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The Effect on Electricity Consumption of the Commonwealth Edison Customer Application Program Pilot: Phase 1

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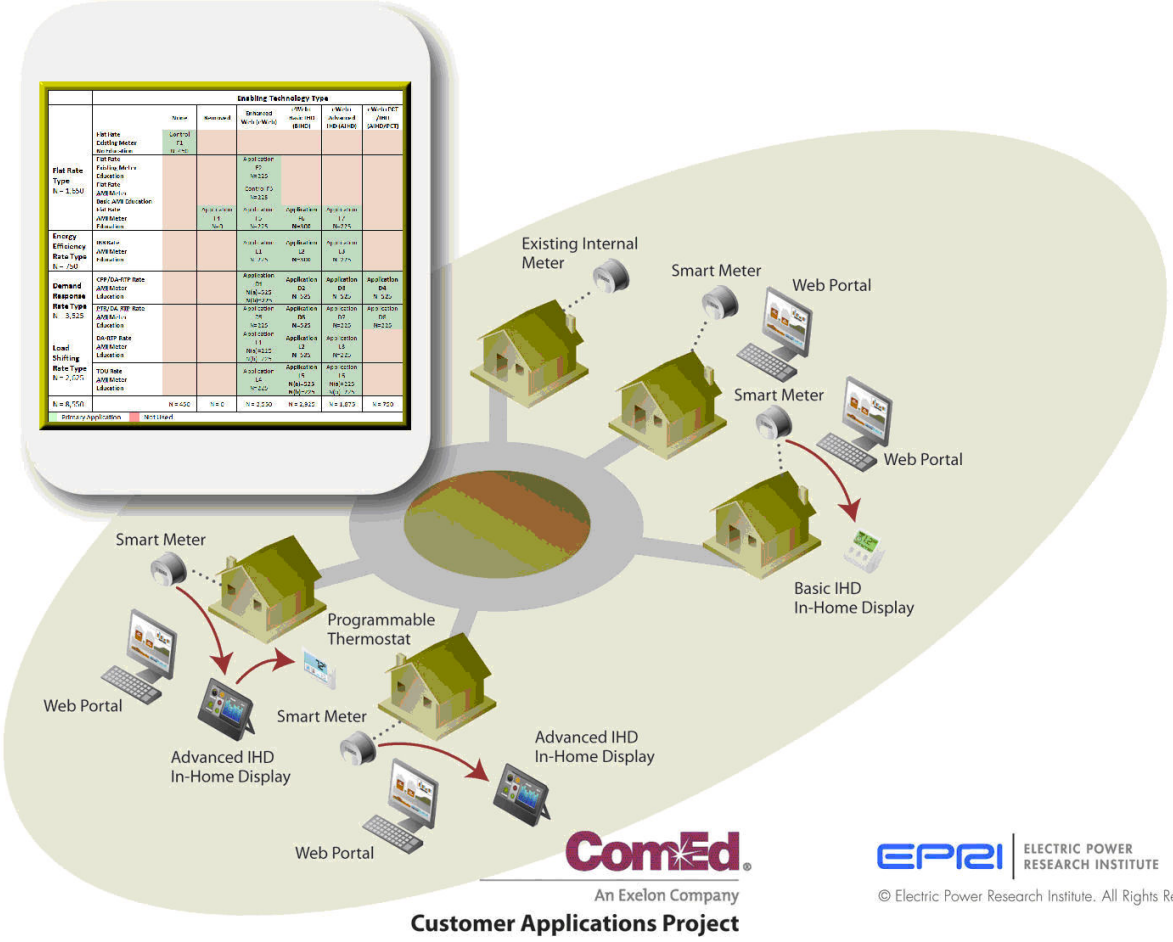

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1022703

Technical Update, April 2011

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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

For further information about EPRI, call the EPRI Customer Assistance Center at 800.313.3774 or e-mail askepri@epri.com.

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PRODUCT DESCRIPTION

This report describes the Phase 1 analysis of some aspects of residential customers' response to Commonwealth Edison's (ComEd) Customer Application Plan (CAP) as well as the plans to extend the analysis and evaluate additional aspects of that plan during Phase 2 of the evaluation.

Results and Findings

The main purpose of the Phase 1 analysis described in this report is to determine the extent to which residential customers' consumption of electricity is affected by various combinations of dynamic rates, enabling technologies, and other inducements, which define 27 different experimental treatments. The Phase 1 analysis is based on the data available from the first three months of the pilot (June through August 2010), and the findings are considered preliminary. The report contains the results of tests for each of 46 hypotheses (listed in EPRI report number 1022266) concerning electricity consumer behavior. Based on these three months of project data, the report shows that only participants in the dynamic pricing applications exhibit price response. However, although fewer than 10% of participants appear to respond, the level of this response was considered significant.

The Phase 2 report, to be available in the fall of 2011, will update these interim findings from the Phase 1 analysis. The update will be based on a full year's data (June 2010 through May 2011) on electricity usage, prices, and a survey of participants in the pilot. With these additional data, it will be possible to update tests of many of the hypotheses as well as test some additional hypotheses that could not be tested using the limited data available for the Phase 1 analysis. The findings will support extrapolating the results of the CAP pilot to the ComEd residential population.

Challenges and Objectives

Demand response is becoming increasingly important as an adaptation to the rising costs of building new generation plants, siting new transmission and distribution facilities, and dealing with a host of environmental issues including climate change concerns. Improvements in communications and controls reduce costs and broaden the potential impact of responsive loads. Many regulators are pressing utilities to use a range of demand response solutions. An analysis of the efficacy of smart grid technologies in facilitating demand response is essential to determining how these technologies might best be used.

Applications, Value, and Use

This report and its successor will be of interest to those who are concerned with the efficacy with which smart grid technologies facilitate demand response.

Advanced metering infrastructure (AMI) -enabled pricing structure and technologies can yield systemwide benefits when it provides, at lower cost, services that are 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. Furthermore, demand response might provide additional flexibility that could help utilities improve reliability with limited resources.

Smart grid technologies promise to facilitate demand response by providing customers with information that might help them make effective electricity consumption decisions, and might also offer customers automated ways to make those decisions. The ComEd project provides data to assess the extent to which smart grid technologies facilitate demand response. This report offers the first set of insights into the results.

EPRI Perspective

This report addresses an important part of determining how the smart grid can best facilitate demand response. It is part of a series of studies contributed by the Electric Power Research Institute (EPRI) to help the power industry exploit technological advances to increase reliability and reduce costs while adapting to increased environmental constraints on the ways that the industry provides its services to customers.

Approach

This report describes the methods used by EPRI researchers to evaluate the efficacy of smart grid technologies in providing demand response to Commonwealth Edison. The report provides the first set of results from this evaluation.

Keywords

Advanced metering infrastructure (AMI)
Alternative electricity price structures
Critical peak pricing
Enabling technology
Inclining block rate
Peak-time rebates
Opt-in and opt-out
Real-time pricing
Time-based pricing

ABSTRACT

The report presents the Phase 1 findings of the Electric Power Research Institute's (EPRI's) evaluation of the impacts attributable to Commonwealth Edison's Customer Application Program (CAP) pilot, based on the analysis plan described in EPRI report 1022266. The findings reported here are based on the analysis of data for the first three months of the CAP pilot (June through August 2010) and are therefore preliminary. Some treatments might require more time to have an effect, and some of the effects require survey data that will be collected at the end of the pilot. CAP effects are addressed in a series of hypotheses, derived from the CAP design, regarding the effects of the various rates, technologies, and education treatments featured in the pilot. The findings support some, not all, of the hypotheses. Phase 2 of the analysis will be completed during fall 2011. It will extend the Phase 1 analysis based on participants' electricity consumption and price data for the entire year of the CAP pilot as well as data collected through a survey of CAP participants. The final findings will contribute to an understanding of the way in which advanced metering infrastructure (AMI) -enabled price structures and technology alter consumer electricity consumption.

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1
INTRODUCTION

This report describes the evaluation undertaken by the Electric Power Research Institute (EPRI) to characterize the impacts of the Commonwealth Edison (ComEd) Customer Application Program (CAP) pilot. EPRI is providing an independent and comprehensive assessment of the impacts and implications of the CAP pilot as part of its Smart Grid Demonstration project.[1] This Phase 1 evaluation involves quantifying how CAP customers modified their electricity usage level and pattern 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, over the summer of 2010. The Phase 2 study will use the whole pilot period data, June 2010 to May 2011.

Description of the CAP Pilot Applications

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

Each of the five rate applications differ structurally from the flat rate that most ComEd residential customers utilize today, but in different ways:

- Hourly and daily conveyed through a day-ahead hourly price schedule issued each day (day-ahead real-time pricing (DA-RTP)).
- Combining DA-RTP with event-specific prices whereby the price of electricity increases to $1.74 per kWh over the DA-RTP price (critical peak pricing (CPP)) or the customer is paid $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)).

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

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 the residential building type (single or multi-family) and the type of space heating (electric or not electric).

[1] See: www.smartgrid.epri.com.

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 participant's hourly usage. Selected participants also have access to basic (BIHD) or advanced (AIHD) in-home displays, to a web-based information system, and to the means for regulating their household thermostat at times when demand response is needed.

The basic IHD continuously displays information, extracted directly from the AMI meter, about household electricity usage with both the current rate of energy usage and a historical comparison. Other pilots that deployed this technology report a wide range of customer responses, from no change to a 5% or greater overall reduction in electric consumption.

The advanced IHD incorporates electricity usage information into a device that serves a variety of roles including access to data via the internet. One hypothesis[2] is that consumers are more likely to pay attention to usage information that is updated often and readily available and will therefore respond to a greater extent. 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 (not explicitly offered to others); and a requirement that participants pay part of the cost for some enabling technologies (while others get it free).

Structure of the Pilot Design

A randomized design was used to select which customers (approximately 8,500 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.[3] Furthermore, it defines a methodology for estimating the significance of impacts measured as one of the following: total energy consumed during the pilot, peak period load or maximum demand, the ration of peak to off-peak usage, and other measures of usage.

A unique and important feature of the CAP is that it employs an *opt-out* recruitment design. Customers were chosen randomly to participate as a treatment or control customer, 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. After 3 months less than 2% of those enrolled had elected to opt-out, but over 1,000 of the original CAP subjects were lost due to finalization—they closed out their account at the premise.

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

[3] EPRI. April 2010. Guidelines for Designing Effective Energy Information Feedback Pilots: Research Protocols. EPRI 1020855.

