	**-0.682**	**-0.870**	**-1.232**	**-0.153**
MFSH	**-0.695**	**-0.846**	**-1.202**	-0.058
Constant	**1.377**	**1.563**	**2.232**	**1.119**

We investigated this finding further using an alternative model with cell-level indicator variables in place of treatment-level indicator variables.[37] The results indicated that the education / event notification impact is most strongly associated with three cells:

- D2: CPP rate structure with BIHD and full education / event notification;

[36] Each model contains 5,778 observations, with one observation per customer. Customers are excluded if they are in treatment cells F1 or F2, are in any of the IBR treatment cells, or are screened due to incomplete data. The control group consists of customers in treatment cell F3 residing in single-family homes with non-electric space heating. Additional details will be provided in an addendum to this report to be published in January 2012.

[37] This model specification replaces the treatment-specific indicator variables (e.g., a CPP regardless of the presence of other treatments indicator variable) with cell-specific indicator variables (e.g., a cell D3 indicator variable that isolates a specific treatment). The cell F3 indicator variable (flat-rate customers with an AMI meter, basic customer education, and eWeb access) is omitted so that these customers serve as the control group. Because each analysis cell contains a bundle of treatments (e.g., cell D2 contains customers who were on the CPP rate, were offered a BIHD, received full education / event notification, and had access to eWeb), the cell-specific version of the ANOVA model tests for the effects of all available interactions of treatments. For example, one may hypothesize that BIHD or AIHD may be more effective when combined with a dynamic rate such as CPP or PTR. The cell-level model allows for such effects to be isolated, whereas the treatment-level model would require the analyst to test a variety of variable interactions (e.g., by interacting the CPP and BIHD indicator variables).

- D4: CPP rate structure with AIHD/PCT and full education / event notification; and
- F5: Flat rate structure with eWeb only and full education / event notification.

The coefficients for all but one cell (D7, which is the PTR rate structure with AIHD and full education) are negative, but only the three listed above are statistically significantly different from zero. While this provides some indication that education and event notification are associated with event-day load reductions, that conclusion is not fully confirmed. The fact that the load impacts are not statistically significant for other cells where full education and event notification are present (all cells except the control group, F3) requires explanation. The findings of the impact of education and event notification from the treatment-level model suggest that more research is warranted.

Non-summer Months ANOVA Results

The results for the non-summer ANOVA model are shown in Table 5-2. The event-hours impact measurement is left out since CPP and PTR events were confined to the summer months.

The housing-type variables provide the expected results, in that both of the electric space heating housing types use more energy in non-summer months than their non-electric space heating counterparts (as indicated by the 1.399 coefficient for the SFSH variable and the 0.493 coefficient for the MFSH variable). However, with the exception of one counter-intuitive result (indicating higher non-summer peak-hour usage for CPP customers[38]), no other variables exhibited a statistically significant coefficient.

Summary of ANOVA Findings

Overall, the regression-based ANOVA findings from the summer and non-summer seasons show little evidence that any of the CAP treatments resulted in statistically significant differences in average electricity usage. The only statistically significant treatment effect, disregarding the counter-intuitive findings, is that full education and event notification are associated with lower summer event-hour usage.

The ANOVA model findings for summer and non-summer months provide the basis for conducting the majority of the hypothesis tests contained in the analysis plan. The Appendix to this report provides a summary of the results of each test and a supplementary appendix that provides details for each test will be provided in January 2012. The present document focuses on the most notable findings from those tests.

[38] The CPP rate during non-summer peak hours is higher than the flat rate, so one would expect CPP customer usage during peak hours to be lower than flat-rate customer usage if customers are responding to the price difference.

Table 5-2
Estimated Coefficients from the Non-summer ANOVA Models[39]

Variable	Dependent variable = average usage across....		
	All Non-summer Hours	**Non-summer Peak Hours**	**Non-summer P/O Ratio**
CPP	0.037	**0.054**	0.016
DA-RTP	0.024	0.036	0.017
PTR	0.035	0.050	0.022
TOU	0.025	0.017	-0.018
BIHD	0.003	0.005	0.006
AIHD	0.014	0.016	0.010
AIHD/PCT	-0.016	-0.025	-0.000
Bill Protection	0.043	0.040	0.005
Purchase Tech.	-0.048	-0.043	-0.006
Educ. / Notif.	-0.046	-0.031	0.022
SFSH	**1.399**	**1.380**	0.053
MFNS	**-0.441**	**-0.414**	-0.001
MFSH	**0.493**	**0.435**	-0.014
Constant	**0.934**	**0.845**	**0.904**

The lack of statistically significant impacts associated with CAP treatments is at odds with the findings of many recent pilots that employed similar rate structures and enabling technologies. However, this outcome may not be as contradictory as it appears. The difference in the average treatment impacts may be the result of the *opt-out* design of the pilot. If automatically enrolling customers in the CAP is not itself an inducement to respond to treatments, then we would expect responses only from those who were already inclined to respond. Based on past pilots, that may be 10 percent or less of the total residential customer population.[40] Those pilots found differences in rate applications and IHD impacts that were significant, but the participation was restricted to volunteers who might be expected a priori to be inclined to be responsive. The CAP includes a random sample of customers who were not recruited to join, but enrolled in the treatment without their explicit consent As a result, the responses

[39] Each model contains 5,471 observations, with one observation per customer. Customers are excluded if they are in treatment cells F1 or F2, are in any of the IBR treatment cells, or are screened due to incomplete data. The control group consists of customers in treatment cell F3 residing in single-family homes with non-electric space heating. Additional details will be provided in a supplementary addendum to this report to be published in January 2012.

[40] Based on a review of pilot reports of subscription rates.

by those predisposed to respond may be masked by the much larger collective load of those not inclined to respond, and did not respond to, the applications. Detecting the responses of a small minority of customers would require much larger sample sizes than the CAP used.[41]

To explore further the nature of CAP effects, we focus on CPP and PTR event-hour responses. Because of the high event-hour prices (incentives, in the case of PTR), this seems the most likely time period in which participants altered their usage based on the treatment. We proceed in three steps. First, we examine observed load data in an attempt to discern whether event-day usage patterns differ from usage patterns on non-event days with similar weather conditions. Second, we estimate fixed-effects models that attempt to explain variations in customer daily average peak-period usage. A fixed-effects model is another method of determining whether there was an aggregate (i.e., rate-level) response to event-day price signals. Third, we estimate the same model separately for each CAP customer in an attempt to determine whether a subset of customers reduced peak-period usage on event days.

Direct Estimation of Event-Day Load Impacts

The absence of significant rate treatment effects for the average customer in the ANOVA analysis motivates employing other analytical techniques to determine if more detailed analysis identifies price-induced load impacts. We begin this sub-section by displaying a series of graphs of average customer loads by rate treatments on event days and other days with weather conditions similar to event days. These portrayals serve to confirm the results from the ANOVA tests that on average there is no detectable rate application treatment response. We then turn to a quantitative analysis that pools daily peak-period data for each customer within the dynamic rate treatments in a fixed-effects model to formally test for load impacts on event days. These results again indicate that any event-day load impacts are small.

Additional analyses are warranted because it may be the case that a few customers within each rate treatment group respond to prices or events, but their response is dominated by the random actions (noise) of the much larger number of non-responders, and hence their impact is masked. To explore this possibility, we apply regression analysis at the individual customer level to identify subsets of CAP customers who appear to reduce load significantly during event periods. We label these customers event-responders, and proceed to conduct additional graphical and regression analysis to confirm and quantify the nature of their load responses. Finally, we apply formal customer demand models to the load data for the event-responders in the CPP and PTR rate treatments to estimate elasticity of substitution parameters that characterize their degree of price responsiveness.

[41] EPRI 1010855

Graphical Assessment of Average Rate-Treatment Loads

Several graphic depictions of treatment customer loads were constructed to illustrate average load profiles for various treatment and control groups on event days and other similar (with respect to weather) weekdays. The two vertical lines on each figure mark the hours (1:00 p.m. to 5:00 p.m., or hours-ending 14 to 17) which are those when CPP and PTR events were called; this is the period when one would expect CPP and PTR customers to reduce consumption relative to their usage on non-event days. These hours are also those when the highest TOU rates are in effect, and when DA-RTP prices are highest.

To provide context, Figure 5-1 plots hourly usage patterns for the F3 control group (which includes customers paying the conventional ComEd residential rate that has no hourly price variation) on an average weekday, an average event day (when temperatures were elevated), and the average day for the week of August 9-13, which by virtue of its relatively high temperatures serves as basis for sorting out weather effects from event day treatment effects. Because the control group receives no price changes when weather changes, loads on the average hot weekdays and on event days are essentially identical during event hours (since events tend to be called on hot days). Control group loads on average weekdays, as indicated by the distinctly lower load profile in Figure 5-1, are lower than on hot days, primarily because less air conditioning is needed.

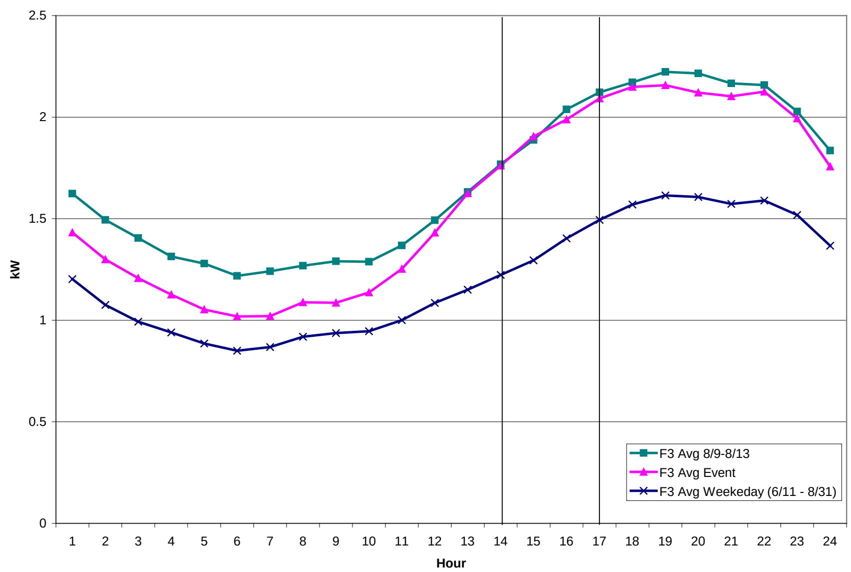
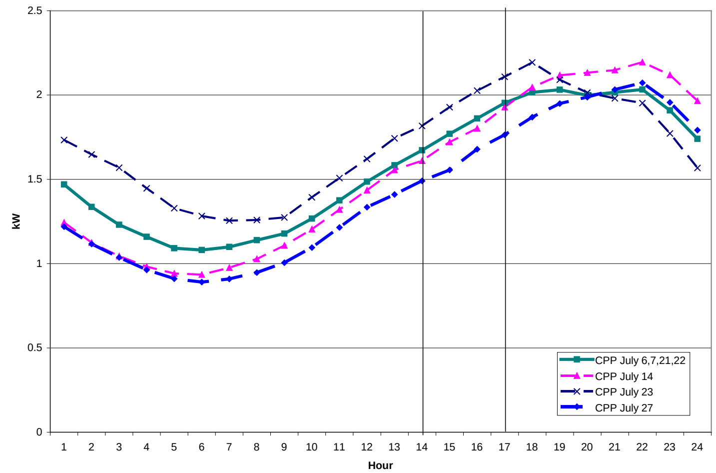
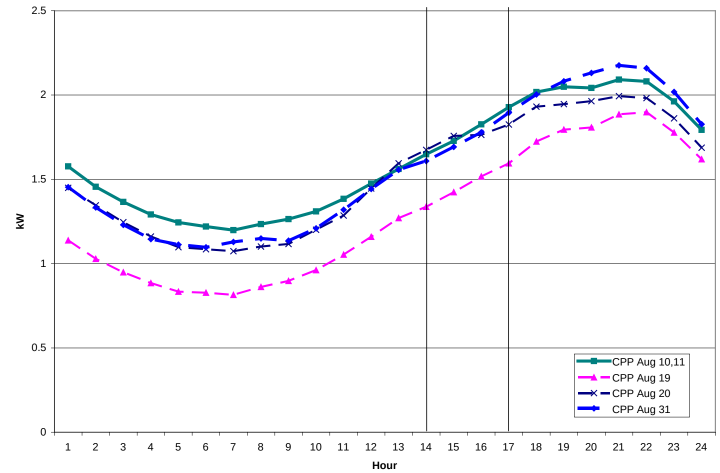


Figure 5-1
F3 Control Group Average Usage, by Day Type

Somewhat in contrast, Figure 5-2 illustrates average hourly usage patterns for CPP customers (combined groups D1-D4) during typical non-event days and on three event days in July (the left-hand illustration) and three events days in August (the right-had illustration)





July **August**

Figure 5-2
CPP Average Usage in July and August for Average Non-Event Days vs. Three Event Days

The solid green line in each figure represents average usage over non-event weekdays with temperature conditions similar to those on event days.[42] The dashed lines are average CPP loads on the three event days in July (left panel) and in August (right panel). At this aggregate level, the only apparent differences in usage are the nearly parallel shifts upward or downward in hourly usage patterns on event days relative to non-event days due to differences in ambient temperatures and possibly other unexplained factors. In particular, usage during peak hours on event days barely appears to drop relative to usage on non-event days. There is no distinct notch in the load profile during the event period. Thus, at this aggregate level there appears to be no visibly discernable effect of high CPP prices on customer behavior.

