Time of Use (TOU) Energy Display

ET19SDG8011 and DR19SDG0003 Report

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Executive Summary

This report documents the demand response (DR) and energy efficiency (EE) effects of the TOU Energy Display in-home-device (IHD). The TOU Energy Display device is a Wi-Fi-enabled, internet of things (IoT) device designed to receive and display residential time-of-use (TOU) rates based on time of day. Informing customers of real-time intraday changes in electricity rates can allow them to reduce their overall electricity consumption. Improved communication of TOU rates can help SDG&E move more customers to TOU rate structures, in turn helping both utilities and customers save money. This evaluation is carried out with the overarching goal of assessing the viability of creating a cost-effective Integrated Demand Side Management program using the TOU Energy Display device.

The TOU Energy Display device aims to achieve demand reduction using two distinct technologies. The first targets daily reductions by informing customers of TOU rates in real time. This information is communicated by the TOU Energy Display in-home plug-in device which uses LED lights and “traffic light logic” to convey the timing of hourly rate changes. Customers are also able to view information on daily rate changes through the TOU Energy Display Mobile App, which displays current and recent rates. The second technology targets reductions using DR calls on event days. Customers are notified by the TOU Energy Display Mobile App of upcoming event days along with the hours in which they should use less electricity. Notifications are first sent to customers the evening prior to the event day and again on the morning of the event day. The lights on the plug-in device flash to indicate event times.

The TOU Energy Display plug-in device is designed to convey simple information regarding TOU rate changes and event days in a salient, easy-to-understand manner. The TOU Energy Display Mobile App complements the plug-in device by providing more detailed information once the customer’s attention has been piqued by the device. In addition to displaying rate and event day information, the mobile app attempts to persuade customers to reduce energy use for the purpose of lowering environmental and economic costs. The mobile app also provides recommendations for energy saving activities and messaging about peer effects and loss aversion.

This report evaluates the effectiveness of the TOU Energy Display device in reducing electricity consumption using a randomized controlled trial (RCT) and population-level normalized metered energy consumption (NMEC). Customer behavior and load impacts are also validated using a short, web-based survey. The cost effectiveness of the energy savings and demand reduction is evaluated using a Total Resource Cost (TRC) test in accordance with the California Standard Practice Manual.

The impact of the TOU Energy Display device is estimated across two dimensions: (1) encouraging customers to reduce electricity consumption during 10 demand response messaging days and (2) promoting overall reductions in peak-hour consumption during the five summer rate months when TOU rates rise steeply during peak hours. A detailed analysis of data from customers participating in the pilot project yields the following findings:

- Customers who activated the TOU Energy Display IHD **reduced peak-hour consumption** by 3 to 8 percent during summer months, a statistically significant change.
- Compared to the control group, customers with TOU Energy Display devices did not reduce electricity usage any further during designated demand response days.
- Reductions in consumption among active TOU Energy Display users are **concentrated almost exclusively on hot summer days** and are typically realized by customers with higher baseload consumption.
- A post-trial survey sent to the TOU Energy Display device group indicated that **shifting usage** to before 4:00 or after 9:00 pm was the most common action taken, followed by turning off unused equipment. Over 1/3 of these respondents indicated that they took actions during all 10 DR events.

Table ES - 1: Summary of Energy Savings and Demand Reductions

	Annual Energy Consumption (kWh/yr)	Annual Energy Savings (kWh/yr)	Peak Demand (kW)	Peak Demand Reduction (kW)
Baseline	-	-	-	-
New Technology	864	6,450	.24	1,450

The project demonstrated that TOU Energy Display devices promote better management of energy use among residential TOU customers during the summer season. Customers who activated the TOU Energy Display IHD used less electricity during summer peak-hours when rates rose steeply, suggesting that the device increased awareness of seasonal, intraday rate changes and enhanced customer agency. Indeed, according to a post-trial survey of participants, nine out of ten customers who activated a device reported changing habits to reduce electricity use, most commonly by using appliances at different times of the day or reducing usage of ceiling fans and air conditioning.

Customers who received day-before and day-of messaging from the TOU Energy Display Smartphone App reported on a post-pilot survey that they took action to reduce energy upon receive the messages. Analysis of consumption data, however, show that these customers did not reduce energy use any further on days when messages were sent. The contradiction between customers' reported efforts and revealed actions can perhaps be resolved by further study of the device's effectiveness in the demand response domain. Having fewer than 250 customers with active devices, the trial, according to preliminary power tests, did not have sufficient scale to reliably estimate changes in energy usage below five percent. A larger trial, with enough statistical power to detect changes on the order of 1 to 5 percent, could better assess its demand response potential.