ComEd employed the *opt-out* pilot design out of necessity, but recognized that it provided an additional research opportunity. ComEd designed the CAP over two years, but implemented it in less than five months in 2010. The experience from other pilots that involve rate and enabling technology treatments, but solicited participants (opt-in), suggested that recruiting volunteers would require several months, increase costs, or both, to achieve the participation level required to produce statistically significant results. Conversely, an *opt-out* deployment can be accomplished relatively quickly and possibly at a lower cost than other similarly constructed pilots.

The traditional *opt-in* recruitment process results in all participants being volunteers. Tests can still be conducted to determine the significant differences and impacts of various applications. However, extending the result of an *opt-in* program to the population as a whole is not straightforward, because it requires identifying candidate customers and a way to identify them among the general population in a full-scale roll-out of the applications. Because *opt-in* customers are representative of the population of customers with AMI meters at the time the sample was chosen—the sampling frame—the pilot results can be used to make inferences to that population (the AMI footprint). Extending those results to the entire ComEd residential population requires additional analyses to correct for the possibility that the customers in the sampling frame differ from customers in general.

Objectives of the Analysis

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

EPRI is conducting the CAP evaluation in two stages. The first stage, which is the topic of this report, involves evaluating data from June through August of 2010. The primary goal of this first stage is to estimate and report the summer months' load changes associated with the various price structures, 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.[4] The CAP pilot made provisions to impose higher PTR and CPP payouts and rates, respectively, which are referred to as events, during the summer of 2010, which were hypothesized to induce load changes by customers on those rates. Seven events were declared during June-September 2010.

The Phase 2 analysis, to be concluded fall of 2011, will include pilot findings for the entire twelve-month period ending May 2011 supplemented with survey data collected to characterize participants' household and demographic circumstances.

[4] One CPP/PTR event and high RTP prices occurred in September 2010, which was beyond the scope of this analysis that used data for June-August.

The Approach to the Analysis

To conduct the several components of this interim evaluation of the CAP, it was necessary to draw on several analytical and statistical methods. Some are appropriate to examine differences in behavior among groups of customers. 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 differences in the average electricity consumption (e.g. average daily consumption, average hourly peak-period consumption, etc.) between treatment and control groups and among treatments.

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 several dynamic pricing treatments (CPP, PTR and DA-RTP), the first 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 the effects on peak load during event and non-event days. Formal customer demand models are also specified to determine whether 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., decisions to *opt-out* of the pilot). Such issues will be investigated by specification and estimation of logistic choice models in Phase 2.

2
RESEARCH AGENDA

The Phase I evaluation involves the characterization and quantification of how CAP participants responded to the behavioral influences (applications) that were administered under experimental protocols during the summer of 2010. Those applications involve different rate structures, enabling technologies, and educational and promotional 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 the result of factors other than the applications. This rigor furthers the CAP goal of providing data to characterize, 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, or manner in which customers change their pattern and level of electricity consumption when they are exposed to the applications. Some hypotheses involve direct 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 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, electricity prices ($/kWh) differ between the peak and off-peak periods during weekdays.
- Under the inclining block rate (IBR) schedule, the electricity price ($/kWh) during each billing month varies 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 twelve month pilot period (June 2010- May 2011).[5] 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 revenue neutrality.[6] As a consequence, selection of customers in the AMI footprint to participate in IBR was conditioned on the availability of five years of historical billing records for the customer. As discussed in Section 5, this resulted in customers with above average usage populating 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 day-ahead real-time prices. For two of them, however, the hourly rates differ for the period from 1:00 to 5:00 p.m. on event days, which are the days when ComEd invokes its option to replace the previous days' DA-RTP prices during event hours with a pre-determined and very high ($1.74)/kWh) price. The salient 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.[7]
- Under the critical-peak pricing rate (CPP), customers are charged higher prices (approximately $1.74 per kWh) during peak periods on event days (see sidebar). On non-event days, CPP customers pay DA-RTP prices.[8]
- Under the peak-time rebate rate (PTR), customers are paid high rebates, or credits (also about $1.74 per kWh) for peak-period load reductions on event days. Otherwise, PTR customers pay DA-RTP prices.

CAP Events

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
- are declared (and all CAP customers are so notified) a day in advance
- are in effect for four consecutive hours, 1:00 p.m. – 5:00 p.m.

The CAP made provision for invoking seven events during the summer of 2010.

[5] 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%, they do not materially change the prices that customers act upon.

[6] Revenue neutrality is a property of a rate that assures that the customer pays the same amount under the CAP rate application as they 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 designed on a customer-specific basis.

[7] To maintain bill neutrality with the flat rate, the DA-RTP prices are adjusted each day so that the average price across all hours approximates that of the customer's preexisting flat rate.

[8] CPP prices are slightly lower in non-event hours, such that if the customer does not reduce load during event hours they should pay no more, over the year, than they would have paid under the applicable conventional residential tariff.

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 energy consumer, in effect penalizing usage (the "stick"). 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 that pay the applicable conventional tariff rate serves as the basis for comparison of usage behavior with the treatment customers who face the CAP rates.[9]

All customers are provided access to a web-based information system that portrays the customer's usage data in several ways, so the effect of this system cannot be separately established using ANOVA tests. The CAP hypotheses include statements concerning the effect of the web portal access that will be addressed in the Phase 2 analysis (fall of 2011) using data collected from a customer survey and data from the CAP administration system that tracks web access.

CAP also involves deploying enabling technology applications that deliver current usage information to customers. These applications involve basic or advanced in-home displays, BIHD or AIHD, respectively, and AIHD combined with programmable controllable thermostat (PCT) that enables automatic thermostat adjustment[10] 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.

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.[11] Like the IHD partial payment requirement, this application was applied on a limited basis. These treatments were only selectively applied- to some but not all rates.

A unique and important feature of the CAP is that it employs an *opt-out* recruitment design whereby customers are: a) selected randomly from the larger population of AMI-enabled customers to participate in one of the treatment cells or in a control group; b) enrolled automatically in the CAP; and c) informed subsequently of their rate and technology treatments at the commencement of the pilot. Customers remain in the pilot unless they elect to *opt-out*. An *opt-out* approach was hypothesized 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

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[9] 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.

[10] Some pilots install PCTs so that the utility can adjust the temperature during events. In this case, the customer decides what control strategy to deploy which is executed through the AIHD.

[11] The CAP implementation plan makes a provision for offering bill protection to all participants that request it, but this provision has not been widely conveyed.

with the pilot experience. Some 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.[12] 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 of the methods report 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:

- To determine how the applications influenced the level and pattern of energy consumption, particularly:
  - changes in overall energy consumption
  - reductions in peak demand
  - load shifts from peak to off-peak periods
- To identify the key drivers of customer attrition over the course of the pilot as a function of bill impacts, customer characteristics
- 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

As established above, the CAP evaluation is being conducted in two phases. In Phase 1, the three objectives above are examined, to the extent possible, using available data during the three summer months, June through August 2010.[13] Special attention is given to identifying load changes associated with Day-Ahead Real-Time Pricing (DA-RTP), Critical Peak Pricing (CPP), and Peak-Time Rebate (PTR). These price structures result in prices that differ each day, and among the hours of the day, sometimes substantially.[14]

The Phase 2 analysis, to be completed fall of 2011, will utilize the pilot findings for the entire twelve months of data, as well as data from the customer survey, administered at the end of the pilot (May 2011). The survey will allow a further assessment of the impact of CAP processes and services.

The Evaluation Methods

To conduct the several components of the evaluation of the CAP, it will be necessary to draw on several analytical and statistical methods. Some are appropriate to examine differences in

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[12] EPRI. December 2010. *ComEd Customer Applications Program – Objectives, Research Design, and Implementation Details*. EPRI 1022266; available at EPRI.com, Search 1022266.

[13] The one event that was declared in September is not included this Phase I study because the metered and billing data were not available during the analysis period. The Phase II study will update the CPP and PTR impacts to include the September 2010 data.

[14] 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 analysis of this report.

behavior among customers by group. Other methods 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 analysis of variance (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.

ANOVA identifies significant aggregate differences in electricity consumption among treatment and control groups, other methods are needed to understand the various ways in which customers in the 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 the effects on peak load during event and non-event days. Formal customer demand models are also specified to determine if 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.

The first four analytical methods described below were employed in the Phase 1 analysis. All five will be deployed in the Phase 2 final analysis.

Analysis of Variance (ANOVA)

Many of the hypotheses are addressed using analysis of variance (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 summer peak-period usage between an individual application and the control group during the pilot period. ANOVA analyses are typically conducted using commercial software such as SAS or 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.[15] That is, if a customer is in a particular treatment, the indicator variable for that treatment in the regression equation is assigned a value of unity for that customer; otherwise it is assigned a value of zero. Regression analysis carried out in this way provides rigorous tests of statistical significance of differences among the observed difference in load among applications.

The Phase 1 analyses were conducted using ordinary least squares (OLS) regressions with indicator variables for each treatment. This is equivalent to ANOVA and facilitates simultaneous comparisons across many treatments. The primary OLS regression model is as follows:

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[15] P. Kennedy, *A Guide to Econometrics*, 3rd edition, 1992, pp. 226-227.

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

Equation 2-1

where i indexes customers, α is the constant term (the effect associated with the specified control group), the βs are estimated parameters (the treatment effects), and e_i is the error term. CPP, RTP, TOU acronyms are rate treatments previously defined, as were the enabling technologies BIHD, AIHD, and PCT. *Bill-prot* indicates that the bill protection treatment was provided to the customer, *Purch* indicates that the customer had to pay to receive the enabling technology, and *Educ* indicates that the customer received additional education about AMI. The other variables are added to account for load differences that may be due to customer circumstances: Single Family space heating (*SFSH*), multifamily non-spare heating (*MFNS*) and multi-family space heating (*MFSH*). As described in Section 4, the constant term, by construction, includes the effect of the web access billing data access service (available to all) and represents single family non-space (*SFNS*) heating residences.

To assess customers' responses to CAP program design and incentives, the analysis focuses on evaluating the 46 hypotheses that are tested using ANOVA or ANCOVA methods and are discussed in greater detail in Chapter 3.[16] 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 constructing ordinal or cardinal metrics 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 that way to ascertain if doing so affected the main treatment effect.