Figure 5-3 illustrates average hourly usage patterns for real-time pricing (DA-RTP) customers (groups L1-L3) for several types of days in July and August: event days, high-priced days (when prices during the four peak hours average more than $0.10/kWh), and moderately-priced days (when peak prices average less than $0.10/kWh). These curves indicate (paradoxically) that DA-RTP loads are higher at higher prices. However, the correlation likely reflects the fact that loads and prices both move together with temperature, and not that loads increase when DA-RTP prices increase.

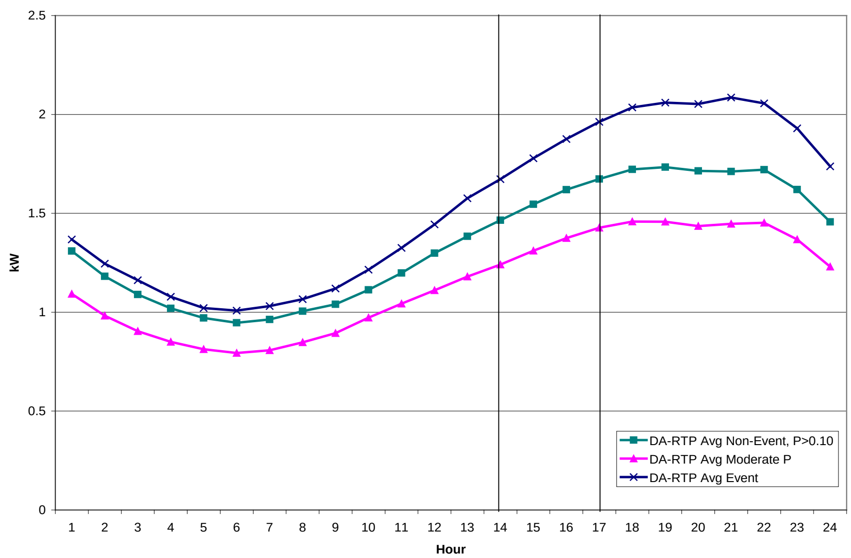


Figure 5-3
DA-RTP Average Usage, by Day Type

[42] The average non-event loads are intended to be illustrative. Since temperatures and day of week differ for each event, no single average non-event load can serve as an indicator of the load profile that would be expected on each event.

A visual inspection of average 24-hour load shapes reinforces the ANOVA results, which failed to reveal any significant application-level effects of rate structure on average customer usage behavior. If customers in the CPP applications, who have a very large incentive to reduce load during event hours, were responding during events, we would expect to see the average load deviate from the normal progression (with a low around 6:00 a.m. to an evening high between 8:00-9:00 p.m.) to a load profile that drops off around noon or 1:00 p.m. when the event commences and then returns to normal levels after 5:00 p.m. when the event terminates, creating a visible notch in the load shape. The graphic portrayal of average CPP loads offers no evidence of this iconic notch. Likewise, the high PTR payment incentive to reduce load and elevated DA-RTP prices show no significant impact.

Fixed-Effects Regression Analysis

The ANOVA analyses described in Section 5.1 simultaneously test a variety of treatments, including rate structures and technology types. However, this breadth of analysis requires a somewhat restrictive customer characterization. That is, all treatment participants are represented by a single data point defined by the average value across the analysis timeframe (e.g., the summer months).

In this section, we explore event-day load impacts for CPP and PTR customers to enable the use of more extensive customer-level data. We use daily observations on average hourly peak-period consumption for each customer to estimate fixed-effects models of event-day load response. Separate models are run for CPP and PTR customers. CPP customers face high event-hour prices, while PTR customers face a high event-hour incentive to reduce load. The other rate types either provide no financial incentive (flat rate, IBR) or a lesser and not event-specific financial incentive (TOU) to reduce loads during event hours.[43] A separate model is estimated for flat-rate (FLR) customers for comparison purposes.

The fixed-effects model utilizes average hourly peak-period load for all customers on CPP, and separately for PTR. The model includes customer-specific intercept terms to account for differences in average usage across customers. The dependent variable is the natural logarithm of daily average electricity usage during the peak hours (1:00 to 5:00 p.m. on non-holiday weekdays). The explanatory variables in the model, in addition to the customer-specific intercept terms, account for weather conditions, day type, and month. The regression model is as follows:

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[43] While only CPP and PTR customers had a financial incentive to reduce load on event days, all CAP treatment customers were notified of event days, raising the possibility that some customers on the non-event based rate structures (i.e., not CPP or PTR) may have reduced their consumption on event days in response to the notification alone. In the analysis of individual customer data below, we attempt to identify any such customers.

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

Equation 5-2

where:

$Q_{c,t}$ represents the average usage from 1:00 to 5:00 p.m. for customer c on day t;

the β's are estimated parameters;

$Event_t$ is an indicator variable that equals one if day t is an event day[44];

$Event7_t$ is an indicator variable that equals one if day t is September 21;

THI_t is the temperature-humidity index, which is calculated across four different time periods[45];

$PKTHI_t$ is the average temperature-humidity index from 1:00 to 5:00 p.m. on the current day;

$PREPKTHI_t$ is the average temperature-humidity index from 10:00 a.m. to 1:00 p.m. on the current day;

$MORTHI_t$ is the average temperature-humidity index from 12:00 a.m. to 10:00 a.m. on the current day;

$LAGTHI_t$ is the average temperature-humidity index for the entire previous day;

$DTYPE_{i,t}$ is a series of dummy variables for each day of the week;

$MONTH_{i,t}$ is a series of dummy variables for each month;

v_c is the customer-specific fixed effect for customer c; and

e_t is the error term.

The weather variables control for current-day weather (through the peak THI, pre-peak THI, and morning THI variables), weather on the previous day (through the lagged THI variable), and for the possibility that the weather effect is not linear (through the squared terms for each weather variable). The day type and month indicator variables account for typical patterns in customer usage. The model is estimated using a method that accounts for first-order autocorrelation of

[44] The event days were July 14, July 23, July 27, August 19, August 20, August 31, and September 21.

[45] THI is calculated as: THI = 0.55 x T_d + 0.2 x T_{dp} + 17.5, where T_d is the dry-bulb temperature in degrees Fahrenheit and T_{dp} is the dew point temperature in degrees Fahrenheit.

the data (i.e., the regression error term is correlated across observations), which is a common trait of time-series data.[46]

Table 5-3 contains the estimated event-day load impacts that result from estimating this model for CPP, PTR, and FLR (the baseline of comparison) customers using data from June 1 through September 30, 2010.[47] Because the dependent variable is specified in logarithms, the estimated coefficient on the event-day indicator variable for each rate structure is interpreted as the average percentage load reduction on event days relative to non-event days, adjusted for weather conditions, month, and day type. For reasons explained below, an additional load-impact coefficient is estimated for the seventh event in late September.

Table 5-3
Event-Day Load Impact Estimates by Rate Type

Model Description	Event Day Coefficient (p-value)	Event 7 Coefficient (p-value)
CPP	0.002 (0.749)	**-0.174** (0.000)
PTR	**0.046** (0.000)	**-0.182** (0.000)
FLR	**0.060** (0.000)	**-0.191** (0.000)

The estimated coefficient on the event-day indicator in the CPP model is not statistically significantly different from zero, indicating that, on average, CPP customers did not change their peak usage level on event days. For PTR, the estimated coefficient on the event-day indicator is *positive* and significant, paradoxically suggesting an estimated load *increase* of 4.6 percent on event days. This counter-intuitive result is likely due to unobserved factors or imperfectly measured weather effects. Flat-rate customers, who had no financial incentive to reduce load, display a similar positive coefficient as was found for the PTR customers, with an estimated 6 percent increase in usage on event days, which is likely due to imperfectly measured weather effects.

A separate indicator variable is included for the last event ("*Event 7*"), which occurred on September 21. The estimated coefficients on this variable are negative and significant in both the CPP and PTR models, suggesting an *incremental* usage reduction for the September event of 17.4 percent and 18.2 percent for CPP and PTR customers, respectively. The large magnitude of this

[46] Baltagi, B. H., and P. X. Wu. 1999. Unequally spaced panel data regressions with AR(1) disturbances. Econometric Theory 15: 814–823. This method is implemented using the "xtregar" command in Stata.

[47] August 3rd is removed from the flat-rate customer model, as it contains an unusually large amount of zero-load observations during the peak hours. This is not the case in the CPP or PTR data.

estimated load impact is very different from the estimates for the average of the other event days, raising two possibilities. First, customers may have learned over time and were better positioned to respond to event-day incentives by the last event. Second, the regression model does not adequately account for atypical conditions on the last event day, leading to a false conclusion that customers reduced load substantially on that day.

Several factors lead us to believe that the more likely explanation is that the large estimated load reductions for the last event day reflect anomalous factors rather than actual event-related customer behavior. First, our estimate of the Event 7 load impact for flat rate (FLR) customers (a 19.7 percent load reduction, which is statistically significant) is very similar to that for CPP and PTR, despite the fact that the FLR customers have no direct financial incentive to reduce load on event days. Why would those customers reduce to the same extent?

Second, the weather on this day was unusually hot for late September, which may affect the ability of the statistical model to indicate properly how customers change their behavior on hot days at that time of year. To illustrate that likelihood, Figure 5-4 contains a scatter plot of daily observations on average peak-hour usage and temperatures for CPP customers. Data for September are shown as larger black squares, while data for the other months (June through August) are shown as smaller black diamonds. Overall, usage tends to increase as temperatures rise above 70 degrees Fahrenheit throughout the summer and into early September.

In early September, customers appear to respond to hot weather in the same way that they had during the summer months. For example, usage levels on September 1st and 2nd, which were moderately hot days that followed hot days at the end of August, fall well within the range of observations for June through August.

There appears to be a change in the temperature/load relationship starting in mid-September. The next similarly hot day does not occur until September 13th. After a spell of mild weather, it appears that customers used air conditioning less intensively on September 13th than they did earlier in the summer, as their peak usage level is well below the levels observed on September 1st and 2nd. On the seventh and last event day (September 21st), peak-period temperatures reached a level not observed since the end of August – the temperature had not reached 75 degrees during the preceding week. Two days later (September 23rd), a similarly hot day occurred, but that was not an event day.

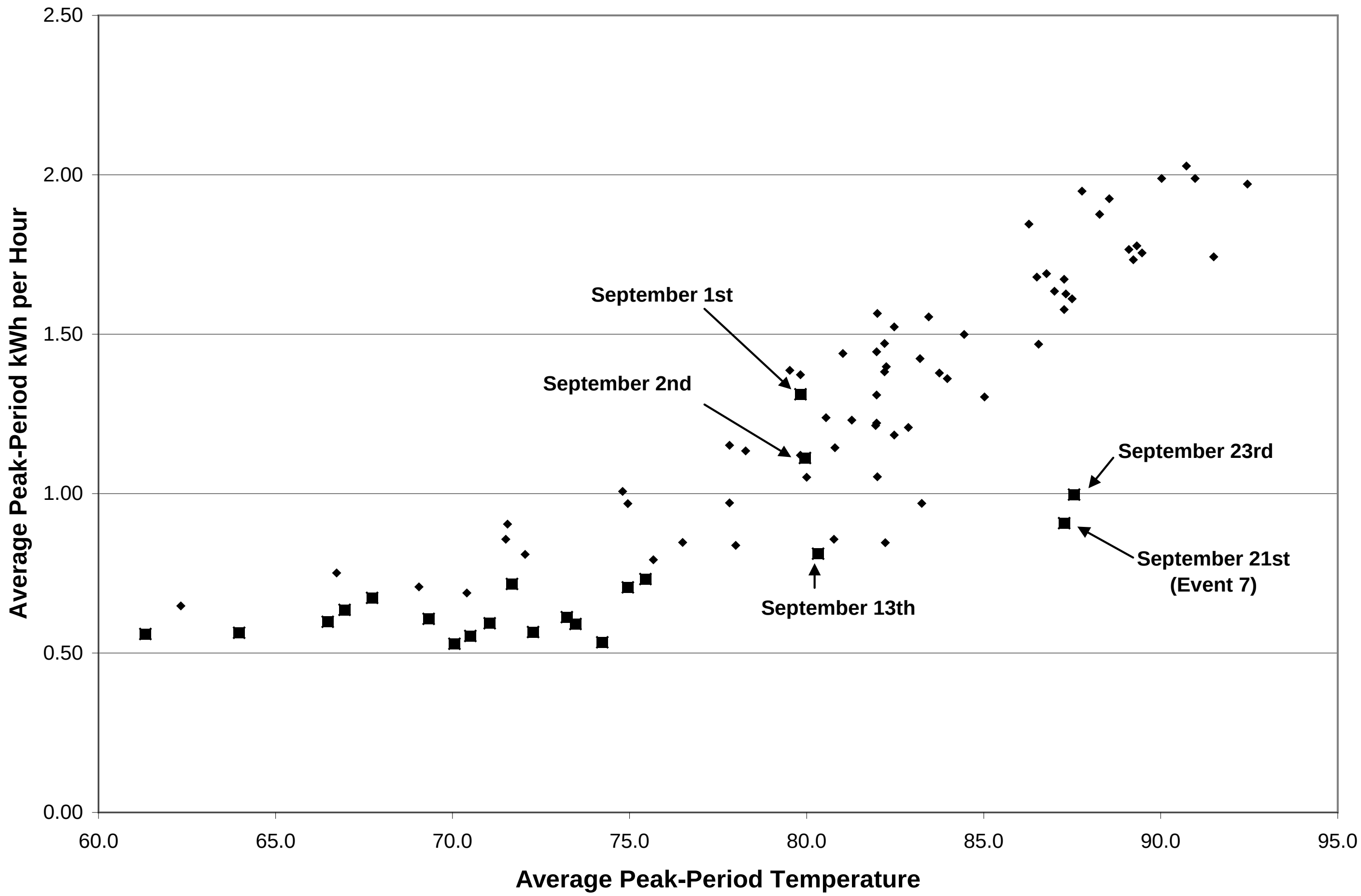


Figure 5-4
CPP Average Usage versus Temperatures, June through September Peak Hours

Peak-period usage levels for both of these late-September days are much lower than were observed at similar temperatures during June through August. This suggests that customers behave differently toward hot temperatures in late September than they do in July and August. One explanation is that customers are less likely to turn on air conditioning on a hot day in late September relative to a similar day in the core summer months. A cooler morning abates some of the impact of the hotter temperature in the afternoon, reducing the need to use air conditioning to be comfortable. There may be fewer people at home due to the resumption of school and regular working hours, compared to summer days.