The outcomes of the project offer evidence that future distribution of the TOU Energy Display IHD could benefit from improved customer guidance. Although 500 customers who requested the IHD received them by mail, only 239 of these customers activated the IHD within eight months of delivery. One out of four surveyed participants who failed to activate the IHD claimed that they did not fully understand the device. A modicum of *non-compliers* is inevitable, but improved cost-effectiveness can be achieved by increasing activation rates among customers receiving the device.

Recommendations

1. The TOU Energy Display IHD can be used as a cost-effective demand-side management tool for reducing peak-hour consumption during the summer rate season.

2. The device's cost effectiveness can be improved by enhancing instructions for installation and addressing difficulties expressed by surveyed customers who failed to activate it. These difficulties include insufficient understanding of the device's purpose and inability to find an appropriate outlet for the device.

3. Device marketing campaigns that target customers enrolled in SDG&E's demand response program should achieve higher conversion rates, as evidenced by the greater device request and activation rates among these customers.

4. The TOU Energy Display device might have greater success when messaging for customers who have super-peak rate schedules that align with additional event messaging. Prior research suggests event-day messaging is more effective when paired with super-peak or critical peak period pricing, which are not rate elements in the TOU-DR2 schedule but are in the TOU-DR1, TOU-SES, TOU-EV rate schedules (Royal, Rustamov 2018; Faruqi, Sergici 2010).

5. As management of the energy grid and utilities shifts away from a unidirectional, linear service delivery structure and into a multi-directional service model, residential customers must become active participants in energy load management (Rocky Mountain Institute 2017). Widespread adoption of integrated demand side management devices, such as the TOU Energy Display IHD, have the potential to help TOU customers understand and respond in real time to price changes. These messages can be tailored to key customer characteristics such as LMI status, occupancy (renter vs. owner), native language, labor force participation and employment status (e.g. whether a customer works multiple jobs).

1. Introduction

The purpose of this project is to evaluate the demand response and energy efficiency effects of the TOU Energy Display in-home-device (IHD). The TOU Energy Display device is an enabling technology that receives and displays the appropriate residential time-of-use (TOU) rates based on the time of day. Properly designed TOU rates can help both utilities and their customers save money. They can reduce utility expenditures by decreasing peak demand and lower customers' bills by moving their consumption to times of the day when energy is less expensive. The challenge in effectively deploying TOU rates is ensuring customers understand and respond to intraday changes in electricity rates. TOU rates use price signals to get customers to pay attention to when they use electricity, but often a lack of convenient access to information can diminish their effectiveness (Trabish, 2018).

The TOU Energy Display device aims to promote awareness of TOU rate incentives among residential customers. In combination with the smart phone app, this in-home plug-in device provides customers with real-time information on their rates and notifies customers of changes in rates, peak pricing events, and demand response (DR) calls. The overall intent of this device is to help customers understand their TOU rate so that they can make informed decisions about their electricity usage.

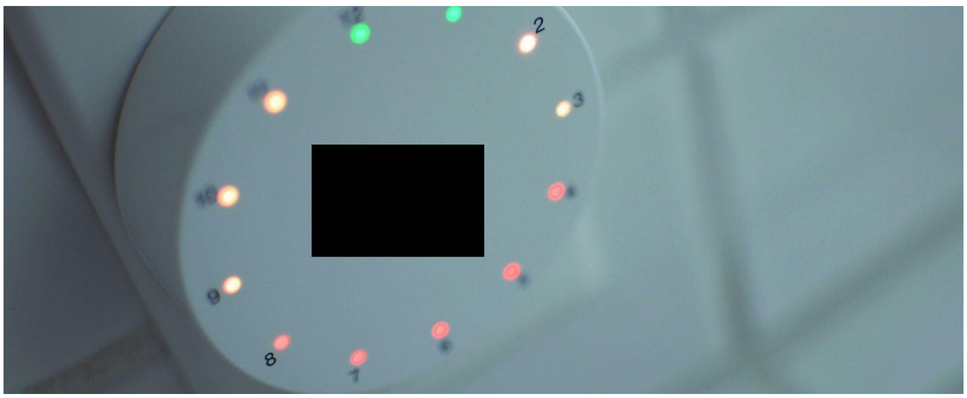
This analysis evaluates the changes in electricity consumption caused by TOU Energy Display devices using a randomized controlled trial (RCT) and population-level normalized metered energy consumption (NMEC) analysis. This evaluation helps to reveal the device's potential for performing Integrated Demand Side Management (IDSM). The device could decrease overall consumption by enabling customers to be more responsive to high TOU rates and by providing energy savings tips through the TOU Energy Display Mobile App. Customer behavior and load impacts are validated using a short, web-based survey.

