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Residential Customer Enrollment in Time-based Rate and Enabling Technology Programs: Smart Grid Investment Grant Consumer Behavior Study Analysis

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Environmental Energy Technologies Division

May 2013

The work described in this report was supported by the National Electricity Division of the U.S. Department of Energy's Office of Electricity Delivery and Energy Reliability under Lawrence Berkeley National Laboratory Contract No. DE-AC02-05CH11231.

Acknowledgments

The work described in this report was supported by the National Electricity Division of the U.S. Department of Energy's Office of Electricity Delivery and Energy Reliability under Lawrence Berkeley National Laboratory Contract No. DE-AC02-05CH11231.

The authors would like to thank Joe Paladino (DOE OE) for his support. The authors would also like to thank the members of the LBNL Technical Advisory Group who contributed their wisdom and guidance: Peter Cappers, Annika Todd, Charles Goldman and Andy Satchwell (LBNL); Catherine Wolfram, Meredith Fowlie, and Lucas Davis (University of California at Berkeley); Michael Sullivan, Stephen George, Michael Perry, Josh Bode, and Matt Mercurio (Freeman, Sullivan & Company); Miriam Goldberg, Curt Puckett and Roger Wright (KEMA); Ahmad Faruqui, Sanem Sergici, and Ryan Hledik (Brattle Group); Mary Sutter and Tami Buhr (Opinion Dynamics); Rich Scheer (Scheer Ventures, LLC); Karen Herter (Herter Energy Research Solutions, Inc.); Roger Levy (Levy Associates); Theresa Flaim (Energy Resource Economics, LLC); Richard Feinberg (Purdue University); and Lisa Schwartz (Oregon Department of Energy).

Disclaimer

This report was prepared by Lawrence Berkeley National Laboratory for the Office of Electricity Delivery and Energy Reliability, U.S. Department of Energy.

This document was final as of XXXX.

If this document is referenced, it should be cited as:

Todd, A., P. Cappers, and C. Goldman. 2013. *Residential Customer Enrollment in Time-based Rate and Enabling Technology Programs: Smart Grid Investment Grant Consumer Behavior Study Analysis.* Lawrence Berkeley National Laboratory, LBNL-XXXX.
http://xxx.xxxxxxxx.com.

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Glossary of Acronyms, Abbreviations, and Terms

AMI	**Advanced Metering Infrastructure –** All components that allow two-way communication between meters and the electric utility's meter data management system to collect electricity usage and related information from customers and to deliver information to customers.
CA	**California**
CAC	**Central Air Conditioning**
CBS	**Consumer Behavior Study**
CBSP	**Consumer Behavior Study Plan**
CPP	**Critical Peak Pricing –** A time-based rate component that increases the price on electricity consumed for participating customers during the hours included in a declared critical event. This higher price is overlaid onto the existing retail rate. Critical events are called either on a day-ahead or in-day basis in response to forecasted or achieved, respectively, high wholesale market electricity prices, short-term system reliability problems, or both. The primary objective of this rate design is to promote reductions in the peak demand of electricity.
CPR	**Critical Peak Rebate –** A demand response program that pays participating customers for reducing electricity consumed in relation to a baseline during the hours included in a declared critical event. Critical events are called either on a day-ahead or in-day basis in response to forecasted or achieved, respectively, high wholesale market electricity prices, short-term system reliability problems, or both. The primary objective of this program

design is to promote reductions in the peak demand of electricity.

DECo **Detroit Edison Company**

Descriptive Results - A finding based on summary statistics. These results may be informative, but do not allow us to draw any causal conclusions.

DLC **Direct Load Control**

DOE **Department of Energy**

Experimental Design – A method of controlling the way that a program is designed and evaluated in order to observe outcomes and infer whether or not the outcomes are caused by the program.

Experimental Results – A finding based on statistical estimates derived from experimentally designed tests. These results enable us to draw conclusions about the causal effect of the treatments being tested.

FE **FirstEnergy Ohio**

FOA **Funding Opportunity Announcement**

GMP **Green Mountain Power**

HEMS **Home Energy Management System**

IBR **Inclining Block Rate –** A rate program design that charges customers for electricity usage based on the how much they consume. Blocks of usage are defined and the price for each block of usage increases as the amount of consumed electricity increases. The primary objective of this rate design is to promote overall conservation of electricity.

IHD	**In-Home Display**
ISO	**Independent System Operator**
kWh	**Kilowatt-hour**
LBNL	**Lawrence Berkeley National Laboratory**
LE	**Lakeland Electric**
	Lessons Learned – Findings based on anecdotal information collected from utilities. They enable us to understand context surrounding the Experimental and Descriptive Results, but not to definitively state findings.
MMLD	**Marblehead Municipal Light Department**
MN	**Minnesota**
NDPT	**Nevada Dynamic Pricing Trial**
NVE	**NV Energy**
NVP	**Nevada Power**
OE	**DOE Office of Energy Delivery and Electricity Reliability**
OG&E	**Oklahoma Gas & Electric**
OK	**Oklahoma**
	Program offer - Different types of time-based rate, technology, and opt-in versus opt-out proposals made to customers when they are solicited to enroll in a study (e.g., an offer of a TOU rate, an offer that includes enabling technology, or an opt-in offer).
PCT	**Programmable Communicating Thermostat**

RCT	**Randomized Controlled Trial** - A research strategy in which customers who volunteer to be exposed to a treatment are randomly assigned to treatment and control conditions.
RED	**Randomized Encouragement Design** - A research design in which two groups of customers are selected from the same population at random and one is offered a treatment while the other is not. Not all customers offered the treatment are expected to take it but, for analysis purposes, all those who are offered the treatment are considered to be in the treatment group.
SGIG	**Smart Grid Investment Grant**
SMUD	**Sacramento Municipal Utility District**
	Solicitation Effort – One complete set of offers made to one group of customers (e.g., one solicitation effort may have an opt-out offer, a TOU rate offer, and no technology offer).
SPP	**Sierra Pacific Power**
TAG	**Technical Advisory Group**
TOU	**Time-Of-Use** - A time-based rate program design that charges customers for electricity usage based on the block of time it is consumed. The price schedule is fixed and predefined, based on season, day of week, and time of day. The primary objective of this rate design is to promote overall shifting of electricity away from the peak period to other periods.
VEC	**Vermont Electric Cooperative**
VPP	**Variable Peak Pricing** – A time-based rate program

design that charges customers for electricity usage based on the block of time it is consumed. The price schedule is variable and differs daily, based on bulk power system conditions during that period of the day. The primary objective of this rate design is to promote targeted shifting of electricity away from the peak period to other periods.

VT **Vermont**

Foreword

As far back as the 1890s, the electric industry has been debating the issue of how to efficiently and optimally charge customers for consuming electricity (Hausman and Neufeld 1984). At that time, there were emerging but very contentious discussions among economists about the merits of pricing the new commodity differentially based on time. The challenge with such pricing schemes revolved around metering—cost-effective technology did not exist at that time to allow electricity consumption to be captured at the required level of detail. Thus, virtually all customers were charged for their electricity consumption at a rate that was time-invariant (i.e., flat).

By the 1970s, the debate had moved beyond issues of economic efficiency and instead turned towards more practical concerns about consumer behavior—could mass-market (i.e., residential and small commercial) customers manage their electricity consumption under time-based rate programs? The results of studies undertaken by the Federal Energy Administration, the predecessor to the U.S. Department of Energy (DOE), indicated such customers were, in fact, capable of managing their electricity consumption by moving it away from the expensive "peak" period to the less-expensive "off-peak" period (see Faruqui and Malko 1983 for a meta-analysis of these experiments). In spite of this evidence, the lack of low-cost interval or period-based metering technology continued to limit the industry's ability to expand the application of time-based rate programs at the residential level through the end of the 20th century.

Over the past ten years, however, the costs of interval meters, the communications networks to connect the meters with utilities and the back-office systems necessary to maintain and support them (i.e., advanced metering infrastructure or AMI) have dramatically decreased. The implementation of AMI and interval meters by utilities, which allows electricity consumption data to be captured, stored and reported at 5 to 60-minute intervals in most cases, provides an opportunity for utilities and policymakers to once again seriously consider the merits of the widespread deployment of time-based rate programs. However, many regulators and other key policymakers have determined that more definitive answers to key policy questions must be addressed before they will fully support a paradigm shift in the way retail electricity providers charge residential and small commercial customers for consuming electricity.

The American Recovery and Reinvestment Act of 2009 included $3.4B for the Smart Grid Investment Grant (SGIG) program with the goal of creating jobs and accelerating the transformation of the nation's electric system by promoting investments in smarter grid technologies, tools and techniques (DOE 2012a). Among other topics, the Funding Opportunity Announcement (DE-FOA-0000058) identified interest in AMI projects that examined the impacts and benefits of time-based rate programs and enabling control and information technologies through the use of randomized controlled experimental designs.

Based on responses to this FOA, DOE decided to co-fund ten utilities to undertake eleven experimentally-designed Consumer Behavior Studies (CBS) that proposed to examine a wide range of the topics of interest to the electric utility industry. Each chosen utility was to design, implement and evaluate their own study in order to address questions of interest both to itself and to its applicable regulatory authority, whose approval was generally necessary for the study to proceed. The DOE Office of Energy Delivery and Electricity Reliability (OE), however, did set guidelines, both in the FOA and subsequently during the contracting period, for what would constitute an acceptable study under the Grant.

To assist in ensuring these guidelines were adhered to, OE requested that LBNL act as project manager for these Consumer Behavior Studies to achieve consistency of experimental design and adherence to data collection and reporting protocols across the ten utilities. As part of its role, LBNL formed technical advisory groups (TAG) to separately assist each of the utilities by providing technical assistance in all aspects of the design, implementation and evaluation of their studies. LBNL was also given a unique opportunity to perform a comprehensive, cross-study analysis that uses the customer-level interval meter and demographic data made available by these utilities due to SGIG-imposed reporting requirements, in order to analyze critical policy issues associated with AMI-enabled rates and control/information technology. Over the next several years, LBNL will publish the results of these analyses in a series of research reports that attempt to address critical policy issues including customer acceptance, retention and load response to time-based rates and various forms of enabling control and information technologies. This report is the first in that series and provides a description of each study.

Executive Summary

Introduction

The U.S. Department of Energy's (DOE's) Smart Grid Investment Grant (SGIG) program is working with a subset of the 99 SGIG projects undertaking Consumer Behavior Studies (CBS), which examine the response of mass market consumers (i.e., residential and small commercial customers) to time-varying electricity prices (referred to herein as time-based rate programs) in conjunction with the deployment of advanced metering infrastructure (AMI) and associated technologies. The effort presents an opportunity to advance the electric industry's understanding of consumer behavior.[i]

With the increased deployment of advanced meters with two-way communication networks that can record and provide at least hourly interval data spurred in part by DOE's SGIG program, electric utilities are now able to more easily offer and implement time-based rate and enabling technology programs for residential and smaller commercial customers. These time-based rate programs are fairly new for residential customers, and utilities, with some exceptions, have had limited success in enrolling mass market customers on these tariffs (FERC 2011). Because AMI business cases often rely on the benefits from customer demand response enabled by these investments, there is increasing interest among policymakers, regulators, utilities and stakeholders in understanding how many customers are likely to enroll and continue in such a program, and which factors can affect these recruitment and retention rates.

While there have been numerous evaluations of the peak demand and energy impacts of time-based rate programs (e,.g., Critical Peak Pricing) and enabling technology (e.g., programmable communicating thermostats), there has been limited examination to date of the customer recruitment rates that these types of programs can achieve. Currently, utility program evaluation reports that are focused on providing impact estimates of energy savings and load shifting rarely mention anything other than aggregate customer recruitment rates (e.g., Charles River Associates 2005; Summit Blue Consulting 2007; Hydro One Networks 2008; Connecticut Light and Power 2009; Faruqui and Sergici 2009;

[i] See www.smartgrid.gov for more information about the goals and objectives of the SGIG CBS effort.

eMeter Strategic Consulting 2010; EPRI 2011). The U.S. Energy Information Administration (EIA) and the Federal Energy Regulatory Commission (FERC) both collect and report on time-based rate enrollment information from all utilities in the United States on an annual basis. However, it is difficult to interpret this data or analyze results across utilities because utilities are not required to report information on the number of customers that were solicited or provide information that may explain factors that influenced their recruitment rates. As such, there is limited information in the public sphere that could help utilities, regulators or other policymakers understand what reasonable recruitment rates would be and what may explain currently observed differences in recruitment rates.

Objectives and Scope

In this preliminary report, we begin to fill this need by providing an initial summary of experiences of the different phases of the enrollment process (qualification, solicitation, recruitment, and selection) across nine of the ten SGIG utilities, who collectively are undertaking a total of 11 consumer behavior studies.[ii] We report three types of key findings: Experimental Results, Descriptive Results, and Lessons Learned.

- **Experimental Results** are statistical estimates derived from experimentally designed tests. These results enable us to draw conclusions about the causal effect of the treatments being tested.
- **Descriptive Results** are based on summary statistics. These results may be informative, but do not allow us to draw any causal conclusions.
- **Lessons Learned** are based on anecdotal information collected from utilities. They enable us to understand context surrounding the Experimental and Descriptive Results, but not to definitively state findings.

The primary focus of the CBS utilities was to experimentally test time-based rates and enabling technology; only a subset of the studies chose to experimentally test enrollment rates. Therefore, the Experimental Results in this report focus on a narrow subset of the CBS utilities. Although these results have strong internal validity, they were observed for

[ii] In order to characterize our empirical approach, we define the term *program offer* or simply *offer* to represent the different types of time-based rate, technology, and opt-in versus opt-out proposals made to customers when solicited to enroll in a study (e.g., an offer of a TOU rate, an offer that includes enabling technology, or an opt-in offer). We define the term *solicitation effort* to represent one complete set of offers made to one group of customers (e.g., one solicitation effort may have an opt-out offer, a TOU rate offer, and no technology offer). We define the *recruitment rate* as the percentage of recruited customers out of the total number of customers solicited in one solicitation effort.

particular populations at particular times and so may have less external validity. The Descriptive Results and Lessons Learned are based on data collected from all of the CBS utilities.