This change in behavior is very difficult for the statistical model to account for because of the predominant influence of the summer when there is such a close relationship between temperature and load; there are only a few days that resemble the last event day (i.e., hot days in late September following a week or more of mild weather). Because September 21st has such a low usage level given the temperatures that occurred, the statistical models impute the low load relative to temperature to the CPP and PTR treatment effect on this event day. The fact that the same effect is observed for flat-rate customers supports the contention that the high CPP and PTR impact associated with Septembers 21st is an anomaly; it is the result of a seasonal change in customer behavior regarding air conditioning that is not captured in the statistical model.

The third reason to doubt elevated CPP and PTR impacts on event 7 is that the impact estimates are highly sensitive to the model specification regarding weather variables. That is, small changes in how weather variables are constructed lead to large changes in the estimated load impact. Table 5-4 shows estimated CPP load impacts for the average event day and for event 7 across a variety of model specifications. Row 1 contains the base model results contained in Table 5-3. While the event 7 estimates in rows 2 and 4 are similar to the base model results, the results in row 3 show that the estimated event 7 load impact is no longer statistically significantly different from zero if the quadratic weather terms are removed from the specification. The results in row 5 show that the estimated event 7 load impact is *positive* 21 percent if the model is estimated using only September data. This wide range of results (including negative and statistically significant, not statistically significant, and positive and statistically significant) across reasonable alternate model specifications further calls into doubt a conclusion that CPP load impacts were large and significant in September, when there is no discernable effect during the prior six events.

Table 5-4 further illustrates the lack of robustness of the average event-day load impact estimate that applies to events 1 through 6. The results change dramatically across models with different sets of weather variables. For example, the base model described in equation 5-2 above produces an estimate that is not statistically significant (shown in row 1). But, if the model is estimated using average peak-hour cooling degree hours (CDH)[48] in place of THI, the estimate

[48] CDH is defined as MAX(0, temperature in degrees Fahrenheit – 65), where a separate value is calculated for each hour and averaged across hours as appropriate (e.g., across 1:00 p.m. to 5:00 p.m. for peak hours).

indicates a statistically significant 5.1 percent load reduction during event hours (shown in row 2). Alternatively, if the quadratic weather variables are removed from either the THI- or CDH-based models (shown in rows 3 and 4), the estimated event-hour load impact is *positive* and statistically significant.

Table 5-4
Comparison of Event-Day Load Impact Estimates for Alternative Specifications, CPP Customers

Model Description	Event Day Coefficient (p-value)	Event 7 Coefficient (p-value)
(1) THI, full model (eq. 5-2)	0.002 (0.749)	**-0.174** (0.000)
(2) CDH, full model	**-0.051** (0.000)	**-0.167** (0.000)
(3) THI, no quadratic weather variables	**0.075** (0.000)	-0.011 (0.407)
(4) CDH, no quadratic weather variables	**0.019** (0.000)	**-0.166** (0.000)
(5) THI, no quadratic weather variables, September only	n/a	**0.212** (0.000)

Neither the fixed-effects models nor the predecessor ANOVA analyses provide consistent evidence of event-day average usage reductions for CPP or PTR treatments. The earlier graphs of observed load data on event and non-event days provide additional support for the conclusion that CPP and PTR customers on average did not substantially reduce loads during event hours. However, there may have been a substantial and significant response by a few of the customers in the treatments that is obscured by the non-response by the overwhelming majority of treatment participants.

In the next section, we report the results of changing our approach from a fixed-effects analysis across all rate treatment customers to one in which we estimate customer-specific regression models for each individual customer to determine whether a subset of customers can be found who reduced usage on event days, but whose response is masked in aggregated or pooled models due to the "noise" in the data for non-responders.

Identification of Event-Responder Customers

In this sub-section, we estimate customer-specific regression models to identify subsets of customers who did respond to event-day prices or notifications. We use "event-responders" as the term for these customers that exhibit a measurable response to event-day signals. Identification of these customers is accomplished by estimating regression equations for each individual customer using daily observations on average hourly peak-period consumption for all non-holiday weekdays in June through September. The regression model specification is the same as the fixed-effects model described in the previous sub-section (equation 5-2), except that that the customer-level fixed effect variables are removed and instead the estimated model uses average hourly peak period usage data for each customer.

Despite the fact that only CPP and PTR customers faced a direct financial incentive to reduce usage during event hours, we estimate models for all CAP customers. While the DA-RTP, FLR, TOU, and IBR customers faced no additional price incentive (over that which the rate treatment provides for any peak period hour) to reduce consumption during event hours, they were notified when events were called (notification was provided a day in advance to the event). Thus, some of those customers might have responded out of altruism.

Based on the regression results, customers were classified as event-responders if the estimated coefficient on the event-day variable is negative (indicating event-day peak-period usage reductions) and the estimate is statistically significant at the 80 percent level.[49]

Table 5-5 shows the number and percentage of customers on each rate who are classified as event-responders by these criteria. We are not surprised to find that there are event-responders in the CPP, DA-RTP, and PTR treatments (9.5 to 11.6 percent) since other pilots report such a finding.[50] Identifying so many event-responders in the other rate structures (as high as 8 percent for TOU) is surprising.[51]

There are a couple of plausible explanations for why customers on those other rate structures were characterized as event-responders. First, they could have responded to the event notification by reducing load for the good of the system, despite the absence of a direct financial incentive to do so. Utilities often make public appeals to their customers to reduce load when they anticipate the possibility of a capacity shortfall. The CAP notice of an event day may have served that role. Alternatively, customers might have had usage that was unusually low on event days for reasons unrelated to the declaration of the event. For example, some customers may have been on vacation during one or more events, resulting in lower than average electricity use.

We expect that some customers that are offered a large inducement to change load are price responsive. As shown in the table, 11.6 percent and 9.9 percent of CPP and PTR customers, respectively, were found to respond to high price

[49] In the Phase 1 report, responders were identified using a different econometric specification that, for CPP, PTR, and DA-RTP customers, used a price variable in place of the event variable employed in this study.

[50] Based on a review of pilot reports of subscription rates.

[51] While DA-RTP customers did not face the high CPP prices, the RTP prices tended to be somewhat higher than average on event days, and the event notices may have reminded some of them of the price variability.

signals (CPP) or bill credits (PTR). Similar percentages of TOU and DA-RTP event-responders were found, along with smaller percentages of IBR and FLR customers. Note that event-responders account for a slightly smaller share of the usage by rate type, indicating that event responders tend to use less during the peak period (on non-event days) than do non-responders. It is impossible to know how many of the event responders may have been misclassified due to factors that could not be accounted for in the regression models. However, the graphical depictions below lend strong credibility to the assertion that there are indeed some event-responders in the CAP rate treatment samples.

Table 5-5
Numbers and Percentages of Event-Responders, by Rate Treatment

Rate Treatment	Event-Responders	Total Customers	Responder Share of Customers	Responder Share of Usage
CPP	219	1,896	11.6%	10.2%
DA-RTP	94	991	9.5%	8.1%
Flat Rate (FLR)	45	791	5.7%	4.8%
IBR	42	621	6.8%	5.0%
PTR	97	984	9.9%	8.1%
TOU	111	1,180	9.4%	8.0%

Average Event-Day Load Impacts of Event-Responder Customers

To illustrate the load response of customers that were deemed to be event-responders, we averaged those customers' loads by rate group and estimated a new regression model based on hourly observations for each weekday. The new model, which includes event-hour indicator variables to isolate and quantify load reductions during event periods, allows us to examine the hourly pattern of event-day load changes. Doing so may help discern whether customers reduced load during only event hours, during non-event hours of the event day because customers increased their thermostat setting in the morning before leaving the house and then turned it back down after returning home in the evening, or during all hours of the event day. Any of these behaviors would indicate that the method of identifying event responders incorrectly includes customers whose usage level would have been low anyway (e.g., the customer was away on vacation).

The hourly regression model is as follows:

$$\ln(Q_t) = a + \sum_{i=1}^{24}(\beta_i^{EVT} \times h_{i,t} \times EVT_t) + \sum_{i=1}^{24}(\beta_i^{THI} \times h_{i,t} \times THI_t) + \sum_{i=1}^{24}(\beta_i^{THI\_SQ} \times h_{i,t} \times THI\_SQ_t)$$
$$+ \sum_{i=1}^{24}(\beta_i^{LAG\_THI} \times h_{i,t} \times LAG\_THI_t) + \sum_{i=2}^{24}(\beta_i^{MON} \times h_{i,t} \times MON_t) + \sum_{i=2}^{24}(\beta_i^{FRI} \times h_{i,t} \times FRI_t)$$
$$+ \sum_{i=2}^{24}(\beta_i^{h} \times h_{i,t}) + \sum_{i=2}^{5}(\beta_i^{DTYPE} \times DTYPE_{i,t}) + \sum_{i=7}^{9}(\beta_i^{MONTH} \times MONTH_{i,t}) + e_t$$

Equation 5-3

where:

Q_t represents average event-responder customer usage in hour t;

the β's are estimated parameters;

$h_{i,t}$ is a dummy variable for hour i;

EVT_t is an indicator variable for event days;

THI_t is the temperature-humidity index;

THI_SQ_t is the temperature-humidity index squared;

LAG_THI_t is the temperature-humidity index from the same hour on the previous day;

MON_t is a dummy variable for Monday;

FRI_t is a dummy variable for Friday;

$DTYPE_{i,t}$ is a series of dummy variables for each day of the week;

$MONTH_{i,t}$ is a series of dummy variables for each month; and

e_t is the error term.[52]

The specification estimates distinct event-day usage changes for each hour of the day, allowing us to illustrate the hourly patterns of event-day demand response for these customers. Figures 5-5 through 5-7 show the estimated hourly load impacts for each rate group, organized in pairs. Figure 5-5 contains CPP and PTR customers, who had a distinct financial incentive to reduce usage during event hours. Figure 5-6 contains DA-RTP and TOU customers, whose rates vary by time of day, but are not different on event days (except that the DA-RTP prices were slightly higher than usual during peak hours). Figure 5-7 contains FLR and IBR customers, whose rate does not change by time of day nor during event hours.

[52] The model is estimated using the Prais-Winsten procedure to account for serial correlation in the data.

The figures show that event-responders on average reduce consumption considerably during the event hours, with a tendency toward increasing usage somewhat in non-event hours. CPP event responders display the largest event-hour usage reductions (e.g., 20 to 25 percent). The pre-event usage increases are generally not statistically significantly different from zero (with the exception of hours ending 3 and 4, or 2:00 to 4:00 a.m.). In contrast, the post-event usage increases beginning in the hour ending 19 (6:00 p.m.) are all statistically significant for all rate structures.

Figure 5-6 shows that DA-RTP and TOU event-responders have a clear notch (trend-deviating reduction) in the load profile during the event hours, though the magnitude of the usage reduction is smaller than it is for the CPP event responders. Figure 5-7 shows somewhat less distinct notches for FLR and IBR event-responders. However, Figures 5-6 and 5-7 provide evidence that a subset of the customers responded to event notifications by reducing peak-period usage without a direct financial incentive to do so.