Regression Analysis of Rate Impacts

The regression analyses are designed to measure the overall average load impacts for each event or in response to different prices. The regression models can be applied at the average aggregate level for any rate, cell, or other group of customers. The models can also be estimated at the individual customer level to identify those customers who appear to respond to prices (CPP and DA-RTP) or financial incentives (PTR).[17] Regression analysis can then be applied to average data for the subset of responders to estimate load impacts and metrics such as the elasticity of substitution, a measure of the degree of peak to off-peak load shifting.

For example, daily data for the entire study period (June – August), for either one customer or an aggregation of customers, are examined to determine whether peak-period usage is lower on event days, controlling for weather conditions. Load impact models also are estimated for customers on all rate structures to determine the extent to which response is caused by event

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[16] The hypotheses themselves are described in detail in Appendix D (forthcoming EPRI report 1022761), as are the model specifications and results of the formal tests.

[17] The daily variability in hourly prices and the different prices or incentives on event days make it possible to estimate load impacts and price responsiveness for individual customers. In effect, their usage patterns on low-price non-event days serve as their own control data.

notification (which is given to most customers) versus event-specific prices (which are limited to CPP and PTR customers).

For episodic price change programs such as CPP and PTR, event-day load impacts are of special interest. Customer-level regression models are estimated for each of the rate applications including rates without event-based pricing so that we can determine whether customers respond to event *notification* rather than event *pricing*. In these models, the dependent variable is average kWh during peak hours, and a number of explanatory variables are included to account for typical usage patterns and the effect of weather on usage. The explanatory variables of primary interest are the indicator variables for each event day. The coefficients on these variables are estimates of the change in usage during that event relative to the counterfactual; what the customers' load would have been in the absence of the event.[18]

Customer Demand Analysis

The foregoing analyses 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. To impose behavioral structure, theoretically motivated electricity demand models were estimated based on data for various groups of customers and at different levels of aggregation. Two such models often used to measure price responsiveness are the constant elasticity of substitution (CES) 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 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% 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 found in Appendix A of the appendix document.

As is discussed in that appendix, employing a CES demand model, assumes that the elasticities of substitution are constant for any individual customer, regardless of the nominal level of prices, weather, or other circumstances that differ by day, for example the day of the week. This is restrictive, and may result in missing important behaviors. The GL model is re flexible in that elasticities of substitution for any customer can differ by day which also allows them to vary by the price level on that day. This feature facilitates testing the extent to which consumers' willingness to shift load differs based on the absolute level of prices, differences in weather, etc., rather than imposing the same responsiveness on the estimates, which could mask important results.

The functional specification of the GL model, which is algebraically complex, is provided in the Appendix. A simplified explanation follows. To estimate the parameters of the GL demand model at the customer level, one must specify a non-linear regression model in which the

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[18] The reference load is equal to the estimated load impact plus the observed (metered load). The regression model removes the need to use baseline loads that are used for PTR settlement purposes. However, it will be useful to compare the regression-based load impacts to the load impacts derived from the PTR baselines as a check of the accuracy of the PTR load reduction estimation methods that rely solely on prior days' usage to establish the counterfactual baseline.

dependent variable is the ratio of the daily peak and off-peak electricity expenditure shares. The right-hand side variables are portrayed as a non-linear function composed of the daily peak to off-peak price ratios and two variables that measure different aspects of the daily weather conditions (indices of heating and cooling degree days). Daily elasticities of substitution are then calculated as functions of the model parameters and the estimated expenditure shares.

In addition to measuring customers' ability and/or willingness to shift load from peak to off-peak periods, these elasticities of substitution may be used to simulate customer response to alternative price levels, and to compare the CAP findings to those from pricing pilots conducted at other utilities.[19] This will be undertaken n Phase 2.

Analysis of the Inclining Block Rate

Because of sampling issues described in Chapter 4, it was not possible to directly compare IBR customers with other treatment cells to estimate usage changes due to IBR.[20] Instead, the analysis of IBR customers' is based on comparing usage before and after the introduction of the IBR rate. These comparisons are based on monthly usage data for the summers of 2009 and 2010. In these regressions, the dependent variable is the natural log of monthly usage while the independent variables are cooling degree days (CDDs) 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 what is observed is not measured continuously, as are 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.

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[19] Since the GL model provides daily estimates for the elasticities of substitution for each customer, in the second-stage meta-analysis of Phase 2 of this project, one can use the estimated load changes, expressed as percentage changes in event-hour usage or as elasticities of substitution, as data in cross-sectional regressions to explain differences among customers' load response due to the effects of customer characteristics such as demographics, behavioral factors, and enabling technologies. (Similar analyses have been performed by T. Taylor and P. Schwarz). "The Long-Run Effects of a Time-of-Use Demand Charge," *The Rand Journal of Economics* 21(3):431-445, 1990, and by R. Boisvert, P. Cappers, C. Goldman, B. Neenan, and N. Hopper. "Customer Response to RTP in Competitive Markets: A Study of Niagara Mohawk's Standard Offer Tariff," *The Energy Journal* 28(1):53-73, 2007). However, this meta-analysis can only be performed once data from the customer survey is in hand. Thus, this additional set of regressions will be an integral part of the Phase 2 analysis. By providing insights into how the level of price response varies among customers according to the structure of the rate plan and customer circumstances, these additional regressions are essential for extrapolating the CAP results to the full population of ComEd residential customers.

[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 (forthcoming EPRI report 1022761).

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, 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. In contrast, analysis of dichotomous choice data using basic OLS methods can lead to predicted probabilities or predicted outcomes that lie outside the one/zero range, and as a result are illogical.

By way of example from the CAP, the dependent variable in the model equals one if the customer opted out of the pilot and zero if the customer did not. The independent variables represent treatments or characteristics that may affect the decision to opt out, including the effect of rate structure and the presence of enabling technology on customer attrition.

Another example is to assess customers' acceptance of technology, which closely resembles the one used to examine customer attrition, except that the dependent variable equals one if the customer implemented an enabling technology, and zero if the customer did not. Only customers who were offered an enabling technology (for no cost or for purchase) are included in the model. The model determines whether customer acceptance of enabling technology is related to customer characteristics or the customer's rate structure.[22]

Choice models will be deployed in Phase 2 to test hypotheses that involve statements about outcomes that are measured integrate states using survey data and other variables constructed by CAP system implementation logs.

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[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.

[22] Once the exit survey data become available it will be possible to examine additional drivers of customer attrition and acceptance of technology, including customers' experience of adverse bill impacts and customer demographic characteristics (e.g., income or education levels). The results from this expanded model will be reported in the Phase 2 study to be completed later this year.

3
STRUCTURE OF THE ANALYSIS

Experimental Design

The experimental design for the CAP pilot is illustrated in Figure 3-1. 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 (EPRI report number 1022266).

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. Defining contiguous geographic areas were required to make the best use of the AMI communication network. These particular areas were selected for their apparent representativeness of all ComEd residential customers. In early 2010, new advanced metering infrastructure (AMI) equipment was installed in all homes in these two areas.

The matrix in Figure 3-1 defines 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 involve statistical tests of differences in the behavior among customer groups in specific cells (applications) of this matrix.

Dual, limited applications 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. Cells D1 and L1 are bifurcated to test the effect of offering bill protection to customers but only for CPP and DA-RTP customers that have no enabling technology beyond the web access): in some cases, customers are aware that they will be made whole at the end of the pilot (the treatment), while in other cases the customers are not aware of this provision. Cells L5 and L6 involve incentives to adopt the enabling technology limited to TOU combined with either BIHD or AIHD: in some cases, the technology is free; while in other cases the customer is offered an incentive to purchase the technology at less than the full cost (the treatment).

Cells F1 (flat rate, existing meter, and no education), F2 (the same as F1 except the application of additional education about the web access capabilities), and F3 (flat rate, AMI meter, and basic education) are designed as control groups (i.e., base cases) against which other applications or treatment groups (i.e., change cases) could be compared to determine usage changes due to the treatment.

Customers in groups F1 and F2 are selected from ComEd's load research sample, which was previously constructed to be representative of all ComEd residential customers' electricity usage profile.[23] The intent was to provide a means for extending the CAP results to the larger ComEd residential population. F3 participants were drawn under random protocols to serve as the control for the AMI footprint populations.

		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

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 effects were expected from the CAP applications portrayed so that they were quantifiable and could be subjected to logical or statistical tests of veracity.

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

[24] EPRI. December 2010. *ComEd Customer Applications Program – Objectives, Research Design, and Implementation Details*. EPRI 1022266.

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

- **H3a**: The 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 AIHD/PCT solution will achieve greater energy efficiency, demand response, and
- load shifting benefits than other enabling technology.

Because they refer directly to difference among the average loads of the applications, which represent different rate and enabling technologies, they 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 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 another 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.
- **H7q**: Customers who contact the customer support center will experience greater energy efficiency, demand response, and load-shifting benefits than customers who do not.

Testing the verity of these statements requires combining data collected or measurements calculated as part of the CAP implementation, such as customer bills, logs of participant who accessed the eWeb site or contacted the customer service assistance center, or data that must be collected for customers, such premises 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 the Phase 1 analysis. They were singled out for preliminary analysis because either they are statements about the directly measured effects of the various treatments, or they involve other influences that can 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. 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 I

- Rate Type: H2a, H2b, H2c, H2d
- Enabling Technology: H3a, H3d, H3e
- Enabling Technology Acquisition: H4a, H4b, H4d
- Bill Protection: H5a, H5b
- Customer Education: H6a, H6b, H6c
- Customer Experience – Comparisons: H7k
- Customer Experience – Notifications: H7m, H7n
- Customer Experience – Customer Support: H7q, H7r, H7s, H7t, H7u

Figure 3-2
Hypotheses Tested in Phase 1

Figure 3-2 lists hypotheses that were slated for inclusion in Phase 1, but were not for various reasons which are described in Section 5.

Hypotheses Originally Scheduled for Phase I, but Intractable due to Design Issues

- H1 – Meter type has no effect on electricity usage behaviors
  - Sample design issues
- H2e – The CPP rate delivers the best combination of energy efficiency, demand response, and load shifting benefits
  - Problems with ranking rates on three categories
- H4c – The adoption rate of purchased enabling technology will exceed free enabling technology
  - Treatment participation too small (will need survey data)

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

Figure 3-4 list hypotheses that can not be evaluated until Phase 2 because they require customer information that will be collected at the end of the CAP.