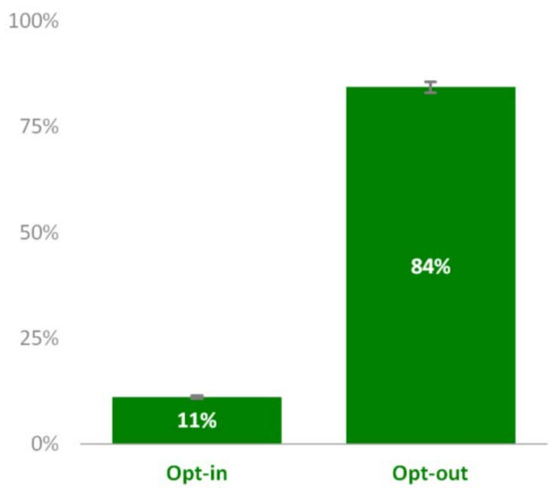
This report can help inform utilities and state regulatory commissions that are considering offering such time-based rates to mass market customers. First, it can help ensure that the number of customers enrolled in a study or pilot program is sufficient to produce valid energy impact estimates (based on statistical power calculations). If too few customers are enrolled, the evaluation effort may not be able to successfully and accurately estimate such impacts. Second, accurate recruitment rates are useful for planning and forecasting purposes when such rates are offered en masse (e.g., in order to gain a perspective on the magnitude of a particular program resource).

Key Findings

Key Finding: Experimental Result 1

More customers enroll into a time-based rate program with an opt-out offer than with an opt-in offer.

Only two utilities included both an opt-in and opt-out offer for randomly assigned customers to be solicited to participate in a study through either opt-in or opt-out offers. 84% of customers solicited to join a study using an opt-out recruitment approach did not reject the offer, whereas 11% of customers solicited to join a study using an opt-in recruitment method approach accepted the offer (see Figure ES-1).



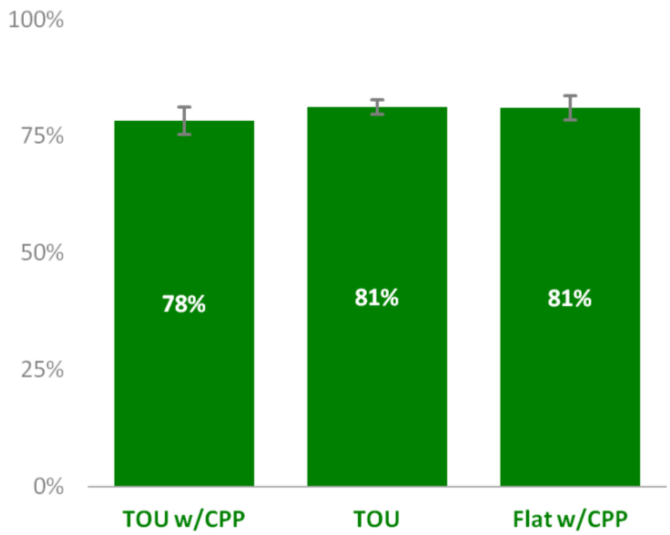
Percentages include the total number of customers across the two utilities that randomized opt-in versus opt-out program offers (99.9% confidence intervals shown; N=100,000).

Figure ES-1. Recruitment rates for tests of opt-in versus opt-out program offers

Key Finding: Experimental Result 2

For opt-out solicitations, the type of time-based rate offer does not substantially affect the customer recruitment rate.

Only a single utility study included more than one opt-out time-based rate program offering to a group of randomly assigned customers as part of their study. The observed recruitment rates were 81% for the TOU offer, 81% for the Flat w/CPP offer, and 78% for the TOU w/CPP offer (the differences between any pairings of the rates were not statistically significant; see Figure ES-2). This suggests that customers are not more likely to opt-out of one time-based rate over the other, despite the rate differences.



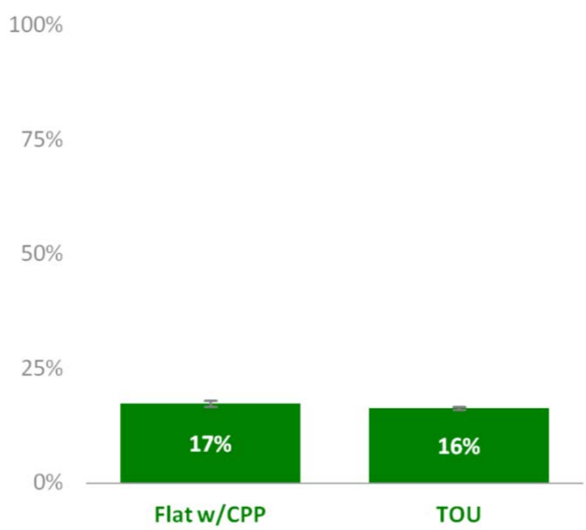
Percentages include the total number of customers within the lone utility that were randomly assigned to receive opt-out offers of one of three time-based rates (95% confidence intervals shown; N=4,000).

Figure ES-2. Opt-out recruitment rate results for tests of time-based rate offers

Key Finding: Experimental Result 3

For opt-in solicitations, the type of time-based rate does not substantially affect the customer recruitment rate.

Only a single utility study included more than one opt-in time-based rate program offering to a group of randomly assigned customers as part of their study. A Flat rate with a CPP overlay offer had a 17% recruitment rate while the TOU offer had a 16% recruitment rate; the difference, although small, is statistically significant (see Figure ES-3). This suggests that customers may, to a very small extent, prefer to opt-in to a Flat w/CPP over a TOU rate. However, the preference is very small.



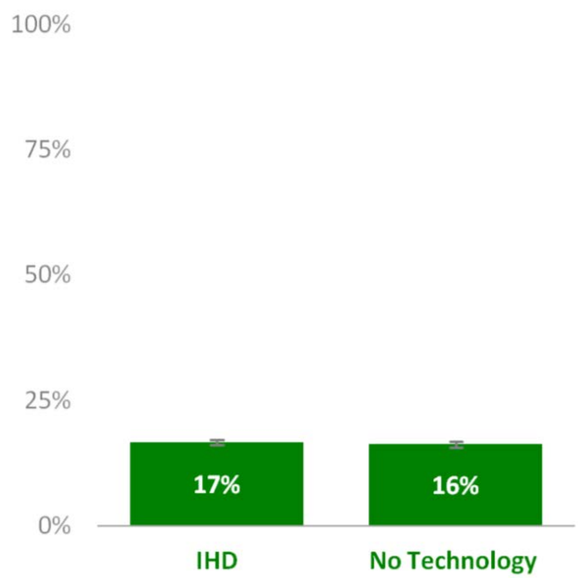
Percentages include the total number of customers within the lone utility that were randomly assigned to receive a CPP offer versus a TOU offer (95% confidence intervals shown; N=50,000).

Figure ES-3. Opt-in recruitment rate results for tests of time-based rate offers

Key Finding: Experimental Result 4

For opt-in solicitations, the offer of technology does not substantially affect the customer recruitment rate.

Only a single utility study included offers of time-based rate programs (i.e., TOU, Flat w/CPP) paired with an IHD and a separate set of offers of the same time-based rates but without an IHD. As shown in Figure ES-4, recruitment rates for the offers with an IHD and without the IHD (i.e., no-technology offer) were around 16-17%; the difference is not statistically significant. Segmenting customers into CPP and TOU solicitation efforts shows similar results. This indicates that customers are not more likely to opt-in to a time-based rate if they are offered an IHD, despite the supposed monetary value of such a device.



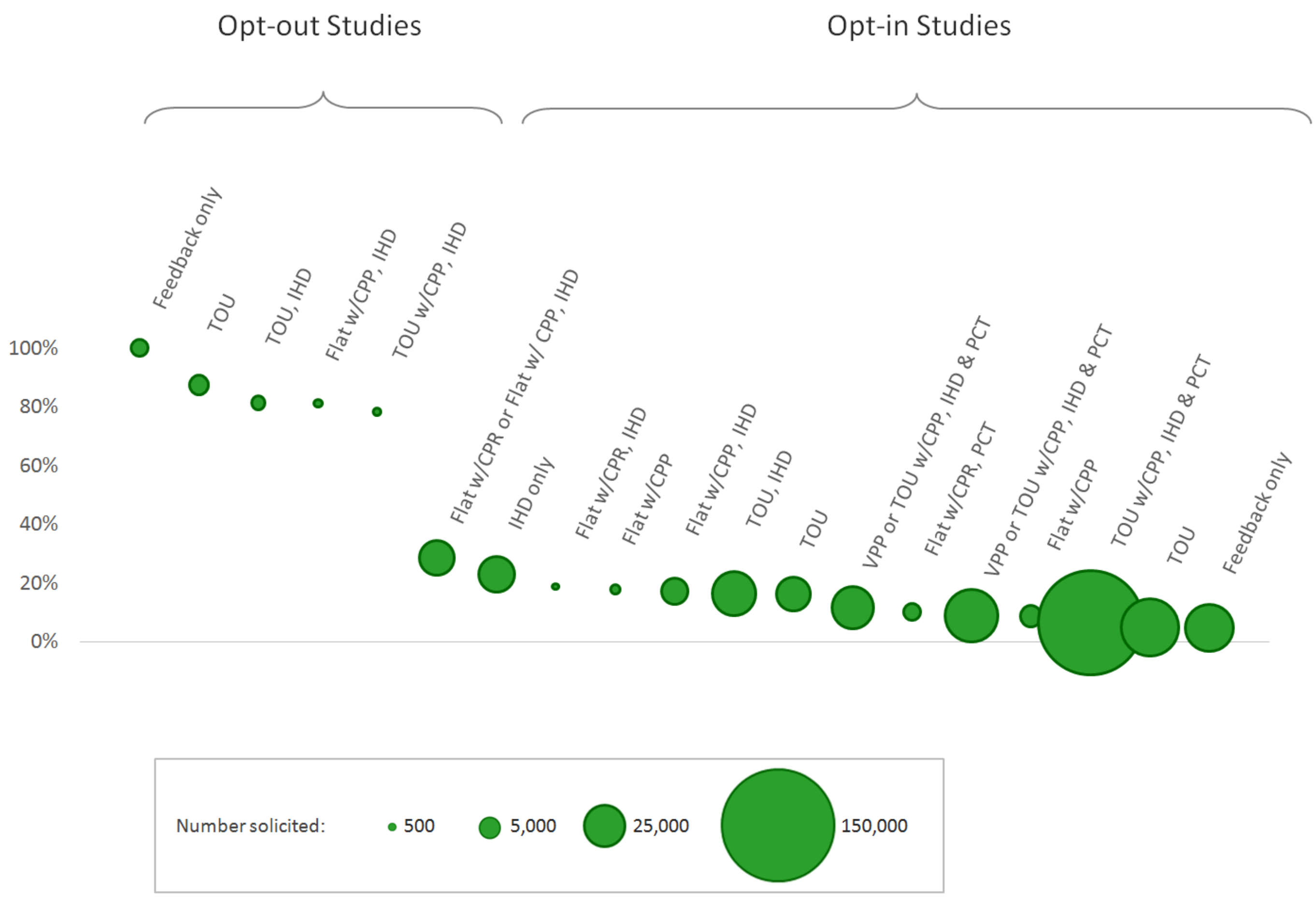
Percentages include the total number of customers within the lone utility that were randomly assigned to receive an IHD offer versus no technology offer (95% confidence intervals shown; N=50,000).

Figure ES-4. Opt-in recruitment rate results for tests of technology offers vs. no technology offers

Key Finding: Descriptive Result 1

For time-based rate and enabling technology studies that use an opt-in program offer, recruitment rates range from 5% to 28%. For those that use an opt-out program offer, recruitment rates range from 78% to 87%.

An assessment of Figure ES-5 suggests that a utility may expect to achieve at least a 5% recruitment rate for opt-in studies. Under ideal circumstances, recruitment rates into such studies could exceed 20%. However, for planning purposes assuming 10% recruitment rate seems most appropriate.



19 total solicitation efforts listed. Circle size represents the total number of customers solicited.

Figure ES-5. Recruitment rates for each solicitation effort

Key Finding: Descriptive Result 2

Most utilities did not accurately predict recruitment rates for their study solicitation efforts. Five of the twelve opt-in solicitation efforts underachieved their recruitment rates such that actual recruitment rates were 7 to 22 percentage points below the actual recruitment rate. This represents actual recruitment rates that were at least a quarter of what was planned.

Figure ES-6 shows the actual and planned recruitment rates for opt-in and opt-out solicitation efforts. Out of the six opt-in solicitation efforts that underachieved their planned recruitment rates (shown in red in Figure ES-6), five had an actual recruitment rate that was 7 to 22 percentage points lower than planned, representing an actual recruitment rate that at least a quarter of what they were planned to be. Five out of the six opt-in solicitation efforts that overachieved had an actual recruitment rate that was no more than 4 percentage points higher than planned. The sixth was 14 percentage points higher than planned, almost double the planned rate. While overachieving recruitment rates may not have severe consequences, underachievement can cause problems with the study evaluation effort which may necessitate changes to the study's design. If a study has planned to recruit a certain number of customers and the actual number of customers recruited is far less, the study may have to be re-designed (e.g., the number of treatments being tested may have to be reduced) in order to achieve statistically valid load impact estimates.[iii]

[iii] Power calculations are used to determine how large a sample a study needs to enroll in order to have faith that the resulting estimates of the treatment effect are credible. For more information on this topic, see Appendix A of Cappers et al. (2013).