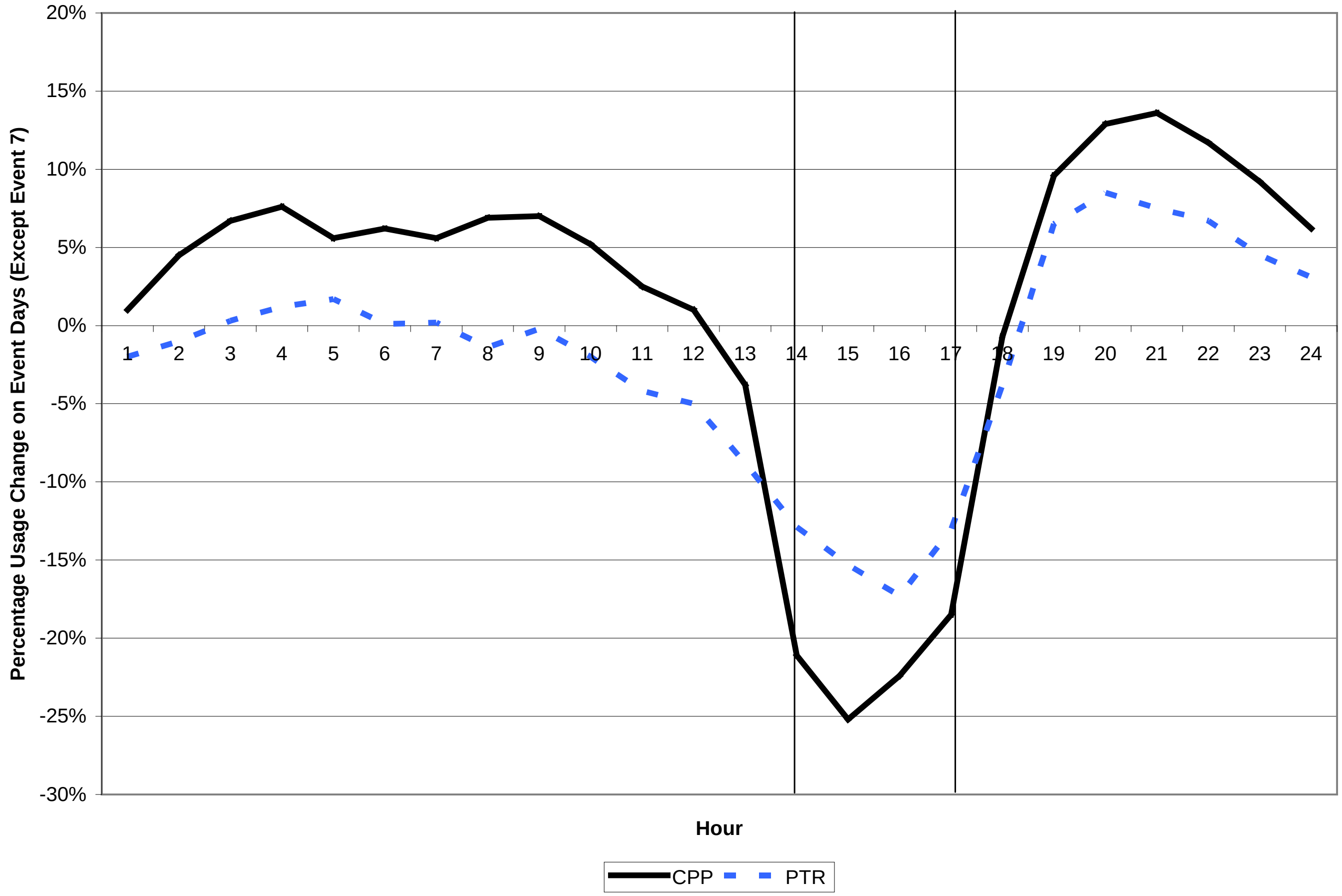


Figure 5-5
Event-Day Load Response Estimates, CPP and PTR Event Responders

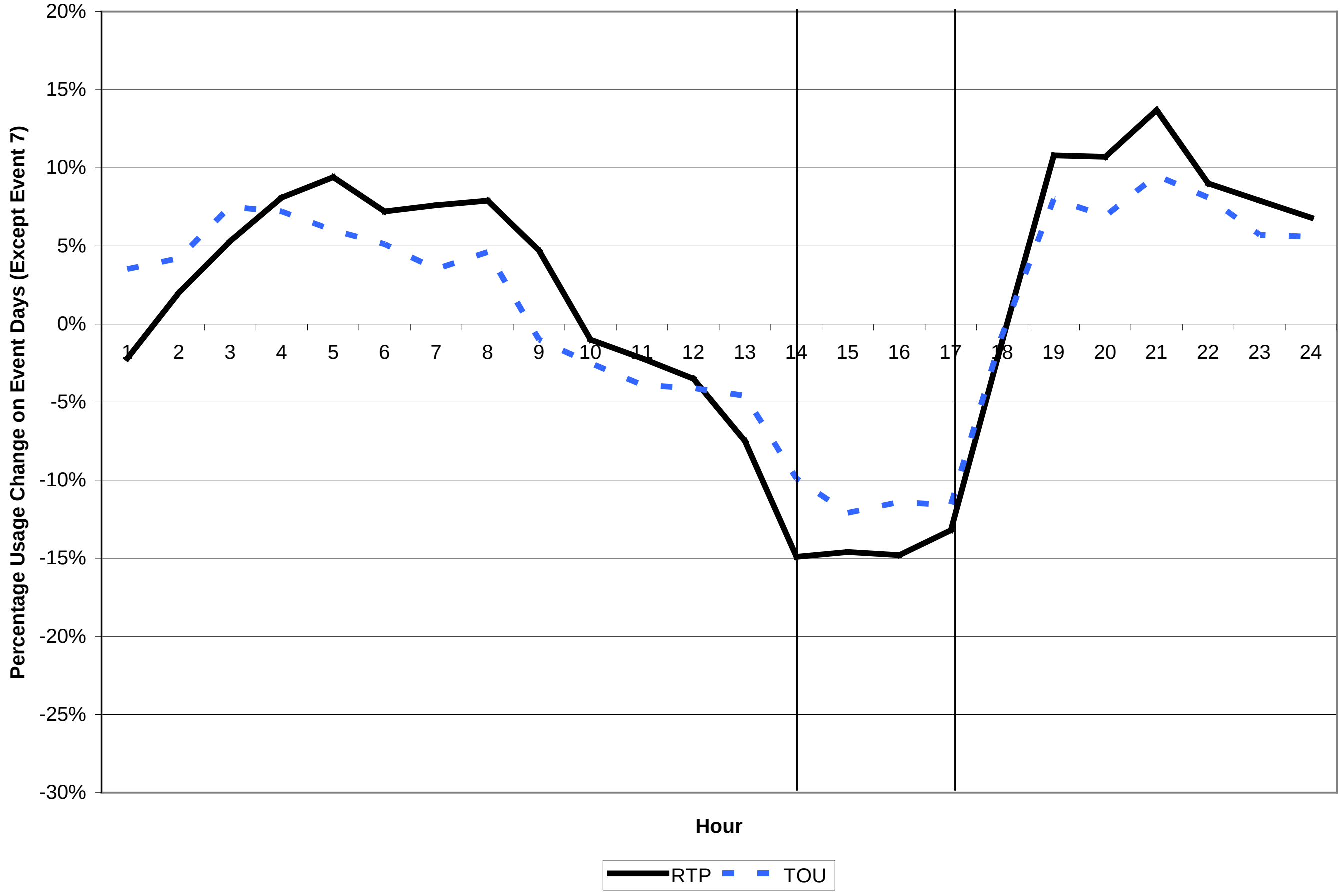


Figure 5-6
Event-Day Load Response Estimates, DA-RTP and TOU Event Responders

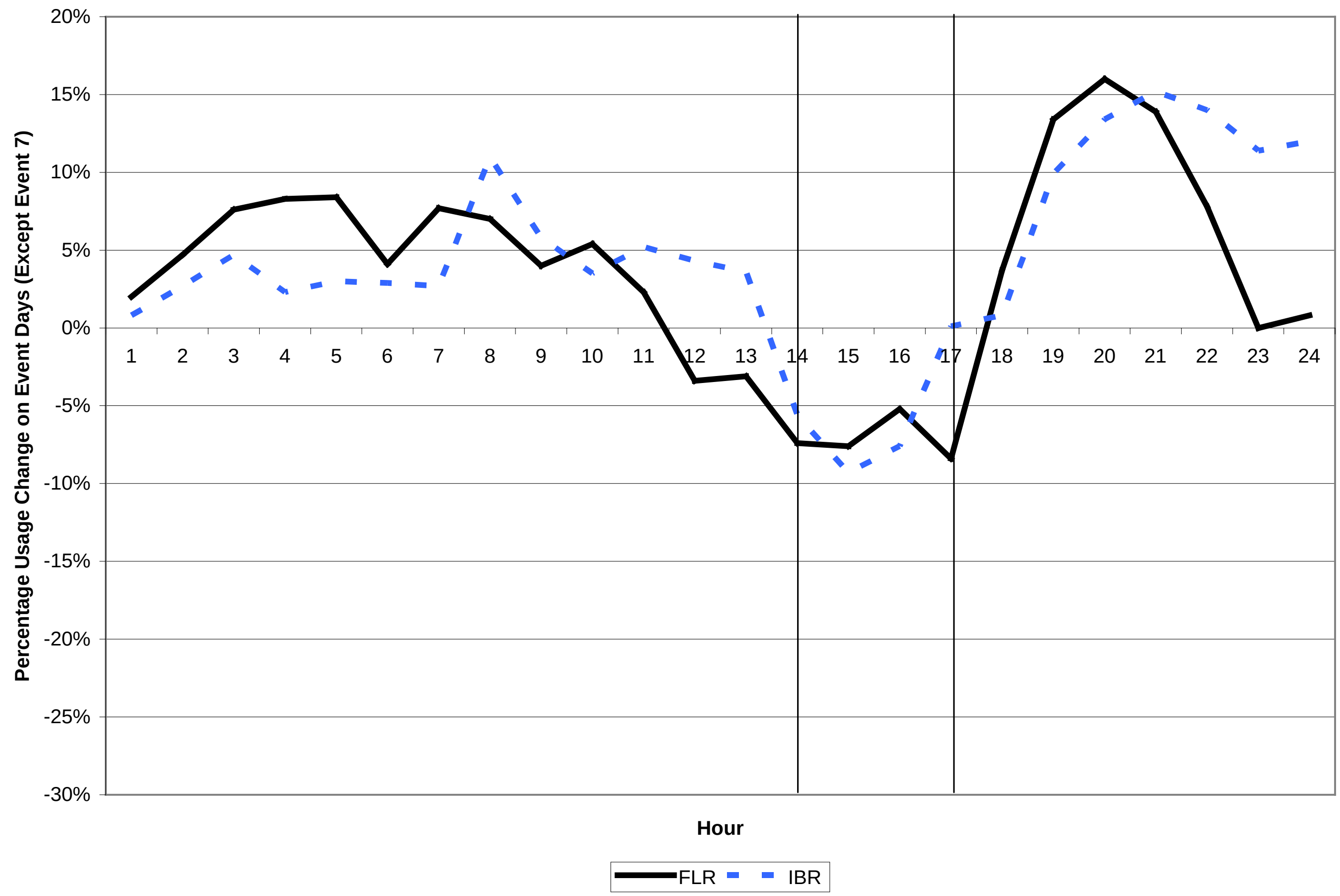


Figure 5-7
Event-Day Load Response Estimates, FLR and IBR Event Responders

Table 5-6 summarizes the average event-hour load impacts shown in the figures above. The last column in the table expands these estimated average load impacts to an approximation of the aggregate percentage reduction in the total CAP load, by combining the event-responders' load impacts with their share of load. This construction assumes that non-event responders in aggregate do not change their usage level during event hours. For CPP, the estimated aggregate load impact is -2.2 percent. The relatively small magnitude of these aggregate usage reductions helps to explain the difficulty in identifying the usage reductions of event-responders when their usage is combined with the other (unobserved) factors driving non-event responder behavior. Therefore, we believe that the findings of no aggregate event-day usage reductions (through the ANOVA and fixed-effects models) are consistent with our findings of significant usage reductions from a subset of customers (through the customer-level models).

Table 5-6
Average Load Impacts of Responders and Implied Total Load Impacts, by Rate

Rate	Event-Responder Share of Load	Average Estimated Load Impact for Responders	Implied Total Load Impact
CPP	10.2%	-21.8%	-2.2%
DA-RTP	8.1%	-14.4%	-1.2%
FLR	4.8%	-7.2%	-0.3%
IBR	5.0%	-5.6%	-0.3%
PTR	8.1%	-14.7%	-1.2%
TOU	8.0%	-11.3%	-0.9%

To illustrate that the load impacts of event-responders on event-days can be observed in the raw load data, Figure 5-8 shows average hourly usage patterns for CPP event-responders for each event day. The solid line represents their hourly usage pattern averaged across non-event weekdays in July and August. The dashed lines represent usage on the six event days in those months. On all of the event days, there is a clearly defined notch (drop) in usage when the event begins. Also apparent is that load moves back up to, or beyond, the typical load after the event, and may also move up somewhat in the hour or two prior to the event period. (Customers are notified of events the day before, so customers have time to pre-cool or undertake other load shifting strategies). Customers' increased usage after the event may reflect making up for some electricity services, such as air conditioning, foregone during the event.