Hypotheses Scheduled for the Final Analysis

- H2f - IBR rate satisfaction
- H3b, H3c, H3f - IHD customers will experience greater satisfaction …
- H4c - purchased enabling technology
- H5c – combined benefits evaluation
- H6d – customer satisfaction
- H7a, H7b, H7c, H7d, H7e, H7f, H7g, H7h, H7i, H7j, H7l, H7o, H7p, H7v – include behavior and satisfaction information that will rely on the final analysis

Figure 3-4
Hypotheses that will be Tested in Phase 2

Phase 1 is a preliminary analysis that utilized data from the first three months of the CAP pilot. Hence, the findings are preliminary. The period for which customers were exposed to the treatments, especially those involving enabling technologies, may have been too short for them to realize the advantages of these technologies and begin implementing them. DA-RTP, TOU and IBR price variation might not have become fully apparent, and as a result significant impacts may not be detected in Phase 1, but may emerge in Phase 2. The CPP and PTR impacts are limited to the summer months of 2010 by design of the CAP, so the analysis of those impacts will be more conclusive, with the caveat that one of the PTR/CPP events occurred outside the study period June – August 2010.

All of these hypothesis tests will be redone in the Phase 2 (final) analysis to utilize the additional nine months of data on how customer responded to the stimuli the applications provided to modify electricity usage.

4
DATA COLLECTION

The data to support the Phase 1 analyses came from several sources, as described below. In collecting and examining the requisite data, EPRI discovered that the customer composition of a few of the applications did not comport with that of the population frame - those customers with AMI, raising challenge to testing hypotheses that used that data.

The Data

The data available for the Phase 1 study period, June-September, 2010, 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 sample customer
- Initial survey data for those participants who respond (to be collected)[25]
- Hourly prices faced by the CPP, PTR and DA-RTP customers
- When CPP and PTR events were declared
- Enabling technology device installation and usage information
- 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.

The Phase 2 report will use data for the entire study year ending May 2011.[26] As discussed previously, tests for some of the hypotheses and the completion of some other parts of the evaluation must be postponed until additional data and information are available.[27]

Data Issues

A study of this complexity presents challenges in implementation. Unavoidable compromises often arise in getting the study into the field that affect the way the data can be used. A careful examination of the data often reveals some issues that must be resolved prior to conducting the analysis, generally in a way that does not affect the type of veracity of the finding of the analysis.

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[25] A high response rate is critical to achieving insightful and extensible results.

[26] Cap participants were enrolled starting late April through early June 2010 based on their billing cycle change. Each will have 12 months on the pilot application(s), ending with the twelfth billing month, either April or May 2011.

[27] See Appendix C (forthcoming EPRI report 1022761) for additional details about data and data issues.

However, others complicate some aspect of the analysis, either because the experimental design or data shortcomings, and thereby render inappropriate the use of the conventional statistical models. In rare cases, the shortcomings are so severe that some elements of the initially anticipated analysis must be abandoned altogether.

A few anomalies in the CAP data have affected the way in which the Phase 1 analysis was 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, but with little consequence for the value of the overall Phase 1 analysis.

Analysis Time Frame

The first 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 billing cycle. Some customers began service in late April 2010 while the last commenced service in early June. As a result, fully time-corresponding data for all customers was not available until June. 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 end participation in the program on different dates depending on billing cycles and decisions to *opt-out* or to end service. 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 the several hundred participating customers as a result of two major service outages this past summer.

Non-corresponding 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 that is not the case, 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, there is no systematic correspondence between when a customer was enrolled in CAP and the application to which it was assigned.

There is no reason to believe this is not the case here. The method by which ComEd selected participants and assigned them to applications was random over the entire AMI footprint customers and independent of the bill cycle – there is no indication of systematic bias. The outages occurred after the sample was composed and were geographically concentrated, but not related explicitly to the 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 in June through August 2010.

But, those data must be valid measurements. In some cases, customer meter records contained zero entries, which are not explained by an outage, and inconsistent with the typical usage

pattern. To avoid extreme value bias, customers for which 2% or more of the observations were zero for the period June through August 2010 were excluded from the Phase 1 analysis.[28]

Issues Associated with how Controls and Treatments Were Populated

Other design and data characteristic issues are more problematic. Five circumstances limited conducting the anticipated Phase 1 analyses.

One has to do with the composition of the two control groups (F1 and F2). They were constructed to represent the ComEd customer population at large and facilitate making residential customer population inferences from the CAP findings. Participants in cells F1 and F2 were created by selecting customers at random from customers that constitute ComEd's current load research sample, which combines samples drawn to be representative of the entire residential population employing stratification by usage level size and another where the stratification was by premise characteristics (single/multi-family, premises with and without electric space heat).

Stratification size is often used in load research where the objective is to estimate the class peak load, or a representative load profile. However, combined with the added complexity of the type stratification sample premises, it confounds both ANOVA and model-based analyses because of the complexity of the sampling error structure.

As a result, it appears that high-usage customers are over-represented, relative to what would be expected in the population, in the load research sample. This outcome can be seen in Figure 4-1, which shows the average kWh usage for the F1 and F2 control groups and the rate application customers. The average hourly electricity usage for both 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). The difference between the control group and the treatments is not due entirely to customer response to prices. 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 somewhat higher peak hours and all event hours usage shares than customers in the five rate treatments, the middle and right-most graphs in Figure 4-1, respectively. This provides a further indication that the control groups constructed from the load research sample are not representative of customers in the CAP, based on average usage.

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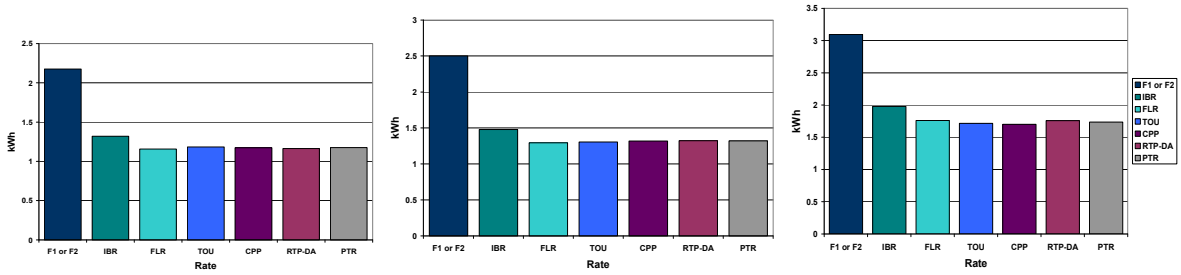
[28] About 1,600 of the approximate 8,000 enrolled customers were excluded through this process. They include accounts that were finalized during that period. The alternative to making these assumptions is to employ a much more complex regression model. For example, we could use monthly customer data, so the dependent variable would be 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 completes the analysis and the interpretation of the models results. Such a strategy may, however, be applied in the Phase 2 analysis.



All Hours **Peak Hours** **Event Hours**

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

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 is not statistically significant.

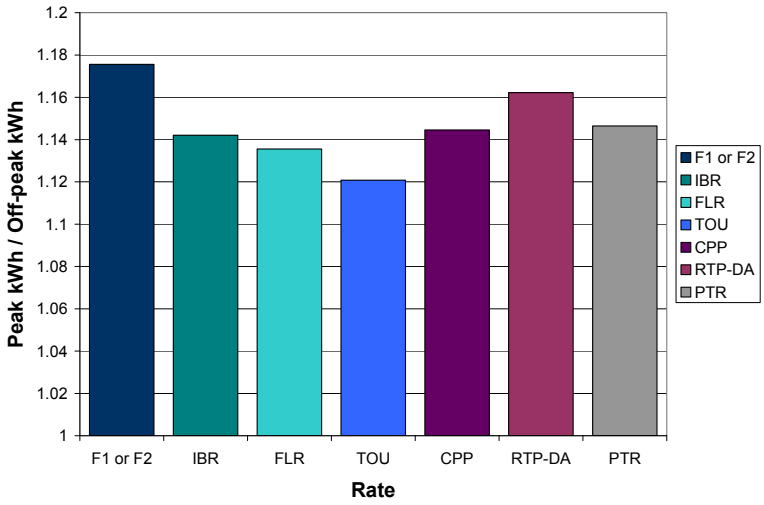


Figure 4-2
Average Peak to Off-Peak Usage Ratio, by Rate

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. On a more practical basis, the result would portray the non-application (control) case as having higher load, and as a result differences between it and application loads, and therefore attributed 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, 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.

Figure 4-1, Figure 4-2, and Figure 4-3 provide evidence that this is the case. Focusing on the IBR values (the second bar in each figure,) reveals that the average hourly kW usage is 10%-15% 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 ANOVA tests of differences in customer energy usage due to the IBR treatment relative to usage by customers in other rate treatments. Changes in electricity consumption are analyzed separately for IBR customers through comparisons of the available monthly billing-level usage data from 2009 and 2010.

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 the 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. Multi-family residences tend to have a lower 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% higher than it is for eWeb customers without IHD.[30] The possibility of bias compromises testing for the separate effects of IHDs on customers' electricity use. However, as discussed subsequently, the very low uptake of IHDs in these applications makes detecting any influence, biased or not, difficult, at least at the aggregate level using ANOVA.

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[29] The BIHD and AIHD rely on a radio-based signal form 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 buildings.

[30] ComEd offers all CAP customer access, through an internet connection, to its eWeb portal which displays billing data and compares customers' usage to that of other (usually neighborhood) customers that are deemed to be comparable in life and premises 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.

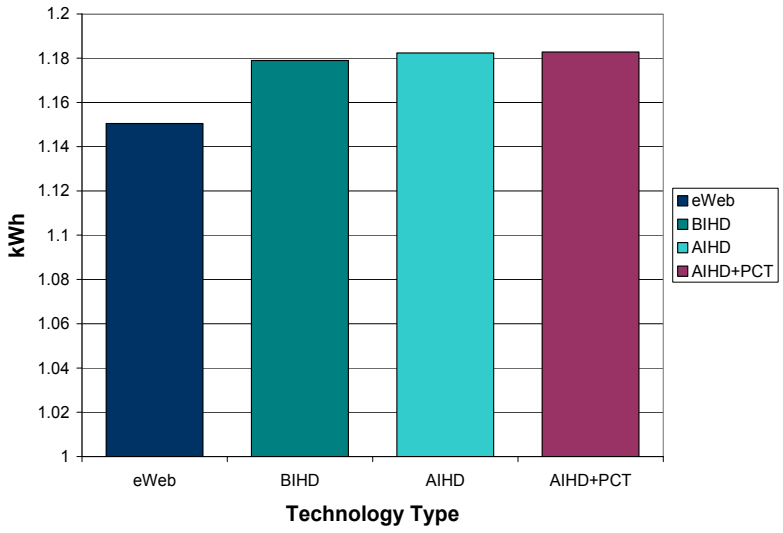

Figure 4-3
Average Hourly Usage, by Technology[31]

Fourth, customer acceptance of programmable communicating thermostats (PCTs) is low; less than 10% of the intended number of PCTs were installed. 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). The rows labeled L5 and L6 in the table, BIHD and AIHD, respectively offered to TOU application customers, indicate how many customers were offered a technology for free and how many of those implemented it (installed and initialized the device); 34% for the BIHD and 13% for the AIHD. However, in the corresponding treatments whereby the customer was required to pay for the device only 2% actually acquired it.