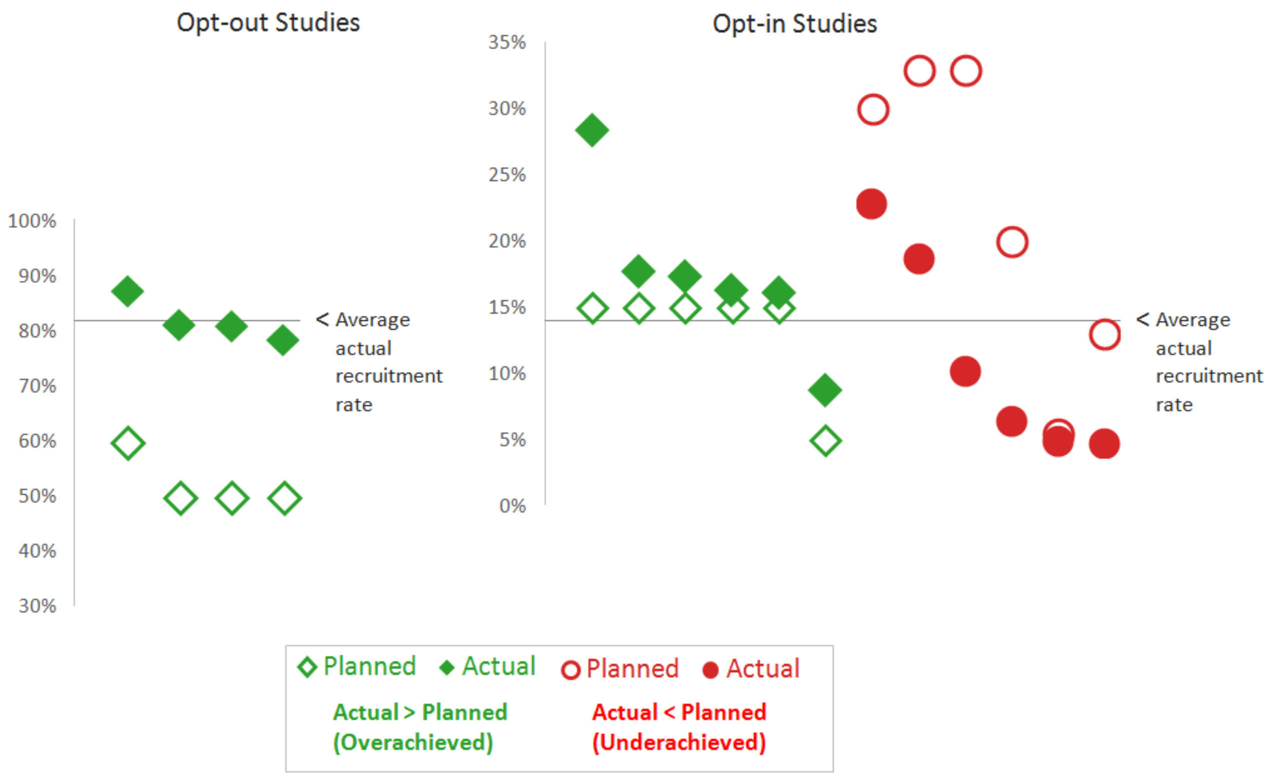


Figure ES-6 – Actual versus planned recruitment rates

Key Finding: Lessons Learned 1

Utilities found focus groups, surveys and other tools to be vital components for test marketing terms and concepts to attract customer interest and engage them to participate in the rate being offered.

Prior to test marketing materials that would be used to solicit participation into studies that included time-based rates, many utilities believed words like “critical”, “emergency”, and “events” would confer the necessary message about what the rate was trying to accomplish and how valuable a customer’s participation in that rate would be. Several utilities subsequently performed focus groups, surveys and other forms of test marketing of their recruitment material which indicated the terms and concepts utilities thought would connote positive concepts with customers actually had the opposite effect. Terms like “response”, “auto”, and “event” were construed as reactionary words that deflated personal control (e.g., “emergencies” are out of a customer’s control). Instead, some participants in focus groups appeared to prefer terms that construed a sense of personal control over one’s own energy usage and resulting bill (e.g., “control”, “choice”, “sense”).

Key Finding: Lessons Learned 2

Utilities learned the importance of validating focus groups with other test marketing efforts across a variety of customer segments and circumstances to develop the most effective messaging for their new time-based rate recruitment campaign.

Utilities also learned from focus groups that customers claimed to be primarily motivated by environmental messaging when it came to recruitment into new time-based rates. Test marketing along with observed recruitment data from various messages (e.g., “saving money”, “environmental stewardship”, “taking control”, “fun”) revealed the primary motivator for the majority of customers was actually financial.

Key Finding: Lessons Learned 3

Utilities were surprised at how much time and resources they needed to allocate between soft launch and hard launch of the solicitation effort to adjust the messaging and other details accordingly based on feedback.

Issues often arise during the recruitment phase of the study lifecycle that can threaten its overall success. Many utilities, therefore, included a two week soft launch window in their enrollment process in order to identify and address any problems that internal planning and test marketing of recruitment materials did not catch. Unfortunately, even with a two week soft launch period, one utility still did not have enough time to incorporate necessary feedback to the solicitation materials in time for the hard launch, at which point changes were very difficult and costly to make.

Key Finding: Lessons Learned 4

Utilities learned that before determining if a new rate or product offering is to be paired with a form of enabling technology, they could benefit from spending time understanding potential customer concerns with that technology and identifying the available pool of participants who would qualify for and be willing to accept such technology so that realistic expectations for recruitment can be set ahead of time.

The recruitment process can also be affected by assumptions about the number of customers capable and willing to receive certain types of enabling technology (e.g., presence of central air conditioning to receive a programmable communicating thermostat). By not accurately quantifying ahead of the study enrollment effort the size of the available population that would pre-qualify for specific enabling technology, the number of customers that would be willing/able to accept, and the number that then have it installed, some utilities substantially overestimated the level of acceptance for a new rate or product offering that was strictly paired with such enabling control technologies.

Key Finding: Lessons Learned 5

Utilities realized the need to ensure that all utility representatives and contractors that interact with customers at any level are informed, committed and enabled to make the experience a positive one for the customer. One way to do this most effectively was by focusing on communications skills as much as technical skills when hiring or recruiting people to fill these positions.

Many of the utilities who included some form of enabling technology in their study decided to enlist internal utility workers or external contractors to help install and provision this equipment at a participating customer's premise. These utilities believed that individuals responsible for installing these pieces of technology at a customer site would have little to no effect on that customer's decision to finalize and complete the enrollment process in the study. Unfortunately, installation of technology by individuals, either internal or external to the utility, who did not have sufficient appreciation for the importance of the public relations role they played and/or were insensitive to the consequences of not playing that role well, resulted in negative ramifications for customer engagement efforts at several utilities.

Next Steps

Because this preliminary report is based on initial results from the subset of SGIG projects that are undertaking a Consumer Behavior Study, it only includes information on the first stages of a customer's choice: whether or not to enroll in a study. Equally interesting and important is information on the next stages of a customer's choice, which concern retention in the study. To address this choice, we would examine the number of customers that dropped out after the study treatment went into effect (perhaps after receiving their first bill); the number of customers that installed and subsequently used the provided enabling technology (if applicable); and the number of customers that remained in the study for its duration. Future reports will examine data for these customer retention stages, in addition to examining the factors which may help explain higher or lower recruitment and retention rates, whether certain segments of customers (e.g., low income vs. high income; high school educated vs. college educated) are more or less likely to choose to enroll, and whether enrollment and retention choices affect the way that customers respond to time-based rates and enabling technology.[iv]

[iv] Understanding the retention rates of customers after the beginning of the study may be particularly important for interpreting enrollment rates for opt-out methods. For example, a customer enrolled via an opt-out method onto a TOU w/CPP rate may not have fully paid attention to the rate change until they experience a direct impact on their bill, at which point they may drop out now having fully understood what was asked of them so many months before. This may result in a recruitment rate that seems relatively high, but a low retention rate after the study has begun. On the other hand, if a customer is enrolled via an opt-out method into a program that would not result in any direct impact financially or on their quality of service (e.g., an information feedback program that allows the customer to see hourly energy use information on a daily delayed basis via a website), the customer may never drop out of the program but may also never actually experience the treatment (e.g., never access the website). In this case data may show a very high recruitment rate (potentially 100%), but future data may reveal that a much lower percentage of customers were actually exposed to the treatment.

1. Introduction

The U.S. Department of Energy's (DOE's) Smart Grid Investment Grant (SGIG) program is working with a subset of the 99 SGIG projects undertaking Consumer Behavior Studies (CBS), which examine the response of mass market consumers (i.e., residential and small commercial customers) to time-varying electricity prices (referred to herein as time-based rate programs) in conjunction with the deployment of advanced metering infrastructure (AMI) and associated technologies. The effort presents an opportunity to advance the electric industry's understanding of consumer behavior.[1]

Methods for enrolling customers in programs vary widely, and different methods may lead to substantially different recruitment rates. For example, opt-in methods, in which customers must actively consent to participation in a program, are likely to lead to lower recruitment rates than opt-out methods, in which customers must actively decline or opt-out of participating in a program. Other factors may also affect customer recruitment rates, such as program differences (e.g., the specific rate and technology offered), differences in marketing approaches, the types of customers solicited, the customer-utility relationship, and many others.

With the increased deployment of advanced meters with two-way communication networks that can record and provide at least hourly interval data (i.e., AMI) spurred in part by DOE's SGIG program, electric utilities are now able to more easily offer and implement time-based rate and enabling technology programs for residential and smaller commercial customers. These time-based rate offerings are fairly new for residential customers, and utilities, with some exceptions, have had limited success in enrolling mass market customers on these tariffs (FERC 2011). Because AMI business cases often rely on the benefits from customer demand response enabled by these investments, there is increasing interest among policymakers, regulators, utilities and stakeholders in understanding how many customers are likely to enroll and continue in such a program, and which factors can affect these recruitment and retention rates.

While there have been numerous evaluations of the peak demand and energy impacts of time-based rate programs (e,.g., Critical Peak Pricing) and enabling technology (e.g.,

[1] See www.smartgrid.gov for more information about the goals and objectives of the SGIG CBS effort.

programmable communicating thermostats), there has been limited examination to date of the customer recruitment rates that these types of programs can achieve. Currently, utility program evaluation reports that are focused on providing impact estimates of energy savings and load shifting rarely mention anything other than aggregate customer recruitment rates (e.g., Charles River Associates 2005; Summit Blue Consulting 2007; Hydro One Networks 2008; Connecticut Light and Power 2009; Faruqui and Sergici 2009; eMeter Strategic Consulting 2010; EPRI 2011). The U.S. Energy Information Administration (EIA) and the Federal Energy Regulatory Commission (FERC) both collect and report on time-based rate enrollment information from all utilities in the United States on an annual basis. However, it is difficult to interpret this data or analyze results across utilities because utilities are not required to report information on the number of customers that were solicited or provide information that may explain factors that influenced their recruitment rates. As such, there is limited information in the public sphere that could help utilities, regulators or other policymakers understand what reasonable recruitment rates would be and what may explain currently observed differences in recruitment rates.

In this preliminary report, we begin to fill this need by providing an initial summary of experiences of the different phases of the enrollment process (qualification, solicitation, recruitment, and selection) across nine of the ten SGIG utilities, who are undertaking a total of 11 consumer behavior study. First, we provide an overview of the consumer behavior studies co-funded by DOE's SGIG program that are included in this assessment. Next, we describe the methodology that will be applied to analyze the various stages of enrollment and recruitment rates. Lastly, we report summary statistics and results from experiments that are testing whether certain program offers affect recruitment rates, and provide lessons learned. Specifically, we report three types of key findings: Experimental Results, Descriptive Results, and Lessons Learned.

- **Experimental Results** are statistical estimates derived from experimentally designed tests. These results enable us to draw conclusions about the causal effect of the treatments being tested.
- **Descriptive Results** are based on summary statistics. These results may be informative, but do not allow us to draw any causal conclusions.
- **Lessons Learned** are based on anecdotal information collected from utilities. They enable us to understand context surrounding the Experimental and Descriptive Results, but not to definitively state findings.

The primary focus of the CBS utilities was to experimentally test time-based rates and enabling technology; only a subset of the studies chose to experimentally test enrollment rates. Therefore, the Experimental Results in this report focus on a narrow subset of the CBS utilities. Although these results have strong internal validity, they were observed for particular populations at particular times and so may have less external validity. The Descriptive Results and Lessons Learned are based on data collected from all of the CBS utilities.

This report can help inform utilities and state regulatory commissions that are considering offering such time-based rates to mass market customers. First, it can help ensure that the number of customers enrolled in a study or pilot program is sufficient to produce valid energy impact estimates (based on statistical power calculations). If too few customers are enrolled, the evaluation effort may not be able to successfully and accurately estimate such impacts. Second, accurate recruitment rates are useful for planning and forecasting purposes when such rates are offered en masse (e.g., in order to gain a perspective on the potential magnitude of participants and load impacts from a particular program).

Because this preliminary report is based on initial results from the subset of SGIG projects that are undertaking a consumer behavior study, it only includes information on the first stage of a customer's choice: whether or not to enroll in a study. Equally interesting and important is information on the next stages of a customer's choice, which concerns retention in the study. To address this choice, we would examine: the number of customers that dropped out after the study treatment went into effect (perhaps after receiving their first bill); the number of customers that installed and subsequently used the provided enabling technology (if applicable); and the number of customers that remained in the study for its duration. Future reports will examine data for these additional customer retention stages, in addition to examining the factors which may help explain higher or lower recruitment and retention rates, whether certain segments of customers (e.g., low income vs. high income; high school educated vs. college educated) are more or less likely to choose to enroll, and whether enrollment and retention choices affect the way that customers respond to time-based rates and enabling technology.[2]

[2] Understanding the retention rates of customers after the beginning of the study may be particularly important for interpreting enrollment rates for opt-out methods. For example, a customer enrolled via an opt-out method onto a TOU w/CPP rate may not have fully paid attention to the rate change until they experience a direct impact on their bill, at which point they may drop out now having fully understood what was asked of them so many months before. This may

2. Consumer Behavior Studies Overview

As part of the Smart Grid Investment Grant program, the U.S Department of Energy is co-funding ten utilities to undertake experimentally designed consumer behavior studies (CBS) that examine a wide range of topics of interest to the electric industry in the area of AMI-enabled time-based rates and customer systems. [3] The ten utilities are undertaking 11 studies, which are designed to rigorously test the impact of time-based rates and/or technology and education treatments on customers' energy usage patterns, and in a few cases to rigorously test the impact on customer acceptance on the same set of treatments.

2.1 Treatments Tested in CBS

This section describes the different types of treatments that are being tested by utilities in their consumer behavior studies: time-based rates; technology and education; and program offers.