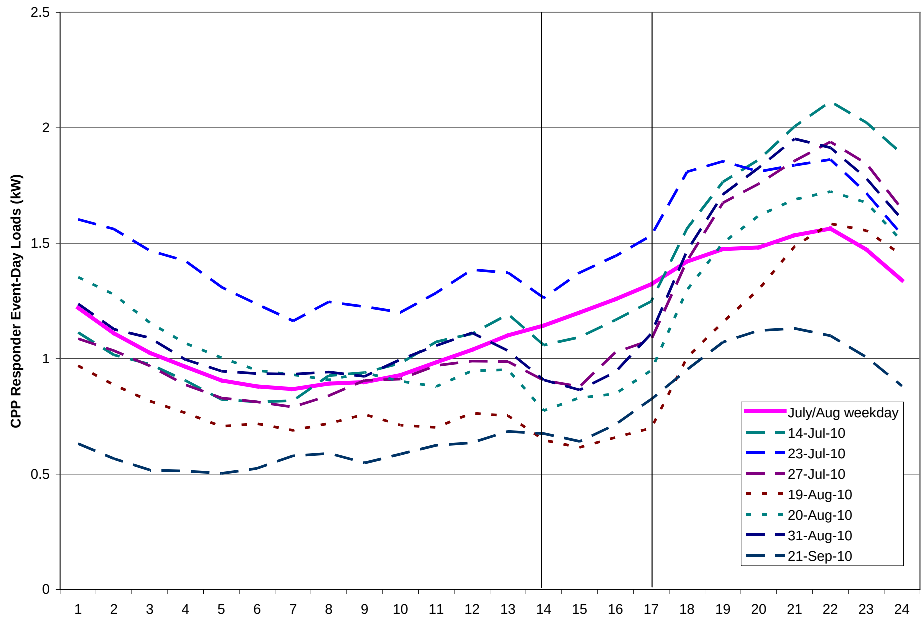


Figure 5-8
CPP Responder Usage Patterns, Average Non-Event Weekday vs. Event Days

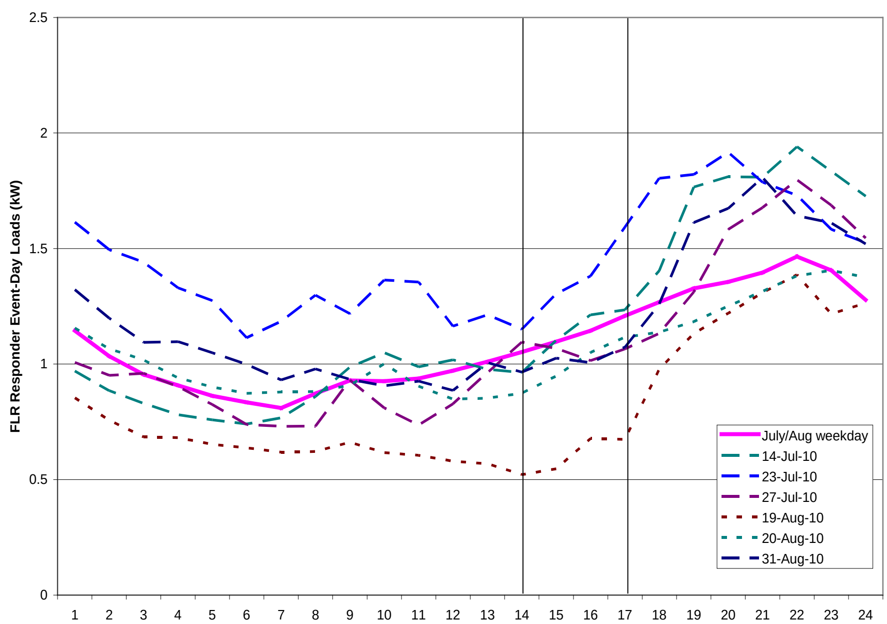


Figure 5-9
FLR Responder Usage Patterns, Average Non-Event Weekday vs. Event Days

Figure 5-9 shows the corresponding chart for flat-rate event-responders. The usage reductions for this group are less consistent and not as distinguishable as those of CPP event-responders. On some event days, usage reductions appear to begin prior to the event hours. On other event days, there does not appear to be a reduction at all. Figures 5-8 and 5-9 reinforce our prior expectation that event-day pricing will lead to usage reductions that are larger and more reliable than a utility could obtain through event-notification only.

In summary, regression models were applied to data for individual customers to identify those that exhibit statistically significant event-day behaviors consistent with responding to higher event prices or event notifications. Finding some event-responders in the CPP and PTR applications comports with what other pilots have found; some customers are price responsive, especially to very large price inducements.

We also found event responders in the FLR, DA-RTP, IBR, and TOU rate applications that seem counterintuitive since prices for those rates did not change during event hours. This result may stem from one of several possible factors. It might reflect customer response to the notification of an event day, particularly given that the information material provided to pilot participants noted the value of reducing peak-period usage on event days, and that notice was provided a day in advance. The result may simply reflect unaccounted for factors that are unrelated to the occurrence of events. Alternatively, as discussed in the next section, some customers may have mistakenly thought that they were subject to event day prices when they were in fact not.

In any case, the nature of the usage changes for CPP and PTR event-responders indicates a stronger and more reliable response than occurred for event-responders in other rate types.

In the next sub-section, we estimate formal demand models using event-responder loads for CPP and PTR customers. This allows us to estimate relative measures of their price responsiveness (i.e., elasticities of substitution), which can be compared to results from other studies.

Estimation of Elasticities of Substitution for Event-Responders

To characterize how event-responders shift loads among hours in response to price changes, we estimated two alternative formal customer demand models. As explained in Chapter 2, the models chosen are the Nested Constant Elasticity of Substitution (NCES) and Generalized Leontief (GL) models. These models characterize load-shifting behavior through a characteristic known as the elasticity of substitution.[53] The advantage of the NCES model is its relative simplicity and ease of estimation. Its limitation is that its two elasticities – a within-day and a between-day elasticity of substitution – are assumed to remain constant across price levels. The advantage of the GL model is its flexibility in allowing the elasticities of substitution to differ by day, depending on the daily peak and off-peak prices.

[53] A customer's "elasticity of substitution" between peak and off-peak electricity use is defined as the percentage change in the ratio of peak to off-peak electricity use caused by a 1 percent change in the ratio of off-peak to peak electricity prices.

Nested CES Model

The nested CES model is derived from a cost function that allocates a customer's electricity costs separately within a day and between days. That is, overall cost is a function of *daily price indexes*, which in turn are functions of the hourly prices (or average prices for daily sub-periods) on each day. The typical specification, which has been applied to analysis of hourly real-time pricing, allows two types of customer response to changing electricity prices. One level allows customers to shift load between hours (or block of hours) *within* a day; the other level allows shifting load *between* days in response to changes in the overall price level between different days.

Certain aspects of the CAP dynamic price structures suggest a modification to the standard NCES model. CPP and PTR customers pay the same prices as DA-RTP customers, except on event days, when CPP customers pay a much higher price (additional $1.74/kWh) and PTR customers have an equal inducement (as a rebate) to reduce load. So while these customers routinely faced day-ahead hourly pricing, there was relatively little hour-to-hour variation in prices during the summer of 2010. Due to a daily revenue-neutrality condition, the price variation was most prominent not among hours of the day, but between peak and off-peak hours. In addition, on event days, the CPP prices and PTR credits took on essentially the same value for each hour of the four-hour event period, again resulting in the large source of price variation being between event and non-event hours of those days.

These conditions call for grouping the hours of the day into time periods for purposes of estimating responsiveness. Four time periods were defined: Overnight (hours-ending 1-10 and 23-24); Pre-peak (11-13); Peak (14-17); and Post-peak (18-22).

Under these conditions, the customer's demand for electricity may be expressed relative to a base, or average reference load, in logarithm form as shown in the following:

$$\ln\left(\frac{E_{dh}}{\overline{E}_h^m}\right) = \sigma_w\left[\ln\left(\frac{D_d}{\overline{D}^m}\right) - \ln\left(\frac{P_{dh}}{\overline{P}_h^m}\right)\right] + \sigma_b\left[\ln\left(\frac{M_m}{\overline{M}^m}\right) - \ln\left(\frac{D_d}{\overline{D}^m}\right)\right].$$

Equation 5-4

E_{dh} represents electricity usage in hour (or time period) *h* on day *d*, P_{dh} is the price in that time period on day *d*, D_d and M_m represent daily and monthly price indexes of a CES form, and σ_w and σ_b are the between-day elasticity of substitution and within-day elasticity of substitution parameters, respectively. The variables with the bars above the capital letter in the denominator of each term are averages of the variable for the comparable time period in the reference period (*e.g.*, the average load in time period *h* on weekdays in a given month).[54]

The daily and monthly price indexes are constructed as weighted averages of relevant rate structure prices, where the weights are load shape parameters (α_{hd} and β_d), which characterize the inherent shape of the customer's load pattern. In estimation, a series of indicator variables for the different time periods and months are also added, as well as a weather variable (daily THI) of the same log-ratio form relative to the reference period as the other variables.

Given the general lack of hourly price variability except on event days, and the fact that only CPP and PTR event-responders had price-related incentives to respond, separate models were estimated for only those two rate treatments, using load data averaged over those customers classified as event-responders.[55]

Table 5-7 presents the estimated elasticity parameters for the time period of June through August, which included six event days. The magnitude of the elasticity of substitution values for CPP and PTR are generally consistent with previous studies.[56] The within-day value for CPP is larger than for PTR (0.095 for CPP and 0.066 for PTR), indicating larger event-period reductions. In the NCES structure, the *between-day* parameter is important primarily to the extent that its value differs from that of the *within-day* parameter. If the two parameters take on the same value, then the effect of a price change in a particular time period on a given day will be largely confined to load in that time period. In this case, both between-day parameters are larger than the corresponding within-day parameters. This presumably reflects the fact that daily usage on event days is lower than on non-event days due to the event-period load reductions, which the model interprets as shifting load away from event days.

Table 5-7
NCES Estimated Elasticities of Substitution, by Rate

	NCES Elasticities of Substitution	
	Within-Day	**Between-Day**
CPP	0.095	0.149
PTR	0.066	0.124

[54] The reference period is an average of several days of mild weather and low prices for the relevant rate treatment group.

[55] Models were also estimated for the overall average customer (including non-event responders) for both rate treatments. However, the estimated elasticity of substitution parameters were small, sometimes wrong signed (negative), and never statistically significant. As a result, only results for the event-responders are reported.

[56] *Price Elasticity of Demand for Electricity: A Primer and Synthesis.* EPRI, Palo Alto, CA: 2007, 1016264.

Generalized Leontief Model

For the purposes of the CAP project, the GL model has been simplified to analyze how customers shift load between peak hours (1:00 p.m. to 5:00 p.m.) and off-peak hours (all other hours). The elasticity of substitution is defined as the percent change in the ratio of peak to off-peak consumption that accompanies a given percentage change in the ratio of off-peak to peak prices. In addition to providing a degree of response metric, the elasticity of substitution can be used to simulate the response in customer load to alternative prices.

The estimation equation for this demand model is given by:

$$\mathrm{Ln}\left(\frac{ES_{pd}}{ES_{od}}\right) = \beta \times CDD_d + \mathrm{Ln}[h_p H_d + \gamma_{pp} P_{pd} + \gamma_{po}\sqrt{P_{pd}\ P_{od}}] - \mathrm{Ln}[h_o H_d + \gamma_{oo} P_{od} + \gamma_{po}\sqrt{P_{pd}\ P_{od}}]$$

Equation 5-5

Where:

- ES_{pd} and ES_{od} are peak and off-peak electricity expenditure shares, respectively, on day d,
- β is a parameter that controls for daily differences in cooling degree days (CDD_d),
- P_{pd} and P_{od} are peak and off-peak prices, respectively, on day d,
- Hd is a variable that is set to be equal to unity on days where the temperature exceeded 85 degrees F, and was zero otherwise; and
- γ_{ij} are estimated parameters[57].

As explained in Appendix A of the Phase 1 report, once the parameters of this model are estimated, one can calculate predicted expenditure shares and corresponding elasticities of substitution. An elasticity of substitution is calculated for each day as a function of prices and the estimated γ_{ij} coefficients. For reporting purposes, as in Table 5-8, they are then averaged across day-types (e.g., high-price and low-price days).

Separate models were estimated for the CPP and PTR rate treatments using load data averaged over those customers classified as event-responders. Table 5-8 shows estimated average elasticities of substitution for those rate treatments, differentiated by event-day vs. non-event day. The values in the table indicate, for example, that for CPP responders a doubling (i.e., a 100 percent increase) in the ratio of peak to off-peak real-time price would, all other things equal, correspond to a 12.7 percent reduction in the ratio of peak to off-peak consumption on event days.

[57] As estimated, the equation contains an additional variable indicating the occurrence of a hotter than normal day, along with its associated coefficient. For simplicity, that variable is not shown in the above equation.

Table 5-8
GL Estimated Elasticity of Substitution for Event-responders, by Rate and Day Type[58]

	GL Elasticity of Substitution	
	Average Event Day	**Average Non-Event Day**
CPP	0.127	0.105
PTR	0.062	0.055

For CPP and PTR event-responders, the values in the table indicate that estimated elasticities of substitution are on average somewhat higher on event days than on non-event days. Note also that the general magnitude of the values, as well as the relationship between CPP and PTR values are similar to those for the NCES model.

Analysis of the Inclining Block Rate

Because of the sampling issues described in Chapter 4, comparison of electricity consumption by customers in the IBR treatment with customers in the other rate treatments could not be accomplished using ANOVA. As an alternative, the electricity usage for IBR customers was compared for the CAP and pre-pilot time periods, covering 22 months of data in total. In the regressions employed for this analysis, the dependent variable is the natural log of monthly usage. The independent variables are: the total cooling degree days (CDDs) during the billing month; total heating degree days (HDDs) during the billing month; and a dummy variable which equals unity for the months that the customer is on the IBR rate (the CAP pilot period), and zero otherwise (before the CAP pilot when they were on the conventional ComEd tariff).

Table 5-9 shows the result of the regression; coefficients that are significant at the 95 percent level (all but for IBR) are in bold. As expected, the coefficient for CDDs indicates that hotter weather (and therefore greater cooling needs) leads to a significant 7.3 percent higher usage, which lends support to the reasonableness of the model specification. Analogously, the coefficient for HDDs indicates a significant, though smaller, effect of cold temperatures on monthly usage. The fact that the estimated coefficient for the IBR indicator variable is not statistically significant suggests that customers on the IBR rate showed no significant change in monthly usage during the CAP pilot.

[58] Additional details will be provided in the addendum to this report to be published in January 2012.