The low incidence of paying for the device 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.

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[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					
L5	485	485	163	100%	34%
L6	205	205	26	100%	13%
For Purchase					
L5b	211	5	4	2%	80%
L6b	205	4	4	2%	100%

5
FINDINGS

This section begins with a discussion of the results of the ANOVA analysis of the aggregate average treatment cell electricity usage. It is followed by a discussion of the impacts of treatments on load characteristics, extended to the calculation of elasticities of substitution between peak and off-peak electricity consumption. Elasticities were estimated for customers that are identified as being responsive to price signals as a result of the load characteristics analyses. A separate analysis, necessitated because of sampling bias, examines how the IBR rate affects customer's electricity usage.

Analysis of Variance (ANOVA)

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

- average overall usage, which serves as a measure of electricity conservation
- average peak-period usage, 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, in which serves as a measure of load shifting

Hourly billing data are used to construct the three application metrics described above- the average level for each treatment cell-- which are then evaluated in using a regression-based test of significance. No weather adjustments are required for ANOVA because by employing a randomized design, weather effects are embodied in the individual responses but isolated from the application effects as a result of evaluating differences among application means- the weather effect drop out. Subsequent, participant-level modeling includes weather adjustment variables to isolate the effect for each individual.

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
- other limited deployment applications - education, bill protection, technology cost sharing
- housing type - included to control for sample selection issues

Housing type variables were added to account for difference 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 will account separately for these factors, and thereby improve 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 establishing a baseline so that the constant term provides a baseline level of usage, and other treatments measure additions to or subtractions from that level- the treatment effect, and additional factors are included so that application effects can be individually quantified as described in the narrative on page 2-5. These effects are portrayed as additions to or subtractions from the base configuration. Each then is further distinguished by whether the measured difference is statistically significant or not. The statistical significance threshold is the 95% confidence interval.

Table 5-1 contains the estimated coefficients from the ANOVA regression models for dependent variables based on four separate measures of electricity usage.[33] The constant term (the last row entry in Table 5-1) measures average daily use associated with the constructed control group that:

- pays the conventional ComEd residential rate applicable to a single-family residence without space heat
- receives only the eWeb application
- has been given only basic education
- was given no notification of bill protection

Given this control construct, the average effects of the individual applications (the row of the table; CPP, DA-RTP, etc.) 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 with no electric space heating (MFNS) and with electric space heating (MFSH). These variables are included in the equations to control 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 (All Hours metric) of Table 5-1, both of which are negative, indicate that average daily use is lower by 0.7438 and 0.6968 kWh for multi-family non-space and space heating, respectively residences relative to the single-family residence that comprises the constant term value. These negative signs are to be expected given that multi-family residences are generally smaller than single-family residences.

For multi-family residences (with and without electric space heating), negative signs are associated with peak hours (the third columns), and event hours (the fourth column) and the peak to off-peak usage ratio (the fifth column), as expected as well. In the table these coefficients are in bold, indicating that the effects are statistically different from zero at the 5% level of statistical significance. The positive signs on the coefficients (for all four metrics) for single family residences with electric space heat (SFSH) in the equations for all hours and peak hours are as expected—the presence of space heating should raise the overall level of for all four metrics. But, they are not statistically different from zero at the 5% level. In other words, we conclude that there is no difference.

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[33] The modeling equation is presented in Chapter 2.

The coefficients associated with the other variables (which correspond to applications) represent the effects on electricity consumption of prices, technology, and other factors. For example, the CPP value of 0.0105 associated with all hours indicates a measurement difference of 0.0105 kW more than flat-rate customers. However, this difference is not statistically significant from zero at the 5% level of significance, and therefore the effect CPP should therefore be considered to be zero based on the data analyzed.

This generally describes the findings. All but two of the rate and technology application differences are not statistically significant from zero. The exceptions are two of the positive coefficients for day-ahead real-time pricing (DA-RTP). However, these results are counterintuitive because the positive signs on the coefficients indicate that despite the generally high peak prices, compared to prices in other hours associated with DA-RTP, customers on DA-RTP have higher peak consumption than do customers who pay a flat rate.

Table 5-1
Estimated Coefficients from the ANOVA Models[34]

	Dependent variable = average usage across….			
Variable	**All Hours**	**Peak Hours**	**Event Hours**	**P/O Ratio**
CPP	0.0105	0.0435	-0.0255	0.0068
DA-RTP	0.0500	**0.1150**	0.1045	**0.0416**
PTR	0.0108	0.0464	0.0150	0.0131
TOU	0.0532	0.0645	0.0512	-0.0112
BIHD	-0.0168	-0.0151	-0.0082	0.0022
AIHD	0.0327	0.0434	0.0733	0.0113
AIHD/PCT	0.0134	-0.0172	-0.0187	-0.0124
Bill Protection	0.0282	0.0493	0.0736	0.0351
Purchase Tech.	-0.0570	-0.0539	-0.0823	0.0036
Full Education	-0.0609	-0.0983	-0.2094	-0.0048
SFSH	0.0641	0.1420	-0.0657	0.0768
MFNS	**-0.7438**	**-0.9693**	**-1.3174**	**-0.1760**
MFSH	**-0.6968**	**-0.9352**	**-1.2928**	**-0.1051**
Constant	**1.5033**	**1.7276**	**2.3905**	**1.1594**

[34] Each model contains 5,262 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-space heating. See Appendix E (forthcoming EPRI report 1022761) for additional details.

Overall, the regression-based ANOVA finds little evidence that any of the rate treatments or treatments for enabling technology resulted in statistically significant differences in average electricity usage between applications.

The lack of statistically significant effects may not be as surprising as might appear on the surface. The explanation may be in part 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 that only those who were already inclined to respond will do so. Based on past pilots, that may be less than 5% of the total population. Some of those pilots found differences in rate applications and IHD impacts that were significant, but the analysis was restricted to volunteers that were expected a priori to be responsive, or at least many of whom would respond in some manner.

In the CAP, the responses by those predisposed to respond (who likely would have been *opt-in* participants if invited) are masked by the much larger collective load of those not inclined to respond, and did not respond to the applications. Detecting these small effects would require much larger sample sizes than the CAP used.[35] To see if this is the case, additional analyses focused first on identifying individual customers displaying behaviors consistent with what we expect from the DA-RTP, CPP and PTR rate treatments and then estimating a demand relationship using their data. It is to these more disaggregate analyses that we now turn.

Direct Estimation of Event-Day Load Impacts

It may still be the case that some customers within each treatment group do respond, but their response is dominated by the random actions (noise) of the majority of non-responders, and not the treatment. In this section, we employ different methods of analysis to identify the subset of CAP customers who appear to change their behavior in response to dynamic prices and then measure the extent to which this behavior is different on event days. Such a subset does appear to exist, and both the proportion of customers that respond and the magnitude of the response from this subset of customers are notably similar to the demand response found in studies of *opt-in* programs.

We begin this section with a graphical examination of price impacts at the aggregate level. These portrayals serve to confirm the results from the ANOVA tests that on average there is no detectable applications treatment response. However, when individual customer loads are plotted, especially on event days, they indicate there are responders and demonstrate that load impacts during CPP/PTR event periods are statistically significant among this subset of customers.

Average Rate-Level Impacts

Several figures are constructed to illustrate average load profiles for various treatment and control groups on event days and other similar weekdays. The two vertical lines on each figure mark the hours (1:00 p.m. to 5:00 p.m.) when CPP and PTR events are called; this is the period

[35] See: EPRI 1010855.

when one would expect CPP and PTR customers to reduce consumption relative to their usage on non-event days.

Figure 5-1 illustrates hourly usage patterns for the F3 control group (which are customers paying the conventional ComEd residential rate that has no hourly price variation) on an average weekday (labeled F3 Ave Wkday), an average event day (labeled F3 Ave Evt), and the average day for the week of August 9-13 (labeled F3 Ave 8/9-13), which was an especially hot week. Because the control group receives no price changes when weather changes, loads on average weekdays for hot days that are not event days and event days that are hot are expected to be essentially identical during event hours, and they are; the two curves overlap during the event hour window.[36] Loads on average (and hence not especially hot) weekdays, the lower curve, are lower than on days in hot weeks, primarily because less air cooling is needed.