2.1.1 Time-based Rate Treatments

Time-based rates are attractive to utilities because they are designed to allow the prices that customers pay to consume electricity to correspond more closely to the actual cost that utilities incur when producing or procuring it. For most utilities, the cost of providing electricity increases with the demand for energy because higher-cost power plants must be brought online to accommodate the additional demand. For example, a Time of Use (TOU) rate design identifies a set of pre-determined "peak" hours of the day that consistently have higher demand and therefore higher production costs for electricity (e.g., on weekdays between 2 pm and 6 pm), and charges a pre-determined higher price during those on-peak hours (e.g., the price is $0.12/kWh higher than at other times; see Figure 1). For other time-

result in a recruitment rate that seems relatively high, but a low retention rate after the study has begun. On the other hand, if a customer is enrolled via an opt-out method into a program that would not result in any direct impact financially or on their quality of service (e.g., an information feedback program that allows the customer to see hourly energy use information on a daily delayed basis via a website), the customer may never drop out of the program but may also never actually experience the treatment (e.g., never access the website). In this case data may show a very high recruitment rate (potentially 100%), but future data may reveal that a much lower percentage of customers were actually exposed to the treatment.

[3] For a more detailed description of the treatments undertaken in each utility study, see the first report in the series of CBS reports, "Smart Grid Investment Grant Consumer Behavior Studies: Summary of Projects"(Cappers et al. 2013).

based rate programs, utilities attempt to identify specific "event" hours of the year in which electricity costs are likely to be highest, and commensurately increase the price of electricity to consumers during only those event hours. Critical Peak Pricing (CPP) rates typically have a day-ahead notice of event hours, and charge a pre-determined higher price during such hours; and Critical Peak Rebate (CPR) programs provide customers with a payment if they use less electricity during event hours, compared to some baseline estimate of what their electricity use would have been. CPP and CPR rates[4] can be overlaid on a TOU rate, which we will denote as TOU w/CPP or TOU w/CPR, but can also be applied to a standard flat rate, which we will denote as Flat w/CPP or Flat w/ CPR.[5] A Variable Peak Pricing (VPP) rate design identifies a set of peak hours for each day in advance, and charges customers using a price schedule that is variable and differs daily, based on bulk power system conditions during the peak hours.

[4] Technically, a Critical Peak Rebate program is not a rate offering, as it does not reflect a price that must be paid **by** customers for consuming electricity but rather a price that is paid **to** customers for not consuming electricity. However, for simplicity of exposition and to maintain consistency with industry norms, we refer to CPR as a time-based rate herein.

[5] In this report, Flat rates denote any rate that does not change on a time-differentiated basis, including inclining/declining block/tiered rates and bulk usage rates. See Appendix A in Cappers et al. (2013) for more information on these rate designs.

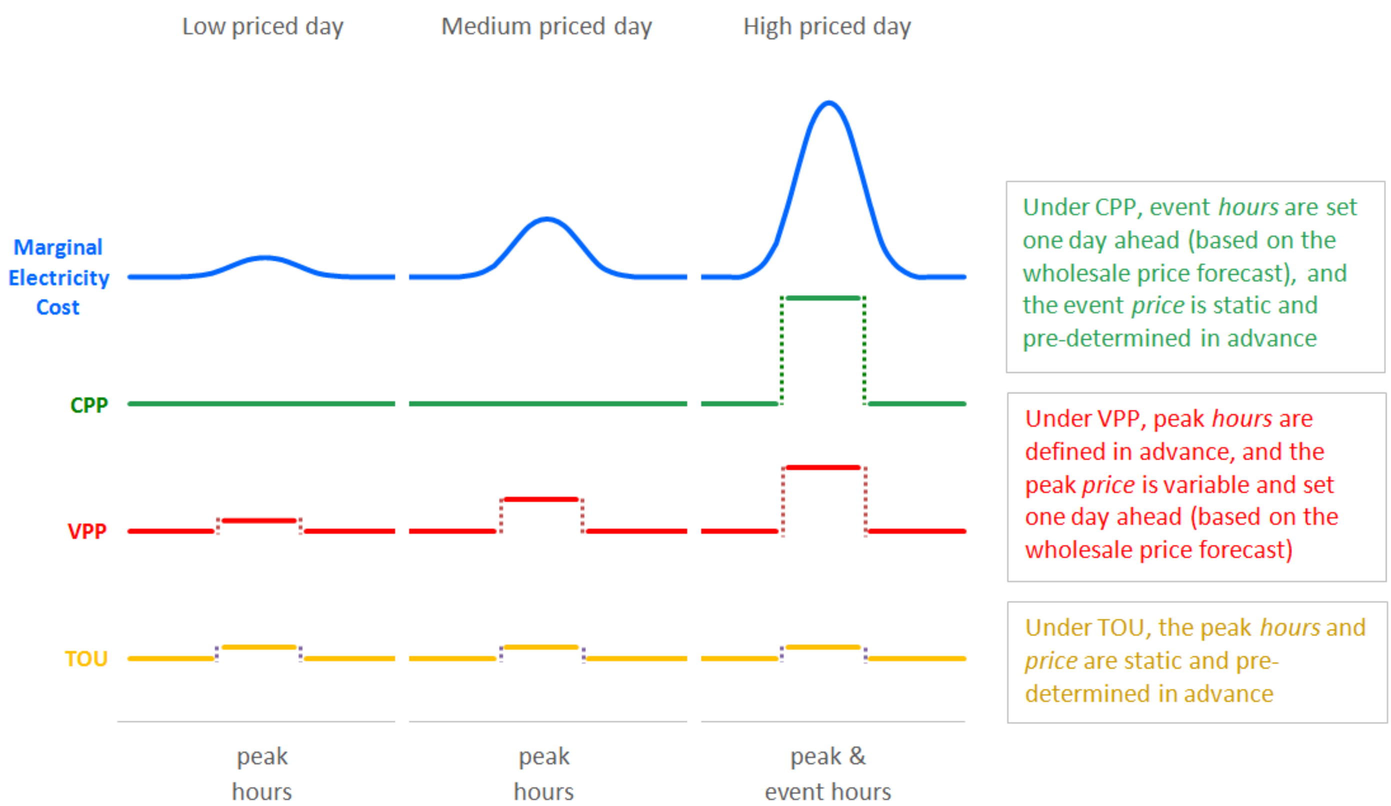


Figure 1. Time-based rate designs

At least one of these four time-based rate designs is included as an explicit treatment in each of the eleven utilities' consumer behavior studies (see Figure 2). Several utilities are testing more than one time-based rate design in their study.

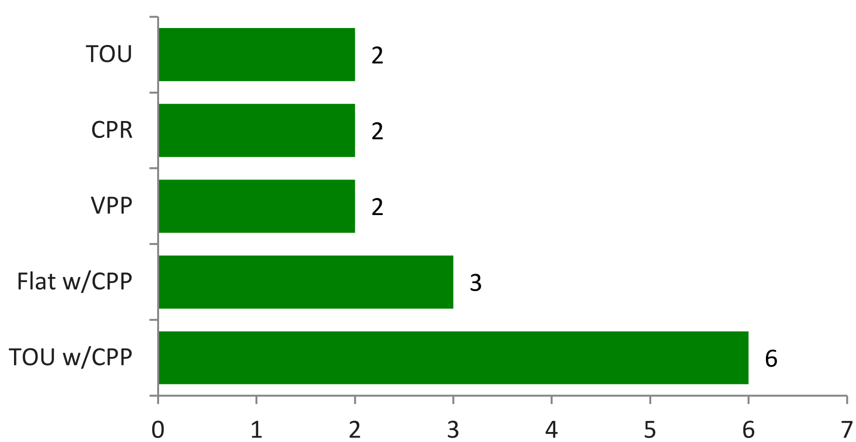


Figure 2. Number of utility studies designed to test various time-based rate treatments

2.1.2 Technology and Education Treatments

Utilities and state regulators are also interested in understanding the role of technology enabled by AMI as well as education efforts to enhance response to time-based rates and affect customers' willingness to take service under such rates. In-home displays (IHDs), programmable communicating thermostats (PCTs), and web-based energy information and feedback are all included as explicit treatments in several of the studies (see Figure 3). As with the rate treatments, some utilities have chosen to test a variety of different non-rate treatments in their study, while one utility chose to explicitly exclude enabling technology and education from their effort, focusing purely on the impacts of time-based rates.

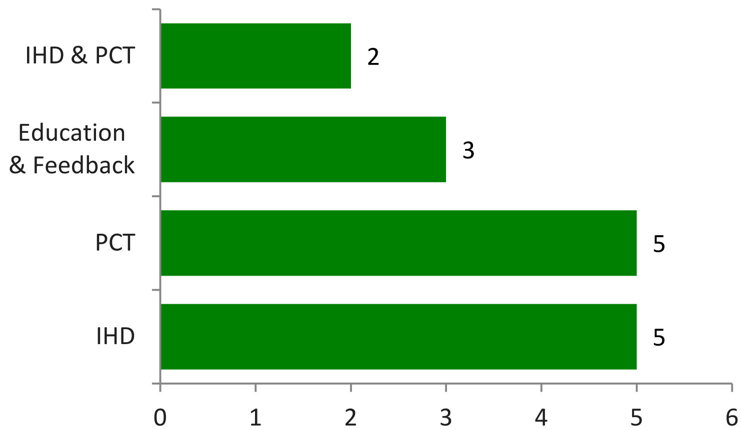


Figure 3. Number of utility studies designed to test various enabling technologies and education treatments

Some utilities included in this assessment are also testing joint applications of both rate and non-rate treatments in their study. For example, one utility study includes a treatment that tests the impact of a Flat w/CPP rate, another treatment that tests the impact of an IHD for customers remaining on the flat rate without a CPP overlay, and a third treatment that includes both a Flat w/CPP rate and an IHD.

2.1.3 Program Offer Treatments

In addition to testing the impact of time-based rates and enabling technologies on electricity consumption patterns, eight utility studies are also explicitly testing how successful different types of program offers are for recruiting customers. For example, in one study with a time-based rate program, customers were randomly assigned to receive either a technology offer of an IHD, or no technology offer, in order to determine if the technology offer enticed more customers to sign up for the rate. Figure 4 illustrates the number of utility studies designed to experimentally test the effect of various types of offers on recruitment rates, including the type of technology offered, the type of time-based rate offered, and an opt-in versus an opt-out offer.

Figure 4. Number of utility studies designed to test various program offers

2.2 Experimental Design in CBS

All of the CBS studies testing time-based rates or technology treatments were initially designed to measure the impact of a treatment using a randomized experimental design, either a Randomized Controlled Trial (RCT) design or a Randomized Encouragement Design (RED). With RCTs, customers sign up for a study either through an opt-in method, in which customers must actively consent to participate in the study, or an opt-out method, in which customers must actively decline to participate in the study. Once they sign up, customers that opted-in (or did not opt-out) are randomly assigned to either a treatment group, which receives the treatment being tested, or a control group, which receives the treatment delayed by a year or does not receive the treatment. With REDs, customers are randomly assigned to either a treatment group, which is encouraged to sign up for the offered treatment through an opt-in or opt-out method, or a control group, which is not notified of the study and thus not encouraged to sign up for the treatment. For both RCTs and REDs, the treatment group is compared to the control group in order to determine the effect of the treatment.[6]

In addition, one utility is augmenting their randomized study with an additional aspect that uses a non-randomized, within-subjects method to test a treatment. A within-subjects method compares the treatment group during times when it receives the treatment to times when it does not receive the treatment. In theory, RCTs and REDs produce unbiased treatment estimates, while within subjects estimates are not. Figure 5 depicts the number of utility studies under assessment utilizing various combinations of experimental designs.

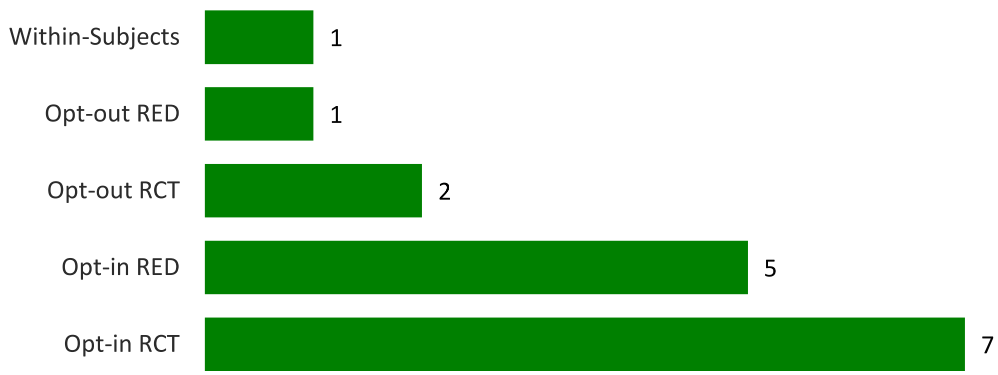


Figure 5. Number of utility studies using various experimental designs

For the studies designed to explicitly test the effect of different program offers, each one used a randomized experimental design (i.e., RCT or RED) in which customers were randomly assigned to be exposed to different types of offers. For example, customers were randomly assigned to receive either an offer of a Flat w/CPP rate, or an offer of a TOU rate.

[6] Although REDs require substantially larger sample sizes than RCTs to achieve comparable levels of power and precision for an estimation of treatment effects, a utility might prefer to implement an RED because it would not have to deny or delay any customer who wants to participate in a study.

3. Approach

Customer enrollment into a study can take on many forms. It is important to precisely characterize how the enrollment effort is undertaken to enable an accurate comparison of customer recruitment rates. In this section we describe the data collected from CBS utilities and also discuss our approach to reporting customer enrollment data.

3.1 Data Description

Customer enrollment into a study goes through many stages. Each stage of enrollment may decrease the pool of available customers (see Figure 6) for subsequent stages. First, out of the total pool of residential customers, the utility may choose a certain subset of *qualified customers* that meet certain criteria (e.g., energy use criteria, geographic criteria, presence of central air conditioning). Second, out of the pool of qualified customers, the utility may only target and market the study to a smaller subset of *solicited customers* (e.g., if marketing to too many customers is too costly). Third, once they are solicited, only some customers sign up for the study (either by opting-in or not opting-out), resulting in a yet smaller pool of *recruited customers*. Fourth, the utility may decide to screen some customers out after they signed up, leading to an even smaller subset of *selected customers* (e.g., if a survey is part of the selection process, customers may be selected based on their answers to survey questions). These stages lead to the final number of *enrolled customers* that will be part of the study.[7] We collected data on the number of customers in each of these customer enrollment stages[8] for each of the nine CBS studies for which enrollment data is available.[9] The enrollment stages generally lasted a few months for each study, and mostly occurred in late 2011 and early 2012. Due to the timing of when our analysis was undertaken relative to when enrollment data was available out of the utilities studies, only nine of the eleven CBS utilities studies are included in this analysis. In spite of not having

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[7] In order to estimate customer response to time-based rates (examined in future LBNL reports), studies that are using a randomized encouragement design may also collect data from a group of control customers that were never solicited. These control customers that were never solicited are not included in the number of enrolled customers.