Table 5-9
Dependence of the Natural Log of Monthly Usage on IBR Status[59]

Variable	Coefficient
IBR	-0.040
CDDs	0.073
HDDs	0.011
Constant	6.116

[59] Additional details will be provided in an addendum to this report to be published in January 2012

Section 6: Survey Findings

Two surveys were conducted over the course of the CAP. The first survey, distributed in March 2010 (during the enrollment process), contained questions related to customer attitudes towards energy conservation, usage behaviors, and customer demographics. Survey participants received a $15 credit on their ComEd bill in exchange for their response. A second survey was conducted from late April through mid July 2011, as customers were returned to the standard ComEd tariff. The latter survey included 50 questions covering topics addressed in the initial survey as well as questions regarding various elements of the CAP. Customers who also completed the final survey received a total of $50 in credits to their ComEd bill.

This section examines responses to several questions in the final survey, particularly those related to the rate treatments. Specifically, we summarize customer satisfaction with the CAP and with ComEd, respondents' understanding of their CAP rate treatment, and the extent to which those customers identified as event-responders in Section 5 are distinguishable from others (non-responders) in terms of perceived behavioral changes and demographics. Where applicable, we apply the survey results to address specific hypotheses about the CAP impacts.

Survey Response Rate

ComEd received 2,423 responses to the final survey representing approximately one-third of eligible CAP customers.[60] Table 6-1 below summarizes response rates by rate treatment. The response rate did not differ substantially across rate types.

Table 6-2 summarizes the survey response rates from event-responders in each rate treatment group. The response rate for event-responders was slightly higher than that for the general population.

[60] "Eligible CAP customers are defined as customers who were enrolled in the CAP as of April 27, 2011.

Table 6-1
Survey response rate by rate type

Rate	# Surveys	# Eligible CAP Customers	Survey Response Rate
CPP	627	1,865	34%
DA-RTP	305	965	32%
FLR	543	1,474	37%
IBR	229	664	34%
PTR	323	1,012	32%
TOU	396	1,194	33%
Total	2,423	7,174	34%

Table 6-2
Survey response rate for event responders, by rate type

Rate	Total # Event-Responders	# Surveys from Event Responders	Event-Responder Survey Response Rate
CPP	219	85	39%
DA-RTP	94	27	29%
FLR	45	16	36%
IBR	42	13	31%
PTR	97	34	35%
TOU	111	41	37%
Total	608	216	36%

Customer Satisfaction

Question #22 in the final survey asks customers to rate their satisfaction with their pricing plan on a scale from 0 to 10, where 0 represents "extremely dissatisfied" and 10 represents "extremely satisfied".[61] As displayed in Figure 6-3, the overall average score is 5.6, with IBR and DA-RTP customers ranking their pricing plans the highest (average score of 5.9) and FLR customers giving the lowest score (average score of 5.1). Satisfaction with FLR is statistically significantly lower than satisfaction with all other rate types, but there are no statistically significant differences between the other rates. Thus, we reject hypothesis H2f, which posits that IBR customers will experience greater

[61] The question reads "Thinking about your experiences with ComEd's electricity pricing plan, how satisfied are you with this pricing plan?"

satisfaction. The low score given by FLR customers is counterintuitive to those that postulate that simpler rates result in higher customer satisfaction.

Question #23 in the final survey asks customers to rate their satisfaction with ComEd on a scale from 0 to 10, where 0 represents "extremely dissatisfied" and 10 represents "extremely satisfied".[62] The overall average score is 6.3, with DA-RTP customers expressing the highest level of satisfaction with ComEd (average score of 6.5) and FLR customers giving the lowest score (average score of 6.1). While the difference between these two scores (DA-RTP versus FLR) is statistically significant, there are no other statistically significant differences in satisfaction across rate types. The lower satisfaction score given by FLR customers may reflect a pre-existing bias rather than sentiment toward the CAP Program. It is also notable that customers have a higher level of satisfaction with ComEd than they do with their CAP pricing plan. Table 6-3 presents the average scores for Questions 22 and 23 by rate treatment.

Table 6-3
Average satisfaction scores by rate type

Rate	Satisfaction with CAP	Satisfaction with ComEd
CPP	5.6	6.3
DA-RTP	5.9	6.5
FLR	5.1	6.1
IBR	5.9	6.3
PTR	5.8	6.3
TOU	5.7	6.2
Overall	5.6	6.3

Customer Understanding of their Rate Treatment

A series of questions in the final survey (questions 2a through 2i) ask customers to indicate if they agree, disagree, or are uncertain about statements describing the basic structure of their pricing plan. Questions 2b through 2f are targeted towards specific rate treatments, while the remaining questions address customer understanding of certain elements of the CAP Program. Responses to these questions provide an indication of the participants' degree of understanding of their rate plan, and perhaps the effectiveness of ComEd's efforts to educate customers regarding the prices that they faced during the pilot. In Figures 6-1 and 6-2, the questions are represented along the X-axis, with responses shown for each rate treatment. The Y-axis measures the percentage of respondents from each rate type who agreed to each question. Responses to each question are summarized below, in the order shown in the figures.

[62] The question reads "Thinking about your experiences with ComEd as your electric utility, how satisfied are you with ComEd?"

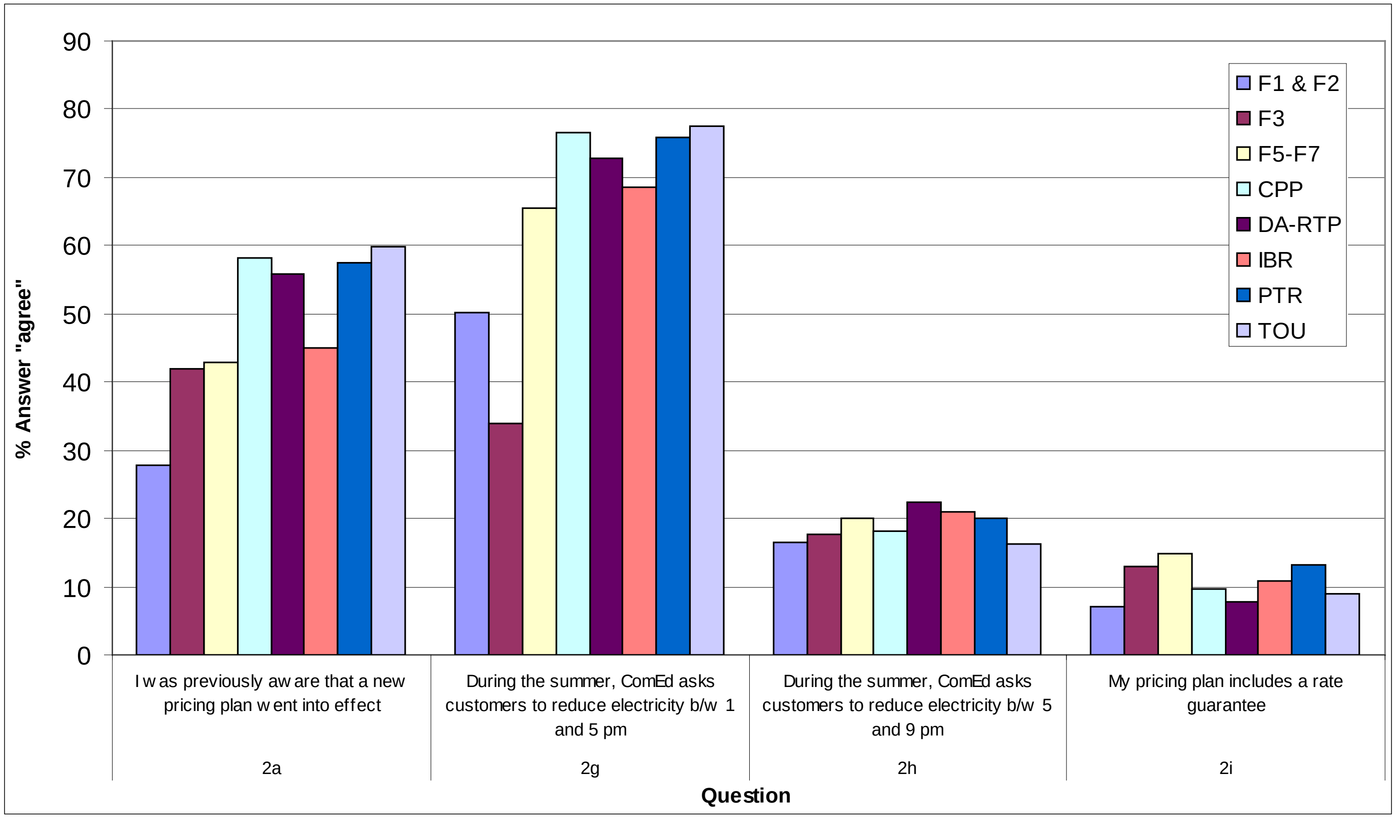


Figure 6-1
Degree of agreement with CAP pricing characteristics, by rate type

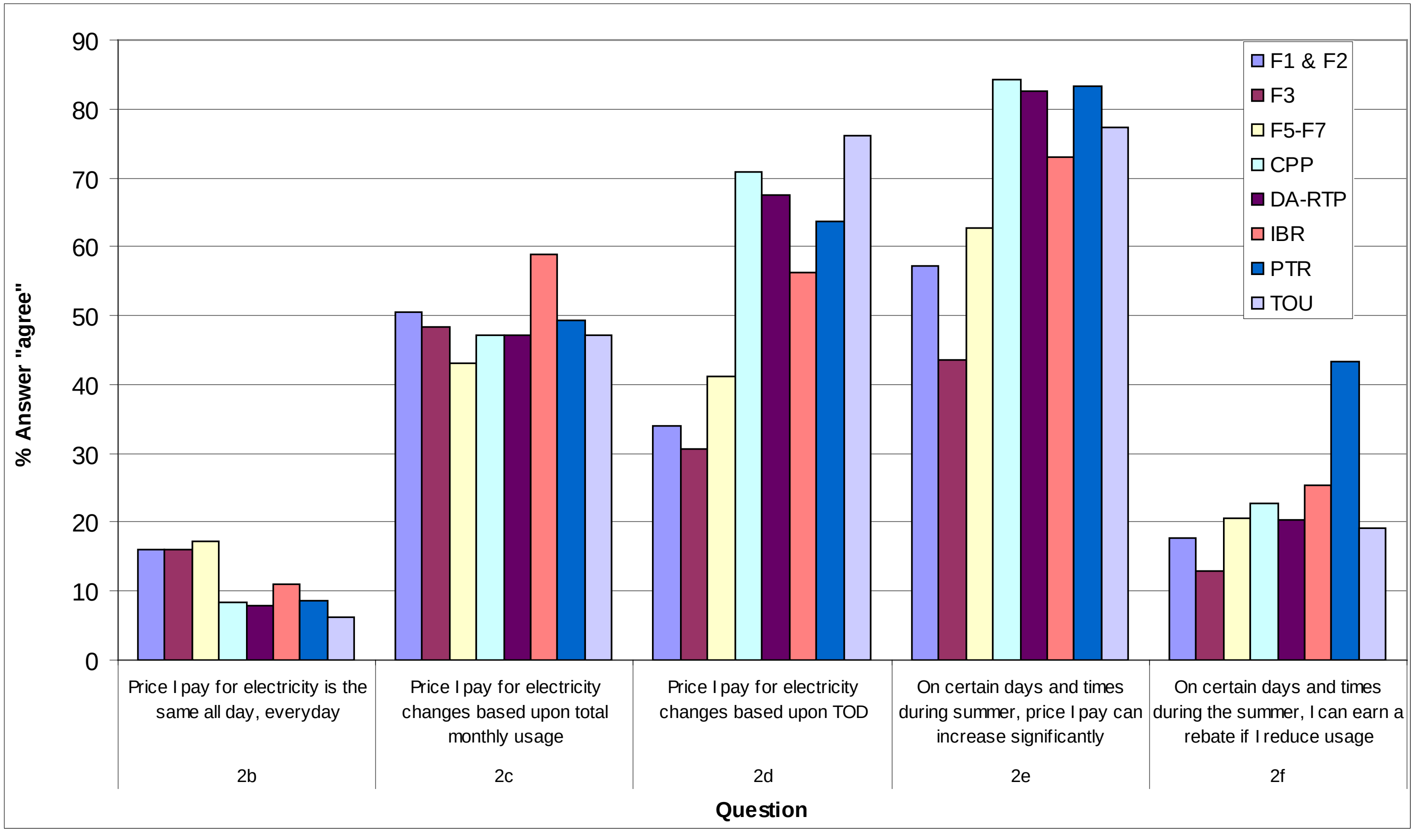


Figure 6-2
Degree of agreement with rate-treatment characteristics, by rate type

Question 2a: I was previously aware that a new pricing plan went into effect.

As expected, FLR customers agreed with this statement less often than other rates, with F1 and F2 customers (who did not receive a new pricing plan) agreeing only 28 percent of the time and 43 percent of all other FLR customers agreeing. IBR customers agreed 45 percent of the time, while 55 to 60 percent of all other customers indicated that they were aware of the new pricing plan.

Question 2g: During the summer, ComEd asks customers to reduce electricity usage between 1 pm and 5 pm.

This question seeks to determine whether customers are aware of peak-period hours, which also constitute the event window on event days. The average rate of agreement is about 70 percent. Flat-rate customers in cells F1, F2, and F3 score the lowest on this question, which is reasonable given that these customers were not notified of event days (unlike the flat-rate customers in cells F5-F7, who were notified of event days).

Question 2h: During the summer, ComEd asks customers to reduce electricity usage between 5 pm and 9 pm.