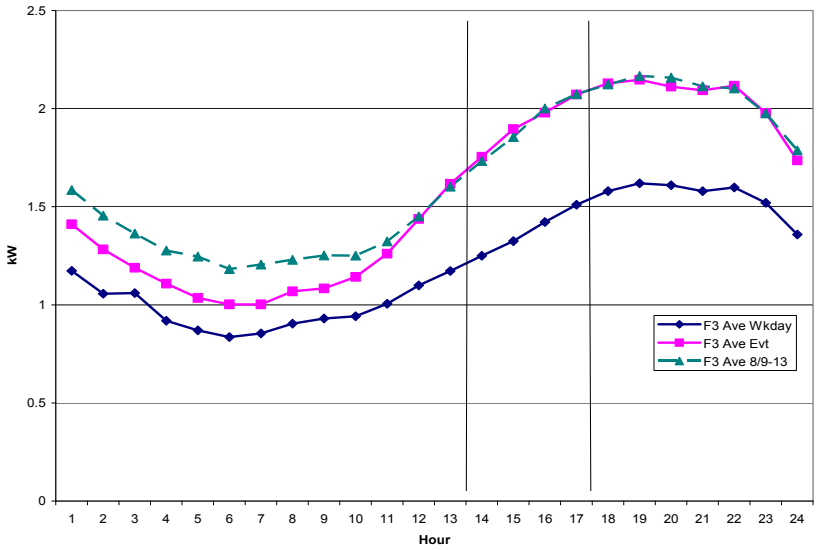


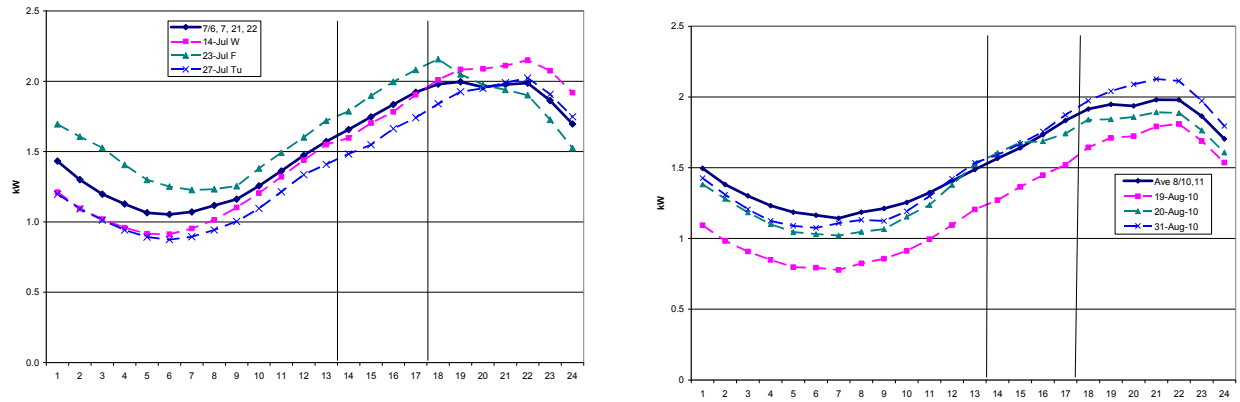
Figure 5-1
F3 Control Group Average Usage, by Day Type

Figure 5-2 illustrates average hourly usage patterns for CPP customers (combined groups D1-D4) during typical non-event days (cooler weather) and three event days (elevated temperatures) in July and in August. The bold (blue) line in each figure represents the average usage over non-event weekdays which exhibited temperatures similar to those on event days.[37] The dashed lines are average CPP loads on the three event days in July (left panel) and in August (right panel), which were relatively hotter days. At this aggregate level of comparison, the only apparent differences in usage are the nearly parallel shifts in usage patterns on event days relative to non-event days which are attributable to differences in ambient temperatures and other unexplained factors, not the price treatment. In particular, event-hour usage on event days barely appears to

[36] ComEd declared CPP and PTR event based on several factors, but elevated temperature appears to have been the primary one.

[37] 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.

drop relative to usage on non-event days. Thus, at this aggregate level there appears to be no discernable effect of high CPP prices on customer behavior.



July **August**

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

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 that DA-RTP loads are higher at higher prices, not lower as one would expect if the customers are price responsive. However, this correlation likely reflects the fact that loads and prices both move together with temperature; there are no discernable load changes due to high prices or events.

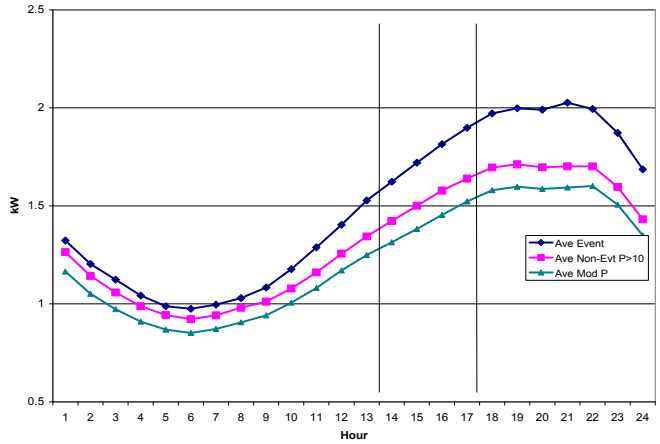


Figure 5-3
RTP-DA Average Usage, by Day Type

The data displayed in the figures reinforce the ANOVA results; neither provides an indication of significant application-level effects. 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 such a peak-period notch.

Determining if a subset of responders exists requires a more detailed examination of load data for individual customers.

Identification of Price-Responsive Customers

To identify customers who exhibit a measureable response to event-day signals (i.e., high prices, rebates, event notification), regression equations were estimated for individual customers using daily data for all weekdays in June through August. In these regressions, the dependent variable is the natural logarithm (log) of average hourly peak-period usage, and the independent variables are weather, month and day-type indicators, and the natural log of the average peak-period price applicable to each rate application. For the remaining rates (TOU, IBR and the conventional flat rate), which have no event-specific price, event-day indicator variables are used in place of the price variable to allow for different loads on those days, perhaps the result of the customers being notified that it was an event day.[38]

A Customer was classified as a responder if the usage reduced in response to price increases (or PTR credit opportunities) as indicated by a negative regression coefficient on the event-day price or event day indictor variable, and if there is at least a 90% chance that this usage reduction is not due to random, unaccounted for factors. Specifically:

- For CPP, DA-RTP, and PTR customers, the coefficient on the price variable must have at least a 90% chance (significance) of being negative.
- For the other rate structures, two or more coefficients on the event-day indicator variables must have at least a 90% chance of being negative.[39]

Table 5-2 shows the percentage of customers on each rate who are classified as responders according to these criteria. First, consider a counterintuitive result. The values in Table 5-2 suggest that 2.7% of CPP customers are responding to the event notification. The same may be said for customers served under IBR (2.9%) and TOU (4.25), which are classified as responders according to the selection criteria. However, this may be an exaggeration of the share of

[38] While these customers faced no price incentive to reduce consumption during event hours, they were notified when events were called, and thus they might have responded out of altruism.

[39] The estimated regression equations included separate variables for each event, allowing a difference measure of responsiveness for each event. However, for purposes of classification, a single criterion was needed. Rather than using a criterion of significant response for, say, one event, or for an average of all events, we compromised with a criterion that at least two event-day coefficients were negative and significant.

customers that respond to event notification, primarily because the regression model cannot account for all factors that affect customer usage levels.[40]

There are a couple of reasons why customers could be characterized as responders. First, they could respond 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 that issue public appeals for load reductions during especially hot weather often see load drop as an apparent result. Alternatively, these customers might have usage that is unusually low on event days for reasons unrelated to the event and based on factors not included in the regression models. For example, some customers may be on vacation, resulting in lower than average electricity use. Hence, the regression coefficient is negative, but not indicative of a purposeful response by the customer.

One way to provide greater insight might be to query these customers about what actions (if any) they undertook on event days, or if they recall that on some days they received event notices. This will be undertaken as part of the final survey of CAP participants.

Responders are in greater numbers for CPP (6.7%), DA-RTP (8.7%) and PTR (4.9%) (Table 5-2). It is impossible to know what fraction of them are likely to have also been misclassified due to factors that could not be accounted for in the models. But, the combined regression model and graphical depiction below lend credibility to the assertion that there are indeed some responders in the CAP dynamic rate treatments.

Table 5-2
Percentages of Customers that are Responders, by Rate

Rate Structure	Responder Share
CPP	6.7%
DA-RTP	8.7%
PTR	4.9%
Flat Rate	2.7%
IBR	2.9%
TOU	4.2%

Average Event-Day Load Impacts of Responsive Customers

To quantify the degree of load response by customers that were deemed to be price responsive, a second new regression model for the aggregate of responders, by rate type, was estimated that included event indicator variables to isolate and quantify load reductions during event periods. Table 5-3 shows average estimated impacts on loads during events. The second column lists the number of responders, and the third column lists that number as a percentage of all customers exposed to that application. The remaining three columns provide an implied reference (non-event) load, the average load reduction (kWh) per customer, and the percentage load change

[40] 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 them of the price variability.

associated with the responding customers. As expected, CPP and PTR customers show the largest percentage impacts, 37% and 32%, respectively, because these are the customers facing high prices (or credits) during events. DA-RTP responders (who are not subject to CPP and PTR event price increases) exhibit a counterintuitive 7% load increase on event days.

Table 5-3
Average Load Impacts of Customer Deemed to be Responders, by Rate Type[41]

Rate	Number of Responders	Responders' Share out of Total Rate Sample	Average Estimated Event Reference Load (kW)	Average Estimated Event Load Impact (kW)	% Load Impact
CPP	108	6.7%	1.50	0.56	37%
PTR	40	4.9%	1.17	0.38	32%
RTP-DA	75	8.7%	1.73	-0.12	-7%
TOU	50	4.2%	1.72	0.39	22%
IBR	18	2.9%	1.57	0.20	12%
Flat	21	2.7%	1.28	0.35	27%

The impacts on loads on event-days are observable in the load data of customers that are deemed to be responders. Figure 5-4 shows average hourly usage patterns for CPP responders. The solid line represents usage on non-event weekdays in July and August, where the load level is adjusted to reflect average usage in the morning hours on the average of several event days. 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 in most cases it also moves up somewhat in the hour or two prior to the event period. Customers' increased usage after the event may reflect making up for some electricity services, such as air conditioning, foregone during the event. The load increase comports with customer pre-cooling or advancing other uses to be able to reduce during the event hours. Both of these behaviors are consistent with purposeful event response.

[41] See Appendix E (forthcoming EPRI report 1022761) for additional details.

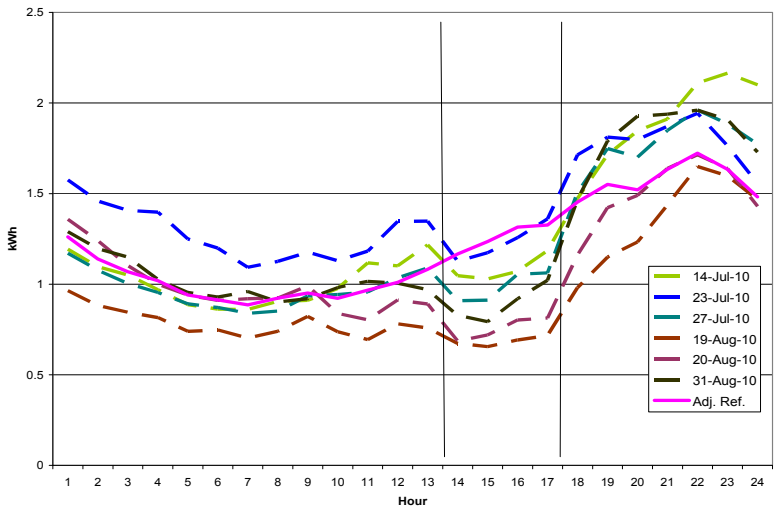


Figure 5-4
CPP Responder Usage Patterns, Average Non-Event Weekday vs. Event Days

To illustrate the inherent day-to-day variability of customer's loads, even when averaged over a number of customers, Figure 5-5 shows CPP responders' usage patterns on several weekdays from mid-July through August, indicated by solid but thin lines, compared to the average load on the six event days, which is indicated by a heavy dashed line. No clearly defined peak-period notch is apparent on the non-event days.