[8] For this study, we only have data on the aggregate number of enrolled customers. In future reports, we will have individual customer demographic and electricity data that will allow customer segmentation analysis.

[9] Two of the eleven utilities undertaking an SGIG co-funded consumer behavior study have not yet begun enrolling customers at the time this report was drafted. As such, they are not included in this preliminary report.

data on two of the CBS utility studies, our analysis includes around 400,000 customers who were solicited and 44,000 who were enrolled.

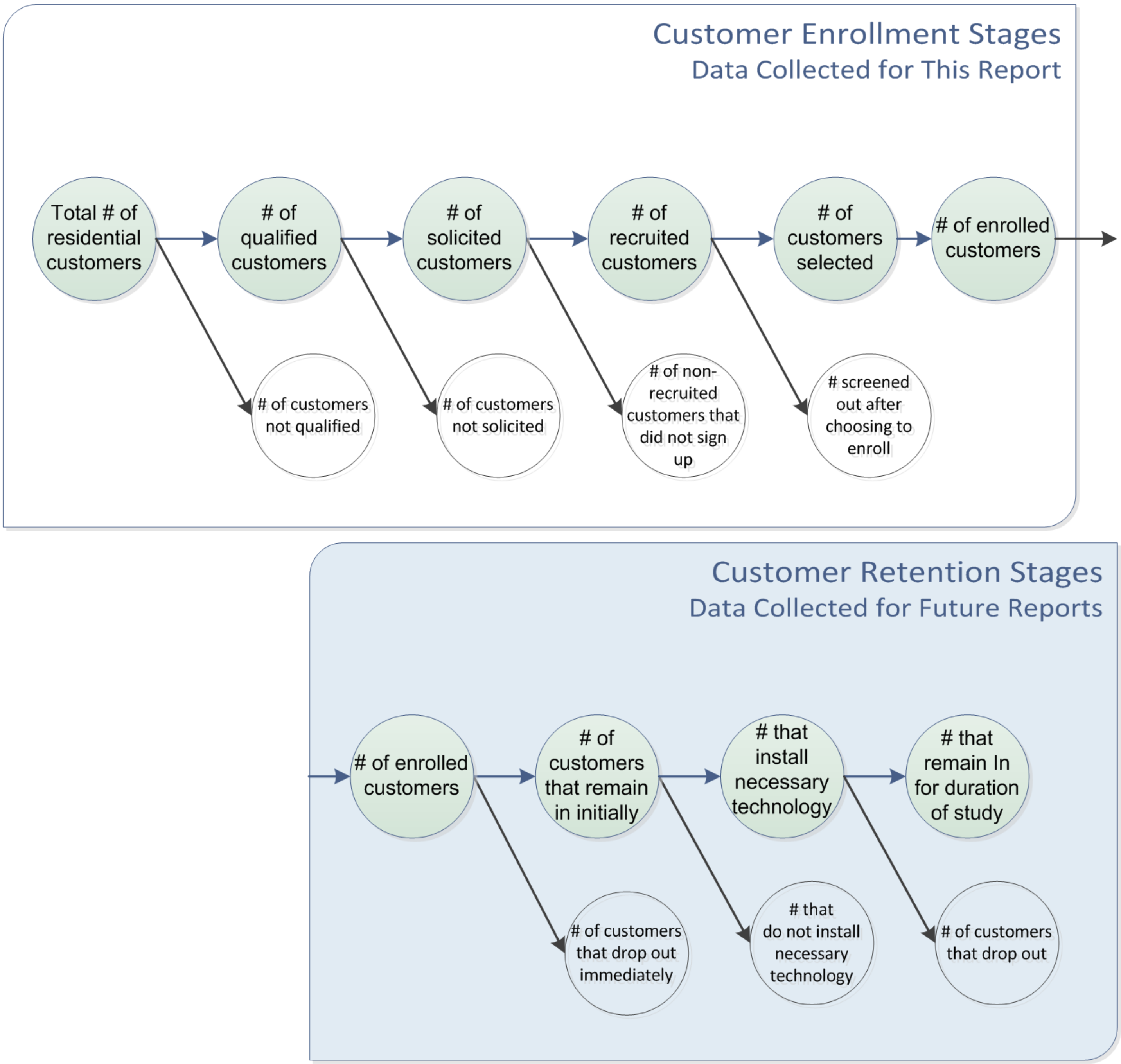

Figure 6. Data elements collected through various stages of customer enrollment and retention

Once the study begins and the treatment(s) go into effect, the customer pool goes through several additional stages of *customer retention* (see bottom panel in Figure 6). For example, an enrolled customer may drop out immediately after enrollment but before being exposed to treatment. Customers may decide not to install the required technology or they may drop out at some point before the end of the study. As mentioned previously, this report only captures data for the enrollment stages of the utility's study; future LBNL reports will examine data for the various customer recruitment stages.

In addition to this quantitative data, LBNL also collects more qualitative information from the CBS utilities on the lessons learned in a variety of areas, including customer enrollment in the CBS projects. Specifically, LBNL collects the experience of the CBS projects as a whole, identifying their initial expectations concerning a certain issue, relating how their actual experience differed, and sharing what they took away from this for future efforts. This qualitative data is collected through a variety of different channels on an ongoing basis from the CBS projects, including the CBS Utility Forum, the Technical Advisory Groups, and personal communications with LBNL staff.[10]

3.2 Empirical Approach

In order to characterize our empirical approach, we define the term *program offer* or simply *offer* to represent the different types of time-based rate, technology, and opt-in versus opt-out proposals made to customers when they are solicited to enroll in a study (e.g., an offer of a TOU rate, an offer that includes enabling technology, or an opt-in offer). We define the term *solicitation effort* to represent one complete set of offers made to one group of customers (e.g., one solicitation effort may have an opt-out offer, a TOU rate offer, and no technology offer). There are two types of *solicitation efforts* depending on the experimental design of the study:

1. **Recruitment into a specific treatment** (see example 1 in Figure 7)**:** The utility first selects a group of customers that are targeted for solicitation. These customers are then split into two (or more) pools, where each is assigned to be solicited for a specific treatment pool. Once a customer signs up for the study, the customer is

[10] The CBS Utility Forum provides an opportunity for the SGIG CBS utilities to share information among themselves. Each CBS Utility is provided by LBNL with a small group of industry experts (i.e., Technical Advisory Group) who provide technical assistance to the utility concerning study design, implementation and evaluation issues.

assigned to the specific treatment pool for which he or she was solicited. Customers in a specific treatment pool are then randomly assigned to either the treatment group, which receives the treatment, or the control group. For example, a utility makes the following solicitation: one group of customers is solicited specifically for a TOU rate, and customers that sign up are placed in the TOU treatment pool; a second group is solicited specifically for a Flat w/CPP rate, and customers that sign up are placed in the Flat w/CPP treatment pool. A utility would pursue this approach to recruitment if it wanted to explicitly understand customer preferences for different combinations of rate and/or technology treatments. We represent this case as two *solicitation efforts* for this utility; one TOU solicitation effort and one Flat w/CPP solicitation effort.

2. **Recruitment into a generic study** (see example 2 in Figure 7): The utility first selects a group of customers that are targeted for a solicitation. These customers are then solicited for a single, generic study that includes two or more treatments. Once a customer signs up for the study, only then does the utility split customers into specific treatment pools. Customers in a specific treatment pool are then randomly assigned to either the treatment group, which receives the treatment, or the control group, which does not receive the treatment. For example, a utility solicits a group of customers for a study in which, should they sign up, they may be placed into a TOU rate treatment pool, or they may be placed into a Flat w/CPP rate treatment pool. A utility would pursue this approach to recruitment if it wanted to ensure that customers in different treatment groups within its study are similar, so that the results can be compared (i.e., all of the customers in all treatment groups are the same type of customers that would choose to enroll in a generic study).[11] We represent this case as one *solicitation effort* for this utility; one "TOU or Flat w/CPP" solicitation effort.

[11] Results across different treatment groups cannot be directly compared when customers are recruited into specific treatments, because different types of customers may decide to sign up for different treatments. Different treatments would then have different types of customers, and so any observed differences between the treatments may be due to the difference in customers, not due to the treatments.

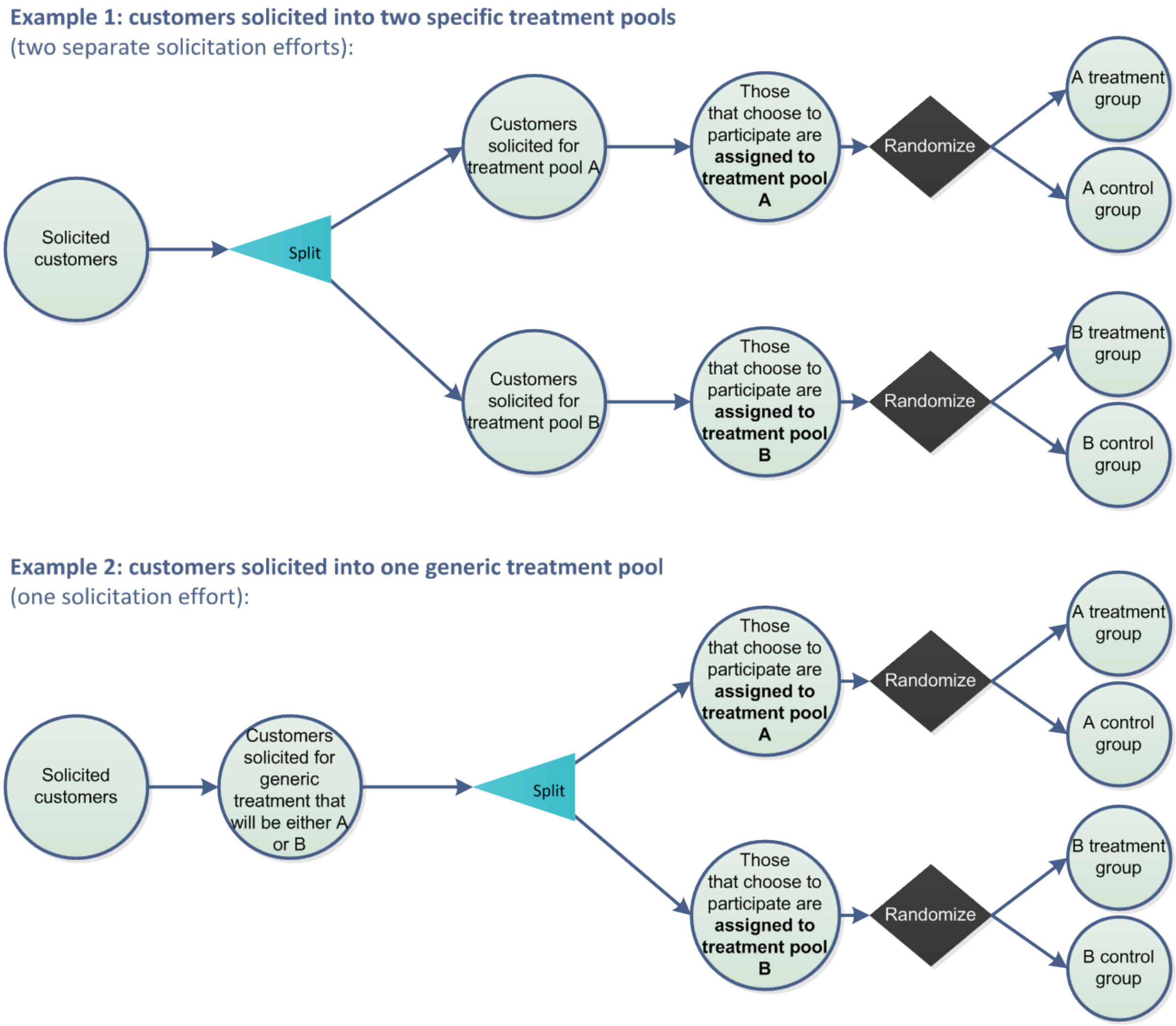

Figure 7. Example of solicitation efforts

Based on this definition of a *solicitation effort*, there are nineteen different customer solicitation efforts across the nine utilities included in this report.

3.2.1 Recruitment Rates

While the number of customers that are retained in each of the customer enrollment stages is important to understand for study planning purposes, in this report most of our analysis is focused on the number of customers that sign up for the program (i.e., recruited customers) out of those that are solicited. We define the *recruitment rate* as the percentage of recruited customers out of the total number of customers solicited in one solicitation effort (Equation 1).

Equation 1: $\text{Recruitment Rate} = \frac{\text{Recruited customers}}{\text{Solicited customers}}$

We focus on the recruitment rate because this is the stage of the enrollment process in which the customer must give an affirmative indication that they will sign up for the study (and potentially be exposed to the time-based rate and/or enabling technology). When utilities are planning a study, this is likely to be the stage that is the least well known and that seems to be outside of the utility's control. We provide an overall summary of the recruitment rates for each of the nineteen solicitation efforts, and then examine three types of program offers:

- An opt-in versus opt-out offer
- Offers of different time-based rates
- Technology offers

For each of these three types of program offers, we report two findings: first, Descriptive Results that are based on summary statistics; and second, Experimental Results from explicit experimental tests of the effectiveness of different types of program offers on recruitment rates.

We also report on how accurately the utilities were able to forecast their recruitment rate. We define the actual versus planned recruitment rate as the percentage difference between the actual and the planned recruitment rate. This is helpful in determining how accurate the utilities were in planning their recruitment efforts.