This question asks about an alternative definition of peak-period, but for an incorrect window of time. Therefore, a low level of agreement indicates a correct understanding of the timing of the peak period. Reassuringly, the rate of agreement is much lower for this question than it is for question 2g, which refers to the correct peak-period and event window.

Question 2i: My pricing plan includes a rate guarantee.

This question could be interpreted in one of two ways: a reference to the bill protection program (which ensures that CAP participants will pay no more under the pilot than they would have in the absence of it); or a reference to a fixed rate or schedule of rates, which would apply to FLR, TOU, and IBR. In either case, the rate of agreement is uniformly low, with a mean of 10 percent.

Question 2b: The price I pay for electricity (per kWh) is the same all day, every day.

As one would expect, flat-rate customers are the most likely to agree with this statement, though the rate of agreement for them is quite low at 17 percent. This reflects either a lack of understanding of their rate, or an awareness of the fact that it changes seasonally.

Question 2c: The price I pay for electricity (per kWh) changes based upon the total amount of electricity I use per month.

As expected, IBR customers are the most likely to agree with this statement. While the difference between the IBR response relative to all other rates is statistically significant, the magnitude of the difference is not especially large, with 59 percent of IBR customers agreeing versus 47 percent of non-IBR customers agreeing.

Question 2d: The price I pay for electricity (per kWh) changes based upon the time of day.

As expected, customers with the CPP, PTR, DA-RTP, and TOU rates were more likely to agree with this statement, averaging 70 percent across rates. It is not clear why IBR customers (whose rate changes with the total amount of usage, but not by time of day) agreed with the statement at a higher rate than the flat-rate customers. Also, the fact that 30 percent of the respondents who faced a time-varying rate did not agree with this statement appears to indicate some lack of understanding of their rate treatment.

Question 2e: On certain days and times during the summer, the price I pay for electricity can increase significantly.

Though this question primarily relates to a characteristic of CPP, the rate of agreement is uniformly high across all but the flat rates. The rate of agreement for the three hourly priced rates (CPP, PTR, and DA-RTP) was higher by a statistically significant margin than the rate of agreement for TOU and IBR. Given that the hourly prices for DA-RTP customers can change somewhat on event days (though the average of the hourly prices is always equal to the flat rate), this is a reasonable response on the part of those customers. The high rate of agreement for PTR respondents seems to validate the use of the value of the PTR rebate as a proxy price in our analysis of PTR price response. It also suggests that customers do not make a distinction between paying a higher price (CPP) and being offered an equivalent rebate (PTR) for load reductions.

Question 2f: On certain days and times during the summer, I can earn a rebate if I reduce my usage.

As expected, PTR customers had the highest rate of agreement with this statement. However, it is somewhat troubling that only 43 percent of the respondents were aware of this central distinguishing feature of their rate plan. In addition, 21 percent of the non-PTR customers agreed that they can earn a rebate on certain days of the summer, which is not the case.

Overall, responses to these questions tend to be in the expected directions, in that customers on particular rate types are more likely to identify a characteristic of their own rate than that of another rate. However, the responses to some of the questions indicate a potentially low overall level of awareness and understanding of the rates.

Responders vs. Non-responders in the Survey

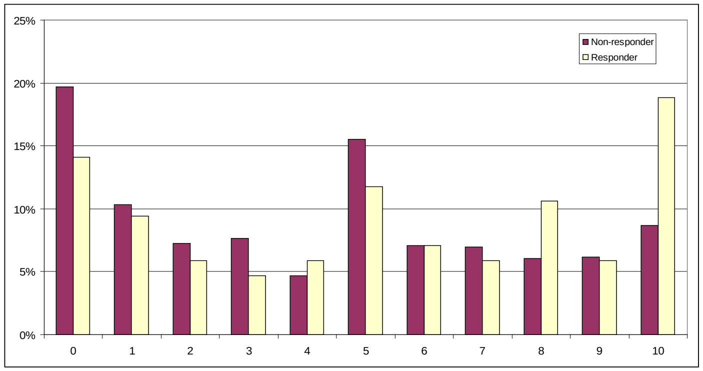
In this section, we use the survey data to determine whether event-responders (as identified in Section 5) differ in observable ways from non-responders; and whether event-responders report that they took actions in a manner consistent with the findings in Section 5. Specifically, we examine demographic differences and survey questions that describe behavioral changes as a result of the CAP.

Several survey questions ask customers to disagree or agree on a (scale of 0 to 10) that various elements of the CAP Program helped them to reduce their electric bills. While answers to these questions are not directly related to event response, they may be indicative of attitudes toward treatment elements or willingness to adjust behavior in response to treatments.

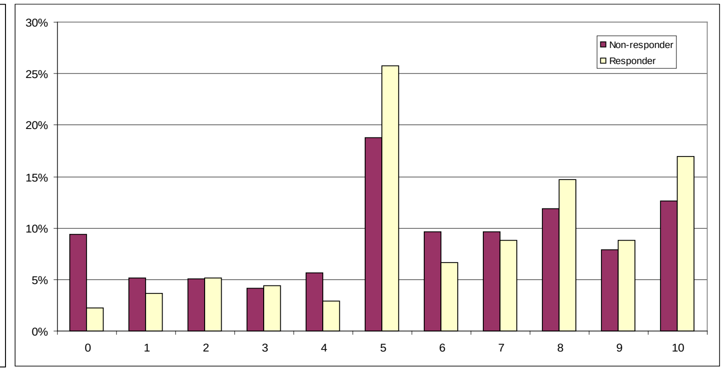
We did not find substantial mean differences between event-responders and non-responders, but there is some variation in the distributions of scores. For example, Figure 6-3 shows the answers to four questions for which the distributions of scores, especially for the extreme value scores (0 and 10), for event-responders and non-responders appear to differ despite having similar mean values.

The first chart shows the distribution of answers to question 5a that asks customers to disagree or agree (on a scale of 0 to 10) that the in-home device helped reduce electric bills. A higher percentage of event-responders (represented by the yellow bars) "strongly agree" with the statement and a higher percentage of the non-responders "strongly disagree." Similarly, but less striking, differences in distributions are apparent in questions pertaining to the effectiveness of the rate notification letter (question 8a), the Smart Tools website (question 15a), and the Smart Tools call center (question 19a).

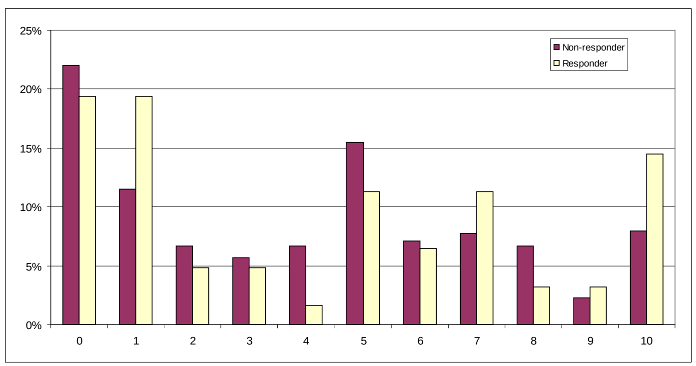
5a



8a



15a



19a

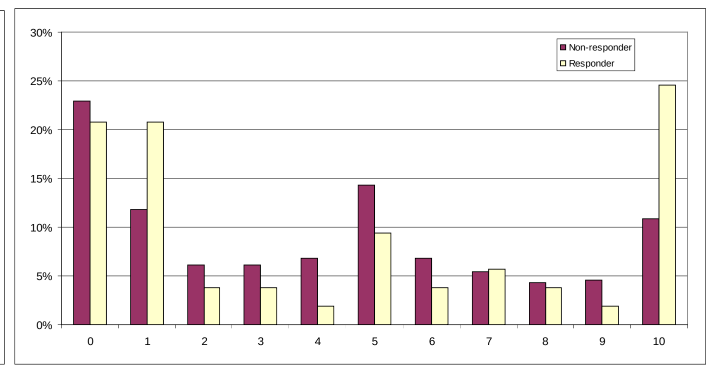


Figure 6-3
Distributions of responses to behavioral questions for event responders and non-responders

Because event-responders are identified as customers who reduce electricity usage during peak hours on event days, we might expect responders to self-report higher levels of load-shifting behavior. Survey question 21a most directly inquires about load-shifting by asking customers if they used appliances during non-peak times to reduce their energy costs.[63] The proportion of event responders and non-responders, by rate treatment, who answered "true" to that question can be found in Figure 6-4. The difference for CPP customers is large and statistically significant, with more event-responders than non-responders reporting off-peak appliance use. None of the other differences shown in the chart are statistically significant.

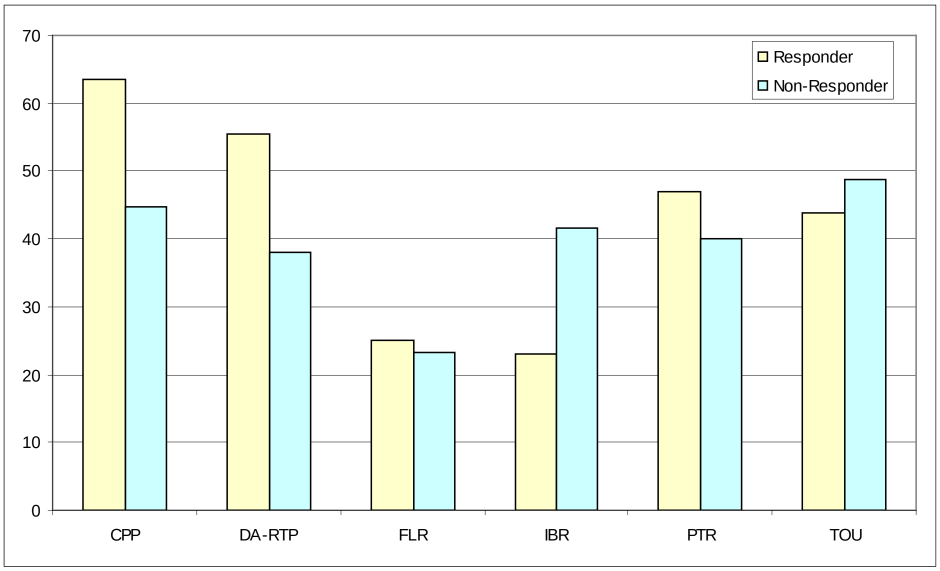


Figure 6-4
Share of customers who report using appliances in off-peak hours by rate type

Table 6-4 contains a comparison of a variety of demographic traits. None of the differences between event responders and non-responders are statistically significant. This suggests that event-responders differ from non-responders in unobservable ways, rather than by differences in demographic characteristics. This may make it difficult to target event-responders when enrolling customers in an *opt-in* program.

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[63] The question reads "21. As a direct result of your participation in ComEd's electricity pricing program, what actions, if any, did you take to reduce your energy cost? (Please check all that apply.) a. Used appliances at a non-peak time, b…."

Table 6-4
Customer characteristics by event-responders and non-responders

		Frequency (%) Across All Surveys	Frequency (%) Across Responder Surveys	Frequency (%) Across Non-Responder Surveys
Education Level				
	HS Grad	25.6%	26.1%	25.6%
	Some College	24.3%	22.8%	24.5%
	College Grad	50.1%	51.2%	50.0%
Age				
	Age <=35	12.0%	12.7%	12.0%
	36<=Age<=50	25.9%	27.3%	25.8%
	51<=Age<=65	38.3%	39.5%	38.2%
	Age > 65	23.8%	20.5%	24.2%
Race				
	White	57.8%	55.6%	58.0%
	Non-White	42.3%	44.4%	42.0%
Income Level				
	Low Income	41.3%	40.4%	41.4%
	Middle Income	30.1%	31.3%	30.0%
	High Income	28.6%	28.4%	28.6%
Household Size				
	Small HH	57.5%	57.8%	57.4%
	Large HH	42.5%	42.2%	42.6%
Household Size Less than 18 years				
	Small HH	67.0%	68.0%	66.9%
	Large HH	33.0%	32.0%	33.1%

Section 7: Summary and Conclusions

ComEd implemented the CAP pilot to create a better understanding of how AMI technology (including pricing structures and in-home technologies) might influence how consumers use and value electricity. An ambitious and expansive experimental design was implemented, following rigorous statistical protocols, for one year. Realizing the full value of this pilot requires distilling the large amount of data that was generated, conducting a variety of analyses to explore several perspectives, and synthesizing the results so that they are understandable and actionable. This was accomplished by conducting an analysis of load and customer data in two phases; an initial Phase 1 study that examined the load data for the summer of 2010, and a second study was conducted using a full year of load data augmented by customer information and perceptions gathered through a post-pilot survey. This report contains the result of the Phase 2 analyses, extending the descriptions and analyses presented in two prior CAP publications; EPRI 1022266, which describes the structure and initial implementation of the pilot, and 10222703, which discusses the Phase 1 analysis.

The Phase 2 CAP analysis sought to quantify the impact of a variety of influences that were hypothesized to result in changes in level or profile, or both, of electricity consumption on residential customer behavior. It used customer consumption and price data from the pilot period (June 2010 - May 2011). In addition, a survey of CAP participants was conducted at the end of the pilot period that provided information regarding customer satisfaction, customer understanding of CAP rates, customer behaviors under the CAP, and demographic characteristics.