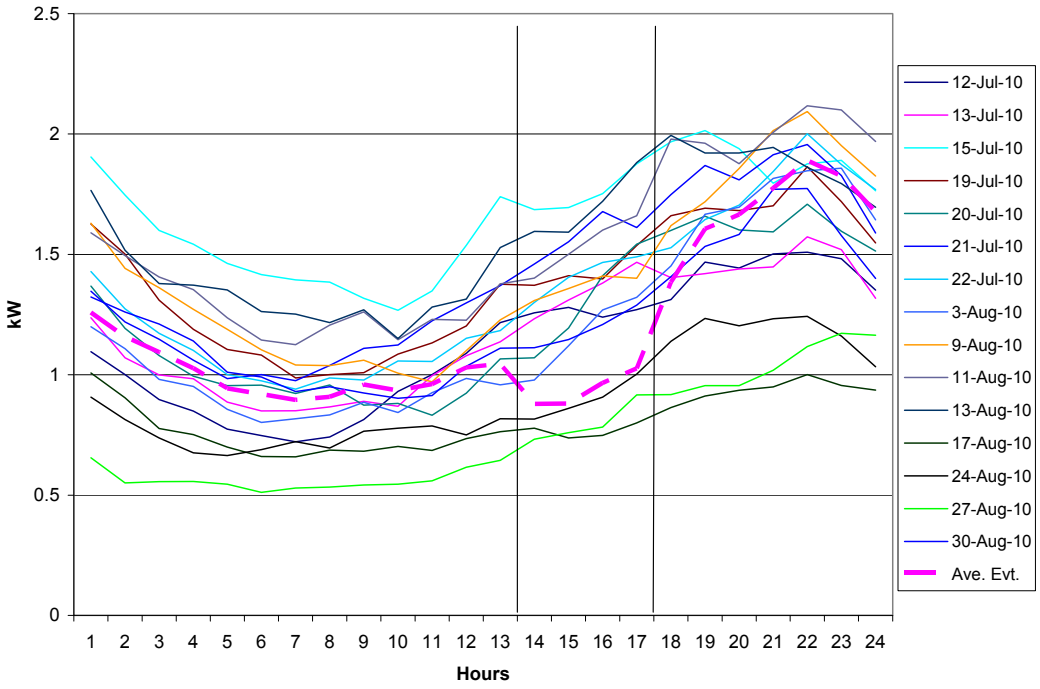


Figure 5-5
CPP Responder Usage Patterns, All Weekdays

Figure 5-6 shows event-day loads, averaged across those customers that were classified as responders, by rate treatment, for July 23, 2010, an event day. CPP and PTR display the expected notches that indicate a drop in load at the beginning of the event. DA-RTP and TOU display less pronounced notches. In contrast, customers on the flat rate who passed the responder test show no notch-distinguished response.

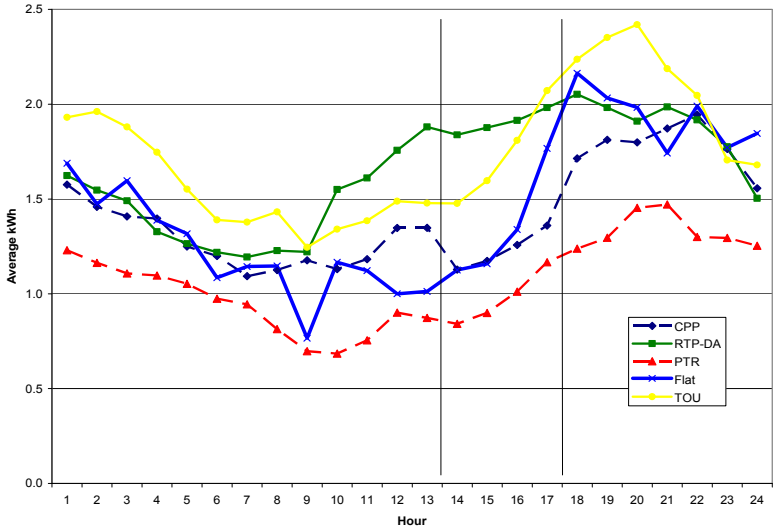


Figure 5-6
Event-Day Loads for Responders, by Rate (July 23, 2010)

Figure 5-7 displays event-day loads for the responders, by rate treatment, for August 31, 2010. The load shapes for responders on the CPP and PTR rates again contain the notches that indicate load reduction at the beginning of the event, and again no event-period response is evident for customers on the other rates.

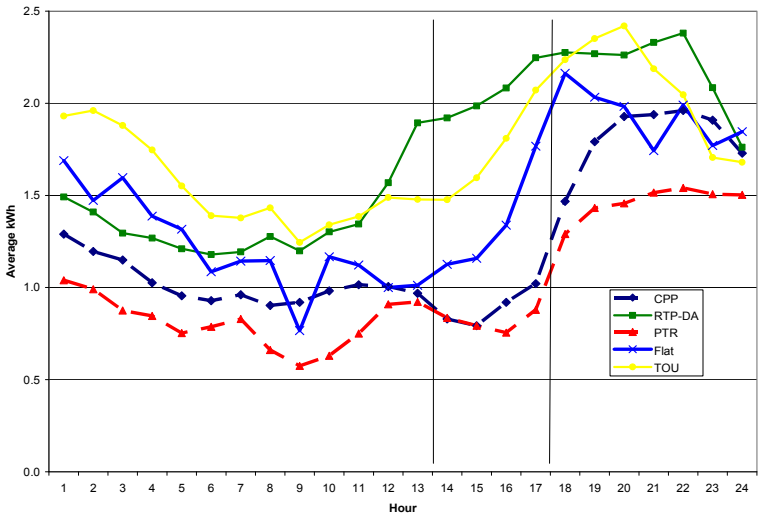


Figure 5-7
Event-Day Loads for Responders, by Rate (August 31, 2010)

In summary, regression models were applied to individual customers to identify those that exhibit statistically significant event-day behaviors consistent with responding to higher event prices. Finding some 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. A smaller number of event responders were identified in the flat, IBR, and TOU rate applications, which seems counterintuitive since their prices did not change. This might reflect customer response to the notification of an event day, but more likely they are the result of a relatively sparse model specification and reflect unaccounted for factors that are unrelated to the occurrence of events.

Some DA-RTP customers exhibit response, but as an increase in load, which is counterintuitive. Perhaps the survey administered to customers at the end of the CAP can shed some light on this finding.

Graphic representations of CPP and PTR responder load data reveal that they exhibit a clear notch or drop in load during event hours, which is consistent with the pursuit of their best interests – reducing loads when prices are high and making up the service when prices go back to normal.

Confirmation that there are indeed responders in the CPP and PTR applications, and the establishment of a relative measure of that response, can be furthered clarified by estimating a demand equation using these customers' loads and applicable prices.

Estimation of Elasticities of Substitution between Peak and Off-Peak Usage

A formal demand model was estimated to quantify the degree to which responders shift loads among hours in response to price. For reasons explained in Chapter 2, and derived in detail in an accompanied appendix volume, Appendix A of the separate Appendix volume,[42] the model chosen is the Generalized Leontief (GL) model. This model characterizes load-shifting behavior through a metric known as the elasticity of substitution. The major advantage of the GL model is its flexibility; it allows the elasticities of substitution to differ by day, depending on the daily peak and off-peak prices, and/or by weather or other daily characteristics that could affect consumption.

For the purposes of the CAP project, the demand 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).[43] 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 relative response metric (zero is inelastic and 1 is unit (very high) elasticity), the elasticities of substitution can be used to simulate the response in customer load to alternative prices.

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[42] The Effect on Electricity Consumption of the Commonwealth Edison Customer Application Program Pilot: Phase 1 – Appendices, (forthcoming EPRI report 1022761).

[43] Each hour can be treated as a separate demand, but at the expense of a substantial computational burden, see: Schwarz, P., Taylor, T., Birmingham, M., Dardan, S. 2002. Industrial Response to Electricity Real-Time Prices: Short Run and Long Run. Economic Inquiry, Vol. 40, No. 4, pp. 597-610.

The estimation equation for this demand model is given by:

$$\mathrm{Ln}\left(\frac{\mathrm{ES_{pd}}}{\mathrm{ES_{od}}}\right) = \beta \text{ x } \mathrm{CDD_d} + \mathrm{Ln}[h_\mathrm{p}\mathrm{H_d} + \gamma_{\mathrm{pp}}\mathrm{P_{pd}} + \gamma_{\mathrm{po}}\sqrt{\mathrm{P_{pd}}\ \mathrm{P_{od}}}] - \mathrm{Ln}[h_\mathrm{o}\mathrm{H_d} + \gamma_{\mathrm{oo}}\mathrm{P_{od}} + \gamma_{\mathrm{po}}\sqrt{\mathrm{P_{pd}}\ \mathrm{P_{od}}}]$$

Where:

- ES_{pd} and ES_{od} are peak and off-peak electricity expenditure shares 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 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
- γ_{ij} are estimated parameters[44].

As explained in Appendix A of EPRI 1022761, once the parameters of this model are estimated, one can calculate predicted expenditure shares and elasticities of substitution. These elasticities of substitution are calculated for each day as a function of prices and the estimated γ_{ij} coefficients. For reporting purposes, they were then averaged across day-types (e.g., high-price and low-price days).

Separate models were estimated for each of the dynamic pricing rate treatments (CPP, PTR and DA-RTP) using load data averaged over those customers classified as responders. Table 5-4 shows estimated average elasticities of substitution for those rate treatments, differentiated by event vs. non-event day (for CPP and PTR) and by average price in the peak period (above or below $0.10 per kWh for DA-RTP). The latter distinction is an indication of the extent to which nominal, not relative peak to off-peak prices, induce load response.