Equation 2: Actual vs. Planned Recruitment Rate = $\frac{\text{Actual Recruitment Rate} - \text{Planned Recruitment Rate}}{\text{Planned Recruitment Rate}}$

For the Descriptive Results, we report the unweighted average recruitment rates for opt-in and opt-out studies, grouped by: the type of time-based rate offered and the type of technology offered.[12] Note that because each utility chose the type of time-based rate and

[12] We provide an unweighted average rather than a weighted average because we believe that unobservable differences across utilities may be more of a factor in a customer's choice to enroll than the variables that we are examining. For example, consider the extreme case in which one utility solicited more customers than all of the other utilities combined, and also had exceptionally high recruitment rates. Then the characteristics of that utility would drive all of the weighted

the type of technology that they deemed best to include in their own study, one cannot interpret any differences in recruitment rates across all utility studies as being caused by the recruitment characteristics.[13] However, one can readily observe the range in recruitment rates that these utilities achieved and use them to set realistic boundaries on recruitment rates for similar efforts.

Eight of the nineteen solicitation efforts explicitly and experimentally tested the relative success of different types of offers by randomly assigning customers to receive different program offers. For these cases, it is possible to draw causal inferences about which specific types of offers would result in higher recruitment rates. We are able to provide Experimental Results from the following randomized trials:

- A test of an opt-out versus an opt-in offer
- A test of an opt-in Flat w/CPP offer versus a TOU offer
- A test of an opt-out TOU w/CPP offer versus a TOU offer versus a Flat w/CPP offer
- A test of an opt-in IHD technology offer versus no technology offer

Specifically, for each of these comparisons, we perform a two-proportion z-test of differences[14] in order to determine which solicitation method resulted in a higher recruitment rate.[15] For situations in which there are two or more utilities testing the same solicitation method (e.g., two utilities that randomize customers into an opt-in versus an opt-out method), we perform a test with the total number of customers aggregated across utilities as well as a separate test segmented by each utility.

3.2.2 Qualification, Solicitation, Recruitment, and Selection

We focus mainly on reporting the recruitment rate as the primary metric of interest. In addition, we provide Descriptive Results for the other enrollment stages for the fourteen

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average rates, but it may be that the high recruitment rate was due to something that we are not capturing, such as a great marketing campaign or utility customers that are particularly amenable to the program.

[13] There may be many other unobservable differences in the studies that actually cause the difference in recruitment rates (e.g., the utilities may have used different marketing materials, and the customers in the utilities may be quite different).

[14] For a comprehensive book on statistics and econometrics, see Greene (2011).

[15] The extent to which the results from this analysis can be extrapolated to different settings depends on the degree to which the solicitation efforts and utility characteristics are similar.

opt-in solicitation efforts.[16] Specifically, we define the *qualification rate* as the percent of customers that qualified for the study out of the total pool of residential customers (Equation 3); the *solicitation* rate as the percent of customers that were solicited out of the pool of qualified customers (Equation 4); the *recruitment rate* is as defined above (the percent of customers that were recruited into the study out of the pool of solicited customers); and the *selection rate* as the percent of customers that were not screened out of the study out of the pool of recruited customers who had already signed up for the study (Equation 5).

$$\text{Equation 3: Qualification Rate} = \frac{\text{Qualified customers}}{\text{Total Residential customers}}$$

$$\text{Equation 4: Solicitation Rate} = \frac{\text{Solicited customers}}{\text{Qualified customers}}$$

$$\text{Equation 1: Recruitment Rate} = \frac{\text{Recruited customers}}{\text{Solicited customers}}$$

$$\text{Equation 5: Selection Rate} = \frac{\text{Selected customers}}{\text{Recruited customers}}$$

3.2.3 Lessons Learned

Although identifying the degree to which recruitment rates differ across different solicitation efforts is important for future utility efforts, it is equally important to understand the context that underlies those recruitment figures. Based on conversations with utility CBS project managers and TAG members, a summary of the qualitative data collected by LBNL on the lessons learned in the area of customer enrollment is presented, which can be used to help further characterize and contextualize the observed recruitment rates.

[16] We did not include the five opt-out solicitation efforts, as it is hard to draw even qualitative observations from only five studies.

4. Results

In section 4.1, we provide summary statistics on the number of customers that are recruited out of the pool of solicited customers (i.e., the recruitment rate), and results from studies that are explicitly testing the effectiveness of different types of program offers through randomized trials (e.g., recruitment rates for opt-in versus opt-out offers, different types of time-based rates and technology offers). Findings on the number of customers that are maintained throughout other enrollment stages are presented in section 4.2, and lessons learned are discussed in section 4.3.

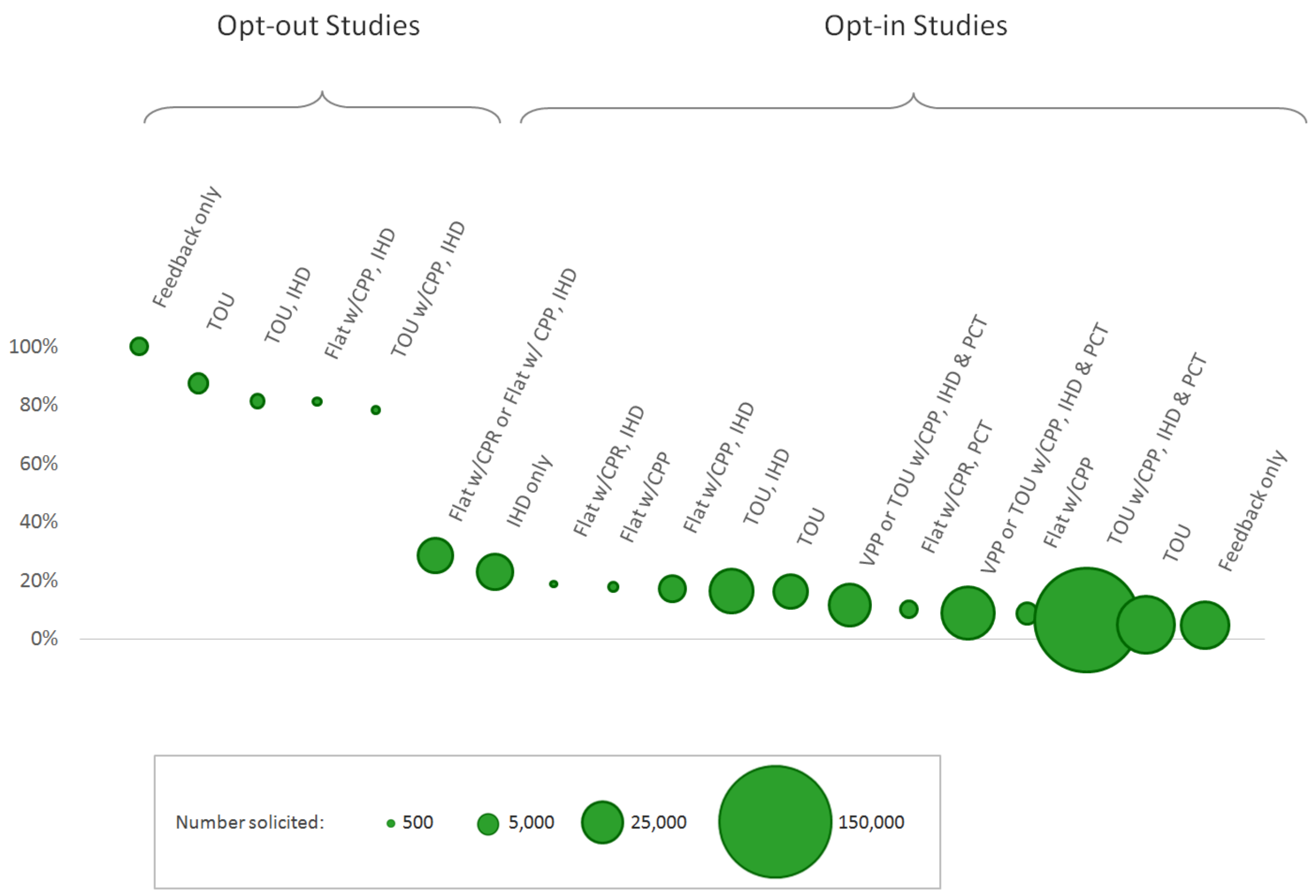
4.1 Recruitment Rates

Figure 8 displays the recruitment rates for each of the nineteen solicitation efforts, grouped into opt-out and opt-in solicitations.

> **Descriptive Result 1.** *For time-based rate and enabling technology studies that use an opt-in program offer, recruitment rates range from 5% to 28%. For those that use an opt-out program offer, recruitment rates range from 78% to 87%.*

One opt-out feedback study, in which customers were given access to their energy use information online, shows a 100% recruitment rate because no one opted-out of being able to access the website. For this kind of study, in which a customer who ignores the study completely will not experience any impact whatsoever, the recruitment rate may be less meaningful than the percentage of customers that actually use the treatment (e.g., website).

When utilities design their studies, they must estimate an expected recruitment rate in order to determine both the number of customers that are needed to enroll in the study as well as the number of customers who must be solicited to ensure that the energy impact estimates are valid (that they meet statistical power and precision requirements).



19 total solicitation efforts listed. Circle size represents the total number of customers solicited.

Figure 8. Recruitment rates for each solicitation effort

Although a few utilities included in this analysis were highly accurate in their predictions for recruitment, many were not. Figure 9 shows the actual and planned recruitment rates.

> **Descriptive Result 2.** *Most utilities did not accurately predict recruitment rates for their study solicitation efforts. Five of the twelve opt-in solicitation efforts underachieved their recruitment rates such that actual recruitment rates were 7 to 22 percentage points below the actual recruitment rate. This represents actual recruitment rates that were at least a quarter of what was planned.*

Out of the six opt-in solicitation efforts that underachieved their planned recruitment rates, five had an actual recruitment rate that was seven to twenty two percentage points lower than planned, representing an actual recruitment rate that was at least a quarter of what was planned (i.e., was 24-69% lower). Five out of the six opt-in solicitation efforts that overachieved had an actual recruitment rate that was no more than four percentage points higher than planned. The sixth was fourteen percentage points higher than planned, almost double the planned rate. Interestingly, for opt-out solicitation efforts, four utilities predicted that many more customers would opt-out than what was observed.[17] While overachieving recruitment rates may not have severe consequences, underachievement can cause problems with the study evaluation effort which may necessitate changes to the study's design. If a study has planned to recruit a certain number of customers and the actual number of customers recruited is far less, the study may have to be re-designed (e.g., the number of treatments being tested may have to be reduced) in order to achieve statistically valid load impact estimates.

Our results suggest that a utility may expect to achieve at least a 5% recruitment rate for opt-in studies. Under ideal circumstances, recruitment rates into such studies could exceed 20%. However, for planning purposes assuming 10% recruitment rate seems most appropriate.

4.1.1 An Opt-out versus Opt-in Offer

4.1.1.1 Summary

As shown in Figure 8, studies using opt-out program offers had higher recruitment rates on average than studies using opt-in offers (the unweighted average recruitment rate is 82% for opt-out offers, and 14% for opt-in offers). We would like to determine whether the higher recruitment rates are caused by the opt-out offer, rather than due to random chance alone or to the differences between the types of customers in the utilities (statistically termed a *selection bias* issue). We examine this in the next section.

[17] Again, for opt-out methods, understanding the customer retention rates *after* the beginning of the study may be particularly important for interpreting the overall enrollment rates. For example, data after the study begins may show that many more customers drop out of these studies.

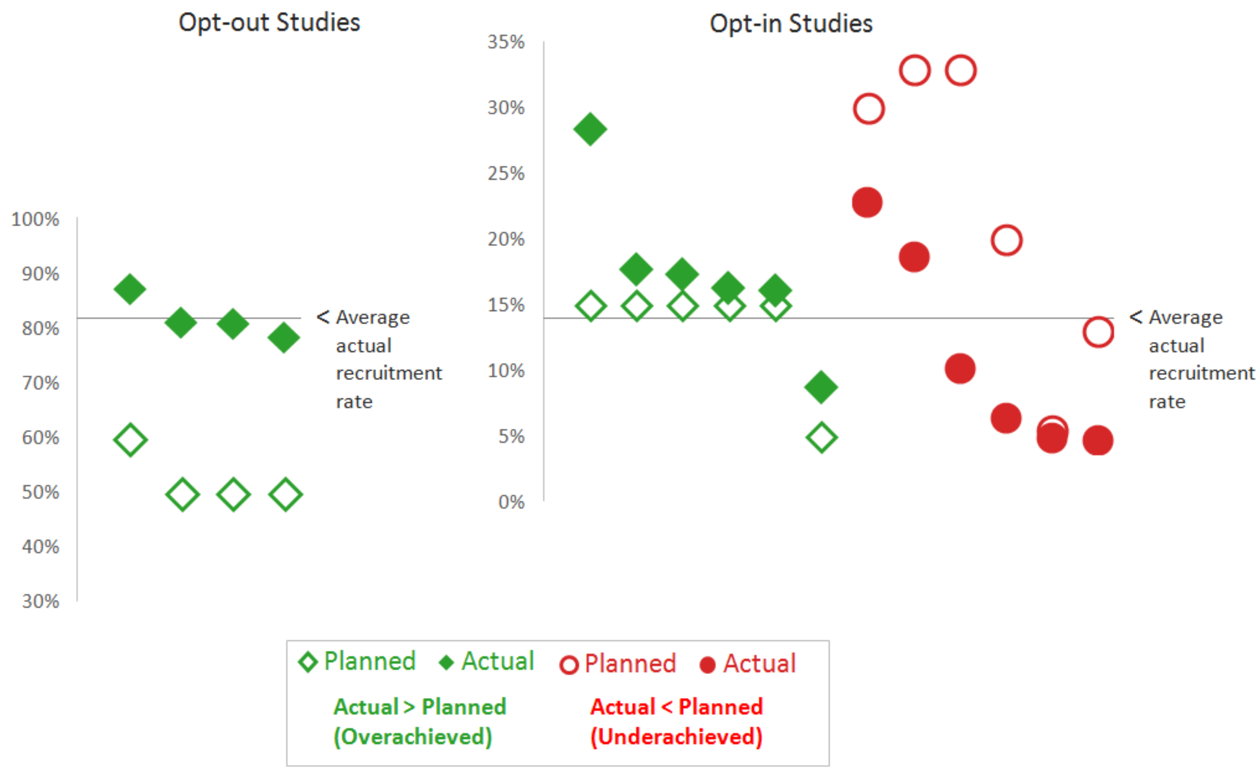


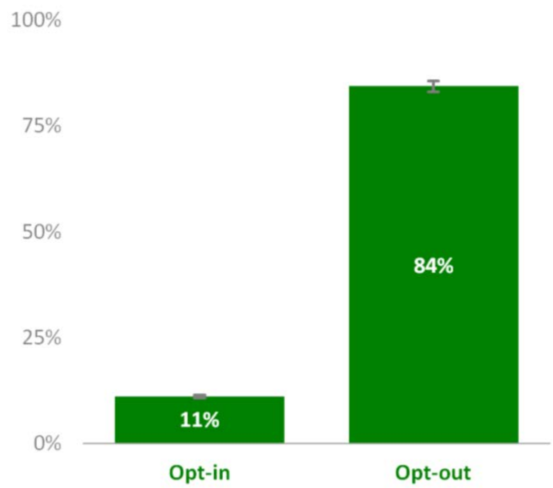
Figure 9. Actual versus planned recruitment rates

4.1.1.2 Analysis Results

Figure 10 shows the recruitment rates for the total number of customers that were ***randomly*** assigned to be solicited to participate in a study through either opt-in or opt-out offers. The data come from the two utilities who explicitly tested for this in their study. One utility randomly assigned ~45,000 of its residential customers to an opt-in program offer and another ~5,000 residential customers to an opt-out offer. The other utility randomly assigned ~53,000 of its residential customers to an opt-in program offer and another ~4,000 to an opt-out offer.