Dynamic Pricing Applications

The most important finding is that statistically significant responses were exhibited by some of the customers served under each of the rate types, but these responding customers constitute only about 10 percent of all CAP participants enrolled in a dynamic rate. The strongest and most consistent responses were observed for CPP customers. EPRI's analysis of individual customer effects found that 11.6 percent of CPP participants reduced their event-period load by an average of 21.8 percent, which amounts to 2.2 percent of the usage of all CPP-enrolled participants. The event-period usage reductions for other rate types were lower, ranging from approximately 14 percent for PTR and DA-RTP event responders to 5.6 percent for IBR event responders. The fact that reductions were observed for customers in non-event based rates (IBR, and to a lesser extent TOU and the flat rate) suggests that event notification itself appears to produce a small amount of demand response from some customers.

While significant load impacts were found for subsets of CAP participants, analysis of aggregate load data was unable to detect measureable event-day load reductions at that level. This absence of aggregate-level event-day load impacts for CPP and PTR customers may seem inconsistent with results from other recent dynamic pricing pilots.[64] However, the results are more consistent after accounting for the structural differences in the design of CAP and other recent dynamic pricing pilots.

Specifically, CAP used an *opt-out* enrollment method, whereas other recent pilots used an *opt-in* enrollment that populated the treatments by recruiting volunteer participants. *Opt-in* recruitment typically experiences relatively low participation rates. One would rightly expect that volunteers are predisposed to respond to the inducement offered with the expectation of benefits. Generalizing, these pilots report CPP and PTR load reductions of 13 to 30 percent during event hours, and even larger (25 to 40 percent) load reductions when price and enabling technology treatments are combined. A common finding when individual customer responses were analyzed in pilots employing comparable CPP and PTR applications is that only a quarter to half of participants show any indication of price response. One might then expect 5 to 10 percent of customers in an *opt-out* program to exhibit price responsiveness to these rates, unless the *opt-out* design itself serves as an inducement for a larger response rate or level.

The ComEd *opt-out* process enrolled customers without their prior and informed consent specifically to test whether that method would result in a higher level of response from the population as a whole. One of the constructed hypotheses proposed that the *opt-out* design employed by ComEd, which included several provisions to make participants aware of the potential benefits from adjusting usage and how those benefits could be realized, would result in greater price response than has been reported for *opt-in* pilots. The CAP findings for CPP and PTR event days suggest that the *opt-out* design itself does not appear to have resulted in greater price response in terms of the number of responders or the level of individual responses.

Other Price, Enabling Technology, and Education/Incentive Applications

A comparison of the load impacts across price and enabling technology applications, (separately for summer and non-summer months), was conducted using a variation on analysis of variance (ANOVA) statistical tests. They revealed no statistically significant effects attributable to rate types or to any of the enabling technology applications coupled with the pricing applications. Furthermore, neither the bill protection nor enabling technology partial payment

[64] For a summary of the load reduction impacts of rate technology pilots see: Faruqui, A., Hledic, R., Sergici, S. Rethinking Prices: January 2010. The Changing Architecture of Demand Response in America. Public Utilities Fortnightly.

applications were found to have a significant effect on the level or profile of electricity consumption. The implication is that none of the applications exhibited statistically significant differences in usage from that of the control group when comparing average use across applications.

One potentially interesting result that emerged from the ANOVA analyses was the fact that customer education and event notification (which must be tested jointly due to the experimental design) were associated with lower event-hour usage. If true, the implication is that customer education and event notification can play a role in encouraging demand response, even in the absence of rate structures that provide direct economic incentives to reduce usage during event hours. However, we suggest that caution should be exercised in interpreting this result, as it is only statistically significant for three of the twenty-four cells with full customer education and event notification.

An additional caution is warranted regarding the finding that enabling technology has no statistically significant impact. The installation rate for IHDs was low: approximately 12 percent for the advanced IHD (AIHD). As a result, statistical tests based on the average load change for each application may not identify application influences that are there but are associated with only a small percentage of the participants. Even if a high proportion of those that adopted the AIHD respond in some manner, the number that receive the application (installed the device) was relatively small given the level of the effect being measured; other pilots suggest that information may result in 1 to 2 percent reduction is usage.[65] Consequently, it is difficult to detect changes in the average usage of CAP application treatments that involved only about 250 customers. Implementation rates for the BIHD are somewhat higher (approximately 17 percent) but still so small that they constitute a low percentage of the participants that were intended to receive that application. This may make identifying an effect difficult at the aggregate-level analysis (ANOVA).

For the dynamic pricing structures (DA-RTP, CPP, and PTR), rates change each day, and CPP and PTR event days impose much higher rate differences ($1.74/kWh) than non-event days. This degree of price variation allows for price responsiveness to be estimated using a customer's own data -- lower DA-RTP priced day loads serve as a control for event day and high DA-RTP price day loads. In contrast, estimating the effect of the other treatments, such as time-of-use rates or IHDs, involves a single change in the customer situation, each is a one-time treatment. A control is required to isolate those effects, which the pilot design provided.

Because of pilot design complications, EPRI could not estimate the impact of the inclining block rate (IBR) directly using ANOVA or through the individual customer analyses used for the dynamic rates. EPRI endeavored to quantify IBR impacts by comparing participants' usage before and after the introduction of IBR to ascertain if the differences that were observed were significant, controlling

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[65] EPRI. April 2010. Guidelines for Designing Effective Energy Information Feedback Pilots. EPRI 1020855

for differences in weather conditions in the pilot and pre-pilot time periods. The finding was that the IBR application had no significant effect on customers' monthly usage

Next Steps

ComEd's CAP is an ambitious undertaking because of what was required to implement and support the complex design that involved 27 different applications. The analyses reported herein sought to isolate and quantify separately the impacts of those applications. This detailed Phase 2 analysis completes the objectives of the study. In a supplementary addendum to this report, to be published in January 2012, the results of additional analyses of the survey responses and full documentation of the methods and results associated with tests of all the pre-specified hypotheses will be reported. This will include a more complete discussion of the differences between the findings for pilot programs using *opt-out* and *opt-in* enrollment methods (i.e., hypotheses H7b through H7e).

The CAP produced a rich trove of information about how prices, information, technology, and other factors influence how residences use electricity. Subsequent researchers may unlock additional findings and insights, especially when the CAP data are compared and contrasted to the result of other pilots.

Section 8: Abbreviations

AIHD	advanced in-home display technology
AMI	advanced metering infrastructure
ANCOVA	analysis of covariance
ANOVA	analysis of variance
BIHD	basic in-home display technology
CAP	Customer Application Program
CDD	cooling degree days
ComEd	Commonwealth Edison
CPP	critical-peak pricing rate
EPRI	Electric Power Research Institute, Inc.
GL	Generalized Leontief
HDD	heating degree days
IBR	increasing block rate
IHD	in-home display technology
MVDB	Measurement and Validation Database
OLS	Ordinary Least Squares regression
PCT	programmable controllable thermostat technology
PTR	peak-time rebate rate
DA-RTP	real-time pricing with day-ahead notice
TOU	time of use or time-of-use rate

Appendix A: Design Hypotheses

Variable	Hypotheses	Accept	Reject	Not Tested
Meter Type	***H1:*** *Meter type has no effect on electricity usage behaviors.*			***X***
Rate Type	***H2a:*** *The IBR rate is most easily adopted by customers.*	***X***		
	H2b: *The IBR rate causes the greatest reduction in overall electricity usage during the year.*		***X***	
	H2c: *The CPP rate causes the greatest reduction in peak load during the summer.*		***X***	
	H2d: *The CPP rate causes flatter load shapes at all times during the year.*		***X***	
	H2e: *The CPP rate delivers the best combination of energy efficiency, demand response, and load shifting benefits.*		***X***	
	H2f: *Customers on the IBR rate will experience greater satisfaction than customers on the other rates.*		***X***	
Enabling Technology	***H3a:*** *The BIHD will have a higher implementation rate than other enabling technology.*	***X***		
	H3b: *The BIHD will have a higher adoption rate than other enabling technology.*		***X***	
	H3c: *A combination of direct and indirect feedback solutions will achieve greater energy efficiency, demand response, and load shifting benefits than indirect feedback solutions alone.*		***X***	
	H3d: *The AIHD/PCT solution will achieve greater energy efficiency, demand response, and load shifting benefits than other enabling technology.*		***X***	

Variable	Hypotheses	Accept	Reject	Not Tested
Enabling Technology (continued)	***H3e:*** *The AIHD/PCT solution in combination with the CPP rate will achieve greater energy efficiency, demand response, and load shifting benefits than other enabling technology and pricing plan combinations.*		***X***	
	H3f: *Customers activating a BIHD will experience greater satisfaction than customers who have received and activated other enabling technology.*		***X***	
Enabling Technology Acquisition	***H4a:*** *The acquisition rate of free enabling technology will exceed purchased enabling technology.*	***X***		
	H4b: *The implementation rate of purchased enabling technology will exceed free enabling technology.*	***X***		
	H4c: *The adoption rate of purchased enabling technology will exceed free enabling technology.*			***X***
	H4d: *Purchased enabling technology will achieve greater energy efficiency, demand response, and load shifting benefits than free enabling technology.*		***X***	
Bill Protection	***H5a:*** *The adoption rate of a dynamic pricing plan will be greater when bill protection is offered than when it is not offered.*		***X***	
	H5b: *Customers without bill protection will achieve greater energy efficiency, demand response, and load shifting benefits than customers with bill protection.*		***X***	
	H5c: *Customers with bill protection will experience greater satisfaction than customers without bill protection.*		***X***	

Variable	Hypotheses	Accept	Reject	Not Tested
Customer Education	***H6a:*** *Customers receiving customer education will achieve greater energy efficiency, demand response, and load shifting benefits than customers who do not receive customer education.*		***X***	
	H6b: *Customers who receive customer education along with an AMI-enabled, non-flat rate and enabling technology will achieve greater energy efficiency, demand response, and load shifting benefits than customers who are not offered customer education.*		***X***	
	H6c: *Customers who receive customer education along with an AMI-enabled, non-flat rate and enabling technology will achieve greater energy efficiency, demand response, and load shifting benefits than customers who receive customer education, a flat rate, and enabling technology.*		***X***	
	H6d: *Customers who receive customer education will experience greater satisfaction than customers without customer education.*		***X***	
Customer Experience – Observable Steps	***H7a:*** *Customers who engage in small, observable steps will achieve greater energy efficiency, demand response, and load shifting benefits than customers who do not engage in those steps.*		***X***	
Customer Experience – *Opt-Out* Enrollment	***H7b:*** *An opt-out strategy will result in a higher enrollment percentage than an opt-in strategy.*			***X***
	H7c: *An opt-out strategy will result in greater adoption of new pricing plans and enabling technology than an opt-in strategy.*			***X***
	H7d: *An opt-out strategy will result in greater energy efficiency, demand response, and load-shifting benefits than an opt-in strategy.*			***X***
	H7e: *Customer satisfaction with an opt-out strategy will not be significantly different than satisfaction with an opt-in strategy.*			***X***

Variable	Hypotheses	Accept	Reject	Not Tested
Customer Experience – Comparisons	***H7f:*** *Customers who are saving money will have a drop-out rate that is less than customers who are not saving money.*			***X***
	H7g: *Customers whose rate comparison shows a monthly loss will change their behavior in subsequent months to minimize that loss.*			***X***
	H7h: *Customers whose rate comparison shows a cumulative loss will change their behavior in subsequent months to minimize that loss.*			***X***
	H7i: *Customers whose rate comparison shows a monthly gain will have a drop-out rate that is less than customers who experience a monthly loss.*			***X***
	H7j: *Customers whose rate comparison shows a cumulative gain will have a drop-out rate that is less than customers who experience a cumulative loss.*			***X***
	H7k: *Customers who experience sequential monthly losses will have a drop-out rate that is higher than customers who do not experience sequential monthly losses.*			***X***
	H7l: *Customers receiving normative comparisons will experience greater energy efficiency, demand response, and load-shifting benefits than customers not receiving normative comparisons.*			***X***
	H7m: *Customers whose normative comparisons show them having higher electricity consumption than their neighbors will lower their electricity consumption.*			***X***
Customer Experience – Notifications	***H7n:*** *Customers who are notified of events will experience greater energy efficiency, demand response, and load-shifting benefits than customers who are not notified.*		***X***	
	H7o: *Customers who choose more than one notification media will experience greater energy efficiency, demand response, and load-shifting benefits than customers who do not.*		***X***	

Variable	Hypotheses	Accept	Reject	Not Tested
Customer Experience – Notifications (continued)	***H7p:*** *Customers who view hourly pricing information online will experience greater energy efficiency, demand response, and load-shifting benefits than customers who do not.*			***X***
	H7q: *Customers who sign up one or more family members for notification will experience greater energy efficiency, demand response, and load-shifting benefits than customers who do not.*			***X***
Customer Experience – Customer Support	***H7r:*** *Customers who contact the customer support center will experience greater energy efficiency, demand response, and load-shifting benefits than customers who do not.*		***X***	
	H7s: *Customers on the CPP rate will contact the customer support center more frequently than customers on other rates.*		***X***	
	H7t: *Customers on the CPP rate will have call durations that are longer than the durations for customers on other rates.*	***X***		
	H7u: *Customers who are eligible to receive the BIHD will contact the customer support center more frequently than customers eligible to receive other enabling technology.*		***X***	
	H7v: *Customers who are eligible to receive the BIHD will have call durations that are longer than durations for customers eligible to receive other enabling technology.*		***X***	
	H7w: *Customer satisfaction with customer support center will exceed satisfaction levels of ComEd's customer care center.*			***X***

Program:

Smart Grid Demonstration

1023644

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