The values in the table indicate, for example, that for DA-RTP responders: a doubling (i.e., a 100% increase) in the ratio of peak to off-peak price would, all other things equal, correspond to a 21.8% reduction in the ratio of peak to off-peak consumption if peak prices exceed $0.10 per kWh and a 22.9% reduction in peak consumption if peak prices are less than $0.10 per kWh.

For CPP and PTR responders, the data in the table indicate that estimated elasticities of substitution are on average somewhat higher on event days than on non-event days. This result differs somewhat from responders on the DA-RTP rate, who appear on average to shift load proportionately more than responders on the other two dynamic rates, but who are slightly more responsive on non-event days than event days; the difference is slight.

[44] 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 5-4
Estimated Elasticities of Substitution, by Rate and Event/Price Level[45]

	GL Elasticity of Substitution	
	Average Event; or (P > $0.10 for DA-RTP)	**Average Non-Event; or (P < $0.10 for DA-RTP)**
CPP	0.150	0.128
PTR	0.131	0.116
RTP-DA	0.218	0.229

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 cannot be accomplished using ANOVA. As an alternative, the electricity usage for IBR customers during the summer of 2009 was compared with the corresponding usage in the summer of 2010, after the introduction of the IBR rate. In the regressions designed for this analysis, the dependent variable is the natural log of monthly usage, and the independent variables are the total cooling degree days (CDDs) during the billing month, and a dummy variable which equals unity for the months that the customer is on the IBR rate, and zero otherwise (e.g. on the flat rate).

Table 5-5 shows the result of the regression, where coefficients that are significant at the 5% level are in bold. As before, the constant term is the baseline usage, and effect differences are the estimate coefficients. As expected, the coefficient for CDDs (.063) indicates that hotter weather (and therefore greater cooling needs) leads to significantly higher usage, which lends support to the reasonableness of the model specification. The IBR coefficient is in comparison small; which suggests that in summer 2010 months, the IBR rate induced no significant difference in monthly usage.

Table 5-5
Dependence of the Natural Log of Monthly Usage on IBR Status[46]

Variable	Coefficient
IBR	0.016
CDDs	**0.063**
Constant	**6.189**

[45] See Appendix E (forthcoming EPRI report 1022761) for additional details.
[46] See Appendix E (forthcoming EPRI report 1022761) for additional details.

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SUMMARY AND CONCLUSIONS

The CAP Phase 1 analysis sought to quantify the impact of a variety of pricing and technology treatments that were hypothesized to result in changes in level and/or profile of electricity consumption for residential customers. It used customer consumption and price data from the first three months of the pilot (June - August, 2010). Accordingly, the results are preliminary: they may be different when the entire year's data are evaluated in Phase 2. Moreover, many of the hypotheses that are to be examined require customer premise and demographic data that will be collected at the end of the pilot, in April/May 2011, and therefore were not addressed in Phase 1.

Dynamic Pricing Applications

The most important Phase 1 finding is that statistically significant responses were exhibited by some of the customers served under the most dynamic pricing applications, those that involved DA-RTP alone and in combination with PTR or CPP. EPRI's preliminary analysis of individual customer effects found that 5% to 7% of CPP and PTR customers reduced event-period load by 32% to 37%. The analysis included six of the seven price change events (those in June – August) implemented in the summer of 2010. The Phase 2 analysis will include the final (September) event, which may modify the findings; additional or fewer participants may have responded and their responses may be larger or smaller.

Based on the model estimates, usage changes attributable to CPP and PTR event prices (about $1.70/kWh) were accomplished primarily by responders shifting load from the event period (1:00 to 5:00 p.m.) to other times of the event day. There is little evidence of a separate, conservation effect of a reduction in the total energy consumed.

The preliminary CPP and PTR results are comparable to those of other recent dynamic pricing pilots that have been published. The other pilots used an *opt-in* design that populated the treatments by recruiting volunteer participants where only about one in five customers agreed to participate. One might 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% during event hours, and even larger (25% to 40%) 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 one-half of the total participants show any indication of price response. One might then expect that at least 5-10% of customers in an *opt-in* would exhibit price responsiveness to these rates, unless the *opt-in* design itself serves as an inducement for a larger response rate or level. That was the case. It appears that the CAP pilot was successful in inducing customers that were likely already inclined to be price responsive to exhibit that behavior.

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 preliminary 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. This finding is however preliminary, and applies only to the CPP and PTR applications.

The robust findings for CPP and PTR are the result of extending the analysis beyond conventional testing of the significance of differences among applications, which involves using the average load change of all customers in the applications. The DA-RTP only participants (those that were not also exposed to the CPP and PTR high event prices) application underwent a similar, participant-level analysis that revealed a higher percentage of responders (8.7% compared to 4.9% and 6.7% for CPP and PTR, respectively) and a higher price responsiveness according to the substitution elasticity value. The percentage load change on event days was less because hourly DA-RTP prices during events were considerably less than the CPP and PTR price of $1.70/kWh. However, DA-RTP customers appear to be more responsive to price on non-event days when the highest price was an order of magnitude lower[47] The Phase 2 analysis may provide additional insight into whether the CPP and PTR options cause customers to focus mainly on event response while DA-RTP alone results in response over a much wider range of price changes.

Other Price, Enabling Technology, and Education/Incentive Applications

A comparison of the load impacts across price and enabling technology applications, (for the period June - August), was conducted using a variation on analysis of variance (ANOVA) statistical tests. It revealed no statistically significant effects attributable to TOU or to any of the enabling technology applications coupled with the pricing applications. Furthermore, neither the bill protection nor enabling technology partial payment 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 difference in usage from that of the control group when comparing average use across applications. Note that these results are preliminary and the Phase 2 Analysis will re-examine the impacts.

The adoption (installation of the device) rate of the IHDs is low (under 10% for the AIHD). As a result, tests based on the average load change for each application may not identify application influences that are there, but that are associated with only a small percentage of the participants. Even if a high proportion of those that adopted the AIHD responded in some manner, the number that receive the application (installed the device) is so small the effect is difficult to detect when examining changes in the average usage of all customers in that application. Adoption rates for the basic IHD (BIHD) are somewhat higher (approximately 15%) 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).

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[47] During events, the DA-RTP average price was 10.0 cents/kWh. On non-event days, the average peak-period price for DA-RTP was 9.3 cents/kWh.

For the dynamic pricing structures (DA-RTP, CPP, and PTR), rates change each day, and CPP and PTR event days provide much higher pricing than non-event days. This price variation allows for price responsiveness to be estimated using a customer's usage data (e.g., for CPP customers, non-event day loads serve as a "control" for event day loads). In contrast, estimating the effect of the other treatments, such as time-of-use rates or IHDs, is more challenging because the applications involve a single change in the customer situation. That is, each is a one-time treatment.

It might take time for customers to become accustomed to and fully aware of the implications of these applications. The Phase 1 study used only three months of data, which resulted in exposure of PTR and CPP customer to seven events, only six of which were included in the Phase 1 analysis. The effects may kick in subsequent to the Phase 1 study period and therefore become observable when the entire pilot year's data are available for the Phase 2 study. In addition, in Phase 2 EPRI intends to explore using additional screening devices to isolate customers that are most likely exhibiting load changes, especially to ascertain if price responsiveness increased over the summer as a result of leaning and experience.

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 RTP, PTR and CPP. 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. The Phase 1 (preliminary) finding is that the IBR application had no significant effect on customers' monthly usage. Given the character of the IBR rate, the Phase 2 analysis may conclude differently. If winter usage is higher for some or all customers, in particular those that have electric space heating, then the impact on electricity cost of the IBR rate may have become more apparent in winter months (December – March), and when the full year's data are evaluated, load changes attributable to IBR may be revealed.

Summary

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 requisite analysis, which seeks to isolate and quantify separately the impacts of those applications is commensurately detailed and complex. The Phase 1 ANOVA tests of application effects found no significant effects attributable to any single or combined applications. The focus then turned to establishing the extent to which the dynamic pricing applications caused changes in individual customer's usage, where important impacts were revealed. Other applications may exhibit significant effects when a year's usage data and customer survey information is available to account for difference in customer circumstances.

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PHASE 2 ANALYSIS

The Phase 2 analysis will update the analyses that are examined in this report, including those of hypotheses that are described in Appendix D of the appendix document. Phase 2 will also examine the remaining nine months of data collected during the twelve-month pilot. It will undertake analysis of all of the remaining hypotheses for which analysis is feasible given data and other constraints. The required data will be partly provided by a participant survey that will be conducted at the end of the pilot. The information that will be collected through the survey includes the following:

1. Customer demographic (e.g., income) and psychographic (e.g., whether the customer is typically an early adopter of technology) variables of interest to ComEd
2. Measures of customer satisfaction with the pilot program[48]
3. The extent to which the customer used (interacted with) the BIHD or AIHD
4. Whether the customer was aware of the bill protection provision (whether notified formally or informally)
5. Whether the customer signed up more than one family member for event notification
6. Whether the customer viewed hourly prices online (if the MVDB[49] does not contain adequate data on the topic)

Participant demographic data are important because they facilitate testing whether observed behaviors attributable to the applications are uniform across participants or whether they differ importantly according factors such as: household income; the number and ages of inhabitants; whether energy efficiency measures have been undertaken (and when) by the household; the stock of appliances and electric devices.

Achieving a high response rate to this survey is essential because these extended analyses can only be conducted from those that respond. For example, if 35% of customers respond to the survey, then only 35% of the available CAP application impact data could be used for extended analyses, which would lower the statistical power of the results and raise the likelihood of omitted variable bias.

The hypotheses that require information anticipated from the final survey are as follows:

- H2f: IBR rate satisfaction
- H3b, H3c, H3f: IHD customers will experience greater satisfaction

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[48] We propose to examine the difference in self-reported customer satisfaction with the overall pilot program by rate structure and enabling technology. However, we could consider asking separate customer satisfaction questions by pilot program element (rate structure, enabling technology, and education).

[49] MVDB stands for Measurement and Validation Database.

- H4c: purchased enabling technology
- H5c: combined benefits evaluation
- H6d: customer satisfaction
- H7a, H7b, H7c, H7d, H7e, H7f, H7g, H7h, H7i, H7j, H7l, H7o, H7p, H7v: include behavior and satisfaction information that will rely on the final analysis.

Additional analyses are anticipated to explore in greater detail the possibility that a relatively small number of participants in the enabling technology applications are responding, but do so purposefully and measurably.

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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
RTP-DA	real-time pricing with day-ahead notice
TOU	time of use or time-of-use rate

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