Experimental Result 1. *More customers enroll into a time-based rate program with an opt-out offer as opposed to an opt-in offer (see Figure 10).*

Segmenting customers into each of the two utilities produces similar results: 17% and 5% for opt-in, versus 81% and 87% for opt-out.[18]. This indicates that customers are more likely to sign up for an opt-out offer than an opt-in offer (i.e., more customers choose to not opt-out of a study than choose to opt-in).



Percentages include the total number of customers across the two utilities that randomized opt-in versus opt-out program offers (99.9% confidence intervals shown; N=100,000).

Figure 10. Recruitment rate results for tests of opt-in versus opt-out program offers

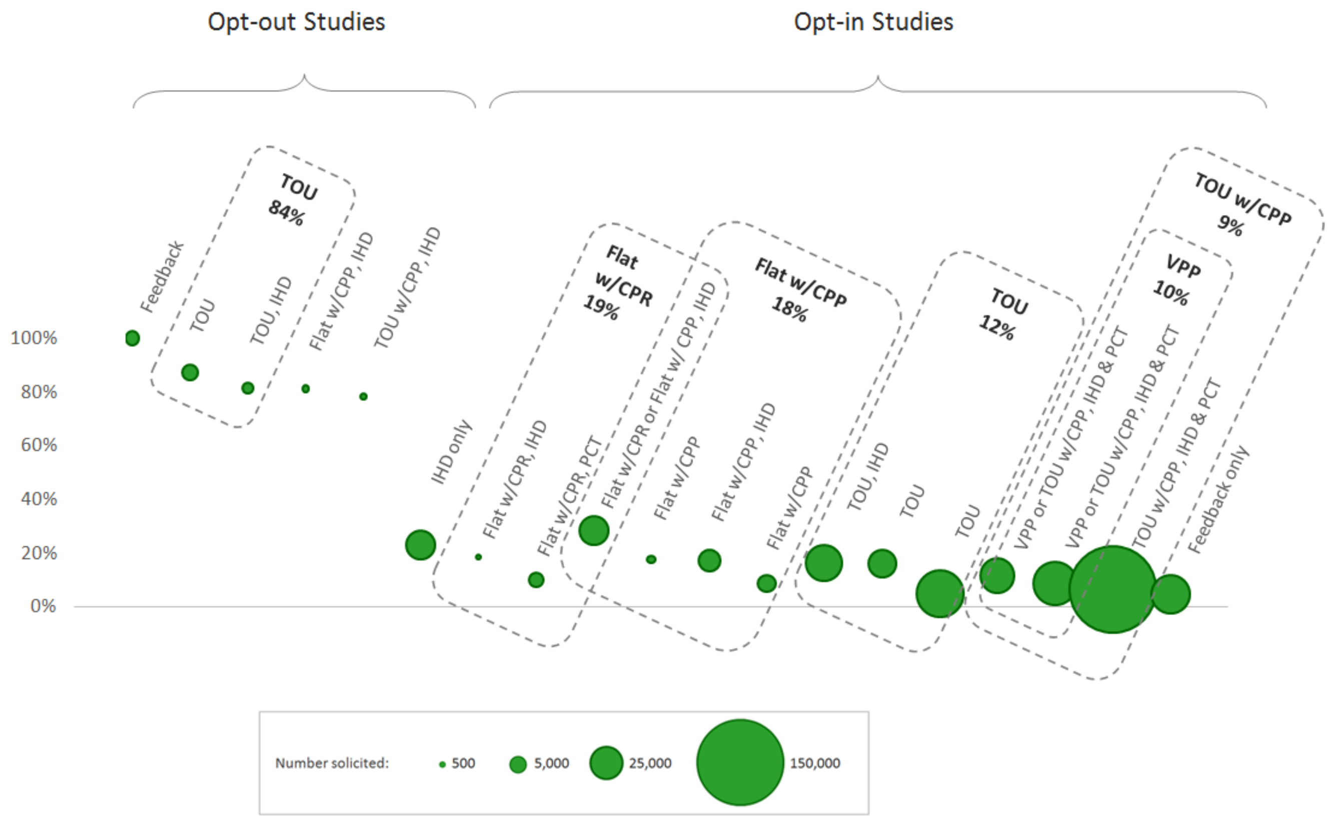
4.1.2 Offers of Different Time-Based Rates

4.1.2.1 Summary

Figure 11 shows the unweighted average recruitment rates (see Section 4.1 for more details) across the nineteen solicitation efforts, grouped into five different time-based rate

[18] One utility further separated the randomized recruitment efforts into separate time-base rate and technology offers. Segmenting into these cohorts also produced similar results: an offer of IHDs with a TOU rate had a recruitment rate of 16% for opt-in and 81% for opt-out; an offer of an IHD with a CPP rate had a recruitment rate of 17% for opt-in and 81% for opt-out. A two-proportion z-test of differences between the opt-in and opt-out recruitment rates are statistically significant in any case. However, what is more appropriate in this case is to test whether the difference is larger than what was *expected* (i.e., the null hypothesis is the a priori belief). In their study plans, the utilities' expected opt-out recruitment rates were 35% higher than the expected opt-in rates. These results show that the opt-out rates are statistically significantly higher than 35%.

offers (i.e., TOU, TOU w/CPP, Flat w/CPP, Flat w/CPR, and VPP[19]), and segmented between opt-out and opt-in. For opt-in solicitation efforts, solicitations that offered Flat w/CPP (18%) or Flat w/CPR (19%) had higher recruitment rates on average than those that offered TOU (12%), TOU w/CPP (9%), or VPP (10%). For opt-out solicitation efforts, those that offered TOU had slightly higher recruitment rates (84%) on average than those that offered Flat w/CPP (81%) or TOU w/CPP (78%).



Unweighted average of recruitment rates across 19 solicitation efforts. Circle size represents the total number of customers solicited.

Figure 11. Summary of recruitment rates for different time-based rate offers

[19] VPP is similar to a TOU w/CPP rate in that both rates allow for the possibility for the peak period price to be altered with some notice. In the latter case, this change in the rate is very infrequent whereas in the former case it happens on a daily basis.

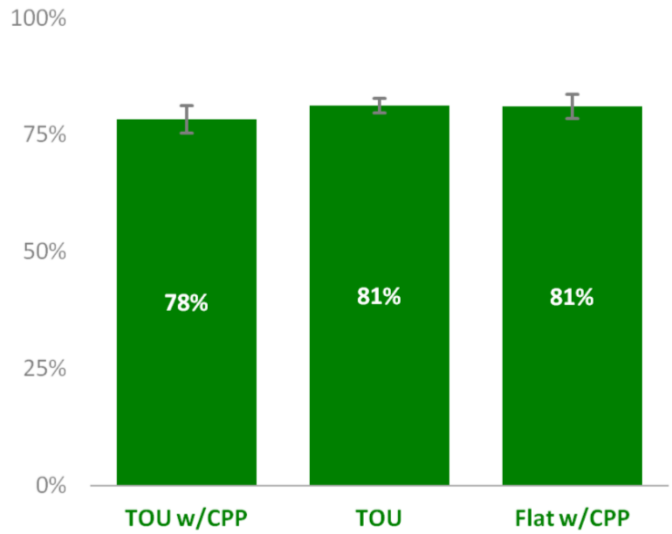
In Figure 11, it is important to note that because the type of time-based rates offered were not randomly assigned to different utilities; we should not interpret any observed differences as causal. For example, it may be tempting to conclude that offering a Flat w/CPP rate would result in 6% higher recruitment rates than a TOU rate. However, the utilities that decided to offer Flat w/CPP rates may simply have different types of customers, who are more willing to enroll in *any* time-based rate. Therefore, the difference in customers (or any other unobservable characteristics of the utility or the study) may be causing the difference in recruitment rates, *not* the type of rate that was offered. In fact, as seen in the next section, an analysis of explicit randomized tests of different time-based rate offers actually does not bear out the differences seen in Figure 11.

4.1.2.2 Analysis Results

Figure 12 shows the recruitment rates for customers that were ***randomly*** assigned to be solicited to participate in a study using an opt-out method with an offer of either a TOU rate, a Flat w/CPP rate, or a TOU w/CPP rate. The data come from the lone utility, where customers were randomly assigned to one of these three program offers. All of these customers were offered an IHD, but were not obligated to accept it in order to enroll in the study. The number of customers solicited was ~2,500 for the TOU offer, ~900 for the Flat w/CPP offer, and ~800 for the TOU w/CPP offer.

> **Experimental Result 2.** *For opt-out solicitations, the type of time-based rate offer does not materially affect the customer recruitment rate (see Figure 12).*

The recruitment rates were 81% for the TOU offer, 81% for the Flat w/CPP offer, and 78% for the TOU w/CPP offer. The differences between any pairings of the rates are not statistically significant (the p-value of two-proportion z-test is 0.88 for TOU vs. Flat w/CPP, 0.18 for Flat w/CPP vs. TOU w/CPP, and 0.08 for TOU vs. TOU w/CPP). This suggests that customers are not more likely to opt-out of one time-based rate over the other, despite the rate differences.



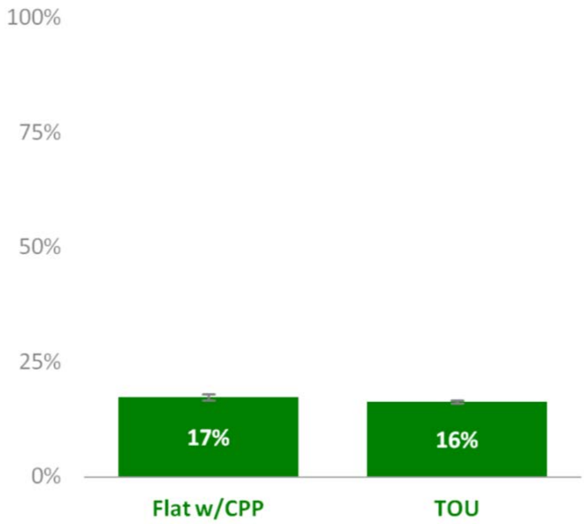
Percentages include the total number of customers within the lone utility that were randomly assigned to receive opt-out offers of IHDs along with one of the three time-based rates (95% confidence intervals shown; N=4000).

Figure 12. Opt-out recruitment rate results for tests of time-based rate offers

Figure 13 shows recruitment rates for customers randomly assigned to be solicited to participate in a study using an opt-in method for either a TOU rate or a Flat w/CPP rate. The data come from one utility, with four different solicitation efforts. Two solicitation efforts include the offer of an IHD but differ in the type of time-based rate offered: one with Flat w/CPP, and one with TOU. The two remaining solicitation efforts do not include a technology offer, and again differ in the type of time-based rate offered: one with Flat w/CPP, and one with TOU. Figure 13 shows the combined recruitment rates for both of the TOU offers (~26,000 customers solicited with an IHD offer, and ~16,000 solicited without a technology offer), versus both of the Flat w/CPP offers (~9,000 customers solicited with an IHD offer, and ~1,300 solicited without a technology offer).

> **Experimental Result 3.** *For opt-in solicitations, the type of time-based rate does not materially affect the customer recruitment rate (see Figure 13).*

The Flat w/CPP offer has a 17% recruitment rate versus 16% for the TOU offer; the difference is statistically significant with a p-value <0.01. Segmenting the customers into those that were offered an IHD and those that were not offered technology, a Flat w/CPP offer is still 1% higher than a TOU offer, but the difference is only statistically significant for the customers that were offered an IHD. This suggests that customers may, to a very small extent, prefer to opt-in to a Flat w/CPP over a TOU rate. However, the preference is very small.



Percentages include the total number of customers within the lone utility that were randomly assigned to receive a CPP offer versus a TOU offer (95% confidence intervals shown; N=50,000).

Figure 13. Opt-in recruitment rate results for tests of time-based rate offers

4.1.3 Technology Offers

4.1.3.1 Summary

Figure 14 shows the unweighted average recruitment rates across solicitation efforts, grouped according to whether technology was offered or not, and segmented between opt-out and opt-in methods. For opt-in program offers, the recruitment rates were slightly higher on average for solicitation efforts that offered technology relative to those that did not (15% vs. 12%). For opt-out methods, the recruitment rates were slightly higher on average for solicitation efforts that did not offer technology (84% vs. 87%).

Unweighted average of recruitment rates across 19 solicitation efforts. Circle size represents the total number of customers solicited.

Figure 14. Summary of recruitment rates for technology offers

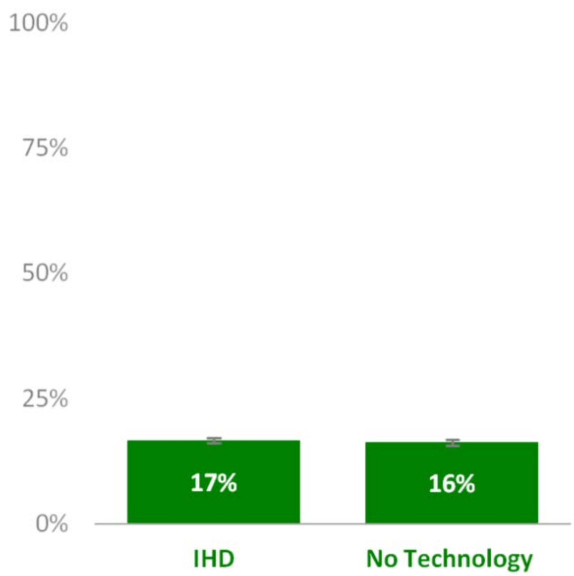
In Figure 14, as with previous depictions of these summary recruitment rates, it is important to note that because the type of technology offered was not randomly assigned to different utilities, we should not interpret any observed differences in recruitment rates as causal (i.e., offering technology does not necessarily *cause* or result in higher recruitment rates). Only an analysis of explicit randomized tests of technology offers allows us to draw causal inferences, which in this case shows that in fact this difference is not born out.

4.1.3.2 Analysis Results

Figure 15 shows the recruitment rates for the total number of customers that were randomly assigned to be solicited to participate in a study using an opt-in method with either an offer of an IHD or no technology offer. The data come from the lone utility that implemented such a study, incorporating four different solicitation efforts. Two solicitation efforts include the offer of a TOU rate but differ in the offer of technology: one with an offer of an IHD and one without a technology offer. The two remaining solicitation efforts include the offer of a Flat w/CPP rate which again differs in the offer of technology: one with an offer of an IHD and one without a technology offer. Customers were randomly assigned to each of these four solicitation efforts. Figure 15 shows recruitment rates reflecting the total number of customers recruited for both of the IHD technology offers (~26,000 customers solicited for the TOU rate, ~9,000 solicited for the Flat w/CPP rate), versus both of the no technology offers (~16,000 solicited for the TOU rate, and ~1,300 solicited for the Flat w/CPP rate).

> **Experimental Result 4.** *For opt-in solicitations, the offer of technology does not materially affect the customer recruitment rate (see Figure 15).*

As shown in Figure 15, both an IHD offer and a no-technology offer have a 16-17% recruitment rate; the difference is not statistically significant. Segmenting customers into CPP and TOU solicitation efforts shows similar results (around 16% recruitment rates for both TOU offers with and without an IHD offer, and around 17% for both Flat w/CPP offers; neither difference is statistically significant). This indicates that customers are *not* more likely to opt-in to a time-based rate if they are offered an IHD, despite the supposed monetary value of such a device.



Percentages include the total number of customers within the lone utility that were randomly assigned to receive an IHD offer versus no technology offer (95% confidence intervals shown; N=50,000).

Figure 15. Opt-in recruitment rate results for tests of technology offers versus no technology offers

4.2 Qualification, Solicitation, and Selection Rates

This section provides basic summary statistics on the various customer enrollment stages before and after the recruitment stage: the qualification rates, solicitation rates, and selection rates. Overall, for opt-in solicitation efforts, the qualification rate ranges from 1.3% to 83%, with an unweighted average of 32%; the solicitation rate ranges from 23% to 100% with an unweighted average of 87%; and the selection rate ranges from 54% to 100% with an unweighted average of 93% (see Table 1 and Table 2).

	Qualification rate	Solicitation rate	Recruitment rate	Selection rate
HD Only	71%	73%	23%	79%
Flat w/CPR, IHD	1%	23%	19%	100%
Flat w/CPR, PCT	3%	94%	10%	100%
VPP or TOU w/CPP, IHD & PCT	4%	100%	12%	100%
VPP or TOU w/CPP, IHD & PCT	6%	100%	9%	100%
TOU w/CPP, IHD & PCT	23%	33%	6%	73%
Feedback only	26%	100%	5%	100%
TOU, IHD	33%	100%	16%	100%
TOU	33%	100%	16%	100%
Flat w/CPP	33%	100%	18%	100%
Flat w/CPP, IHD	43%	100%	17%	100%
TOU	43%	100%	5%	100%
Flat w/CPP	61%	100%	9%	100%
Flat w/CPR or Flat w/ CPP, IHD	83%	100%	28%	100%

Table 1. Qualification, solicitation, recruitment, and selection rate for opt-in solicitation efforts

	Qualification rate	Solicitation rate	Recruitment rate	Selection rate
Feedback only	3%	100%	100%	100%
TOU w/CPP, IHD	33%	100%	78%	100%
TOU, IHD	33%	100%	81%	100%
Flat w/CPP, IHD	33%	100%	81%	100%
TOU	43%	100%	87%	100%

Table 2. Qualification, solicitation, recruitment, and selection rate for opt-out solicitation efforts

There may be multiple factors that drive some of these differences. For example, studies that include different enabling technologies may require possession of certain items of equipment to qualify as a participant (e.g., the presence of central air conditioning to receive a programmable communicating thermostat or a broadband internet connection to receive an in-home display). Some utilities may have budgets for marketing and recruitment efforts that allow them to solicit all of their customers, while others may only be able to focus on soliciting a specific subset of customers. Some utilities have collected sufficient data prior to the solicitation effort to know which customers to target whereas others need to collect that information during the recruitment process to determine who qualifies as a participant. When we have customer level data on the enrollment effort as well as information on retention rates and load impact estimates, we may be able to draw more definitive conclusions about the effects of these enrollment stages and the factors that influence them.

4.3 Lessons Learned on Customer Enrollment

In this section, we provide a summary of the lessons learned from qualitative data collected through various channels on the utilities' customer enrollment experiences.

Prior to test marketing materials that would be used to solicit participation into studies that included time-based rates, many utilities believed words like "critical", "emergency", and "events" would confer the necessary message about what the rate was trying to accomplish and how valuable a customer's participation in that rate would be. Several utilities subsequently performed focus groups, surveys and other forms of test marketing of their recruitment material which indicated the terms and concepts utilities thought would connote positive concepts with customers actually had the opposite effect. Terms like "response", "auto", and "event" were construed as reactionary words that deflated personal control (e.g., "emergencies" are out of a customer's control). Instead, some participants in focus groups appeared to prefer terms that construed a sense of personal control over one's own energy usage and resulting bill (e.g., "control", "choice", "sense").

> **Lessons Learned 1.** *Utilities found focus groups, surveys and other tools to be vital components for test marketing terms and concepts that will attract customer interest and engage them to participate in the rate being offered.*

Utilities also learned from focus groups that customers claimed to be primarily motivated by environmental messaging when it came to recruitment into new time-based rates. Test marketing along with observed recruitment data from various messages (e.g., "saving money", "environmental stewardship", "taking control", "fun") revealed the primary motivator for the majority of customers was actually financial.

Lessons Learned 2. *Utilities learned the importance of validating focus groups with other test marketing efforts across a variety of customer segments and circumstances to develop the most effective messaging for their new time-based rate recruitment campaign.*

Once the messaging and marketing planning efforts were completed, the utilities moved into the recruitment phase of the study. Issues often arise during this time in the study lifecycle that can threaten its overall success. Many utilities, therefore, included a two week soft launch window in their enrollment process in order to identify and address any problems that internal planning and test marketing of recruitment materials did not catch. Unfortunately, even with a two week soft launch period, one utility still did not have enough time to incorporate necessary feedback to the solicitation materials in time for the hard launch, at which point changes were very difficult and costly to make.

Lessons Learned 3. *Utilities were surprised at how much time and resources they needed to allocate between soft launch and hard launch of the solicitation effort to adjust the messaging and other details accordingly based on feedback.*

The recruitment process can also be affected by assumptions about the number of customers capable and willing to receive certain types of enabling technology (e.g., presence of central air conditioning to receive a programmable communicating thermostat). By not accurately quantifying ahead of the study enrollment effort the size of the available population that would pre-qualify for a specific enabling technology, the number of customers that would be willing/able to accept, and the number that then have it installed, some utilities substantially overestimated the level of acceptance for a new rate or product offering that was strictly paired with such enabling control technologies.

Lessons Learned 4. *Utilities learned that before determining if a new rate or product offering is to be paired with a form of enabling technology, they could benefit from spending time understanding potential customer concerns with that technology and identifying the available pool of participants who would qualify for and be willing to accept such technology so that realistic expectations for recruitment can be set ahead of time.*

Many of the utilities who included some form of enabling technology in their study decided to enlist internal utility workers or external contractors to help install and provision this equipment at a participating customer's premise. These utilities believed that individuals responsible for installing these pieces of technology at a customer site would have little to no effect on that customer's decision to finalize and complete the enrollment process in the study. Unfortunately, installation of technology by individuals, either internal or external to the utility, who did not have sufficient appreciation for the importance of the public relations role they played and/or were insensitive to the consequences of not playing that role well, resulted in negative ramifications for customer engagement efforts at several utilities.

Lessons Learned 5. *Utilities realized the need to ensure that all utility representatives and contractors that interact with customers at any level are informed, committed and enabled to make the experience a positive one for the customer. One way to do this most effectively was by focusing on communications skills as much as technical skills when hiring or recruiting people to fill these positions.*

5. Conclusion

This report provides preliminary insights into customer recruitment rates for nineteen solicitation efforts offering time-based rate and technology programs. Overall, we find that recruitment rates range from 78% to 87% for opt-out studies, and 5% to 28% for opt-in studies. We also find that opt-out methods result in much higher recruitment rates (11% for opt-in versus 84% for opt-out), that offering an IHD does not result in a statistically significant difference in recruitment rates, and that the type of time-based rate does not materially affect the recruitment rate (for opt-out methods, the differences between a TOU, a Flat w/CPP, and a TOU w/CPP rate are not statistically significant; for opt-in methods, the difference between a Flat w/CPP and a TOU rate is only 1%).

It is perhaps not surprising that our results show that programs that use opt-out methods result in much higher recruitment rates. An opt-in approach essentially retains the current "default" (e.g., the default rate is a flat rate), while an opt-out approach determines a new default (e.g., a time-based rate). In general, people tend to adhere to the "status quo" or "default" choice.[20] Other areas have used this understanding of customer behavior to adopt policies that are deemed to improve social welfare. For example, employee participation in 401(k) plans increase from 37% to 86% under automatic enrollment (Madrian and Shea 2001). Due in part to such evidence, the Obama Administration recently passed a Retirement and Savings Initiative, which makes it easy for small businesses to automatically enroll their employees in savings plans, and to automatically increase their savings rates over time unless they opt-out (IRS 2009). The energy industry is currently grappling with what type of rate design should serve as the default rate.

One way to frame the recruitment results is through this lens of customer preferences for the default option. Based on the experience of these studies, customers overwhelming accept the default rate design offered to them, regardless of what it looks like: the percentage of customers that actively did not take the default rate (e.g., those that opted-out or opted-in) is between 5% and 28%. Looking at the experimental results, while a higher percentage of customers (16%) actively moved off of a time-based default rate (e.g.,

[20] See Kahneman, Knetsch, and Thaler (1991).

TOU, TOU w/ CPP, etc.) than the percentage (11%) that moved off of a standard rate (e.g., flat, inclining block), this difference (4%) is modest.

However, one could construe a customer's preference for the default as simply not paying attention, and making a choice at all. It may be the case that customers solicited via an opt-out method are more likely to drop-out of the time-based rate program after they experience an actual consequence of "not opting out", such as receiving their first bill on a new rate program, at which point a more affirmative and declarative choice has been made. Once future data are collected for customer recruitment numbers after the time-based rates are in effect for some time (e.g., 3 months, 6 months, 12 months), we may be able to get a more robust picture of customer preferences that could help policymakers determine which rate design enrollment approach (opt-in vs. opt-out) should be pursued by utilities.

Our second result, that customers do not prefer to sign up for one type of time-based rate program over another; or if they do, it is only by a very small amount, is somewhat surprising. This finding is important for policymakers to understand as it indicates that electricity customers are just as willing to accept a rate that requires pervasive behavioral changes (i.e., shifting electricity usage away from the peak period to the off-peak period every day) as they are to accept a rate that requires very infrequent, limited duration but potentially large behavioral changes (i.e., reducing electricity usage only during critical events). Again, it may be true that the type of time-based rate has a greater effect on future drop-out rates, once customers experience the consequences of one rate relative to another; we intend to perform research on this area when data become available in the future.

We also found that offering technologies seems to have little to no effect on opt-in recruitment rates. One might expect that offering customers an IHD or PCT would act as an incentive to participate in a time-based rate program. In the former case, it would allow a customer to be better informed about their own electricity consumption patterns and better understand when altering their consumption behavior would be most valuable. In the latter case, a PCT would enable a customer to automate such behavioral changes through the control technology. Based on the experience of these SGIG utility studies' solicitation efforts, however, we conclude that this does not seem to be the case for an IHD (not a single utility experimentally controlled for the offer of a PCT). Again, it may be the case that the offer of these technologies will help retain customers longer, which is an area we intend to research further in the future.

Because these findings are based on the results of an experiment from only one or two SGIG utility studies, it is important to note that extrapolating these conclusions to other utilities is only valid to the extent in which the customers in other utilities are similar to the utilities that performed the experiments. We hope in future analysis to better characterize the types of customers that joined such studies to help clarify the conditions under which our results can be extrapolated to a broader population of customers. Nonetheless, because these are the only randomly designed and analyzed experiments to date of how rate and technology offers affect real-time program recruitment rates, the findings produce a good foundation on which to set expectations.

These results should be helpful to those electric utilities looking for guidance on reasonable recruitment rates when designing a study or pilot of their own or when rolling out these programs en masse for the first time. However, once more data is available to characterize individual customers and their experience remaining on the time-based rate or technology offer over a longer period of time, we hope to provide even greater insight for program planners that will help them better understand what may drive differences in the initial enrollment stages but also in retention stages over time. In addition, our planned analysis of data on peak demand and energy savings due to exposure to time-based rates and technology will hopefully allow us to address several additional interesting questions concerning how the type of program offer affects the savings achieved by the programs. For example, even though opt-out programs result in higher recruitment rates, it may be that opt-in programs actually result in higher savings per customer because they are targeting the customers that have the highest savings potential and are not weighted down by a lot of non-responders. Future reports will be able to shed light on these important issues.

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