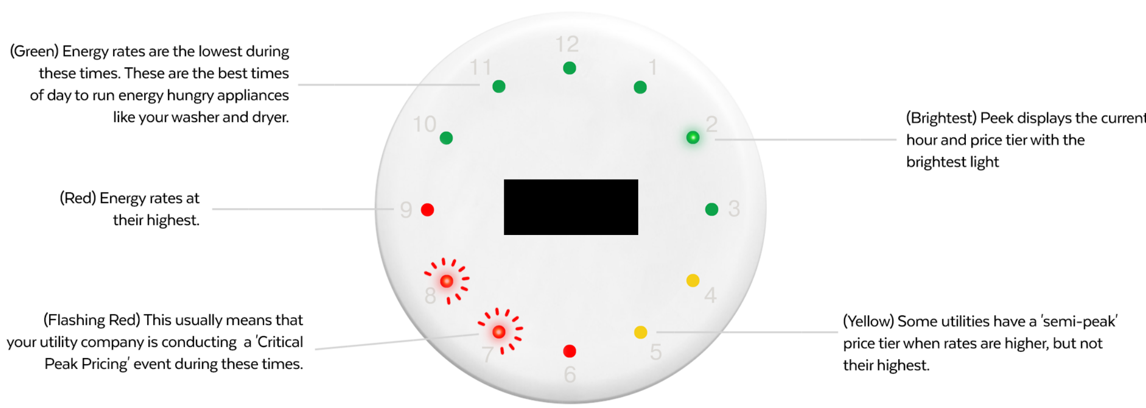
The overarching goal of this evaluation is to assess the viability of creating a cost-effective IDSM program that uses the TOU Energy Display device. The California Public Utilities Commission (CPUC) requires that programs provide positive value to electric ratepayers and therefore require a cost versus benefit analysis prior to approval. This evaluation includes a cost-effectiveness test for both energy savings and demand reduction using the California Standard Practice Manual, the CPUC-approved DR reporting tool, and the 2016 DR Cost-Effectiveness Protocols.

2. Background

The TOU Energy Display device achieves demand reduction during peak usage hours using two different technologies. The first technology targets everyday reductions by providing customers with easily accessible information about their TOU rates. A TOU Energy Display in-home plug-in device uses LED lights and “traffic light logic” to convey information about the timing of hourly rate changes (see Figure 1). Alert messages and information on current and historic rate changes are also accessible through the TOU Energy Display Mobile App.

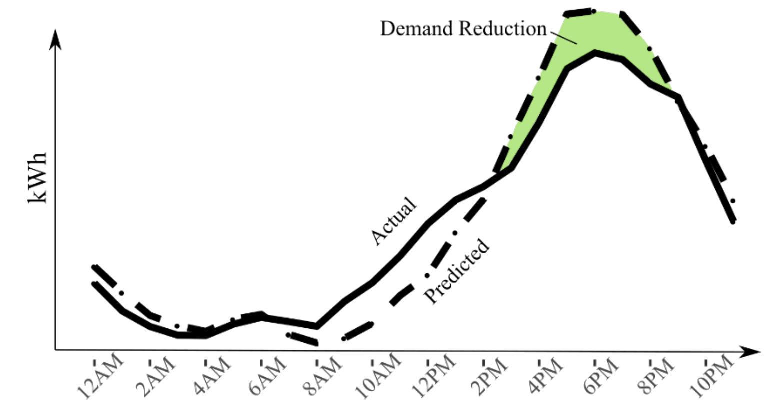
Figure 1: TOU Energy Display In-Home Device





The second technology targets reductions using DR calls on event days. Customers receive notifications through the TOU Energy Display Mobile App informing them of upcoming event days along with the hours in which they should use as little electricity as possible. These notifications are sent to customers at 8:00 pm the evening prior to the event day and again at 10:00 am on the event day. The lights on the TOU Energy Display IHD flash to indicate an event is occurring. The TOU Energy Display Mobile App simultaneously produces notifications to encourage energy reductions during peak usage hours of 4pm to 9pm during the event day.

Figure 2: Targeted Peak Savings



When customers activated the plug-in IHD they also activated the smartphone TOU Energy Display Mobile App used for DR messaging. The trial typically paired the application's messages with DR event calls from SDG&E's existing "AC Saver" program. Figure 3 features an example of messaging designed to encourage peak-hour energy reductions during one of the designated DR days. The messages sent on event days attempt to persuade customers to reduce energy for the purpose of lowering environmental and economic costs. These messages also included recommended energy saving activities and messaging about peer effects and loss aversion. Studies have found that these types of messaging can change behavior even without additional price incentives (Faruqui, Sergici 2010).

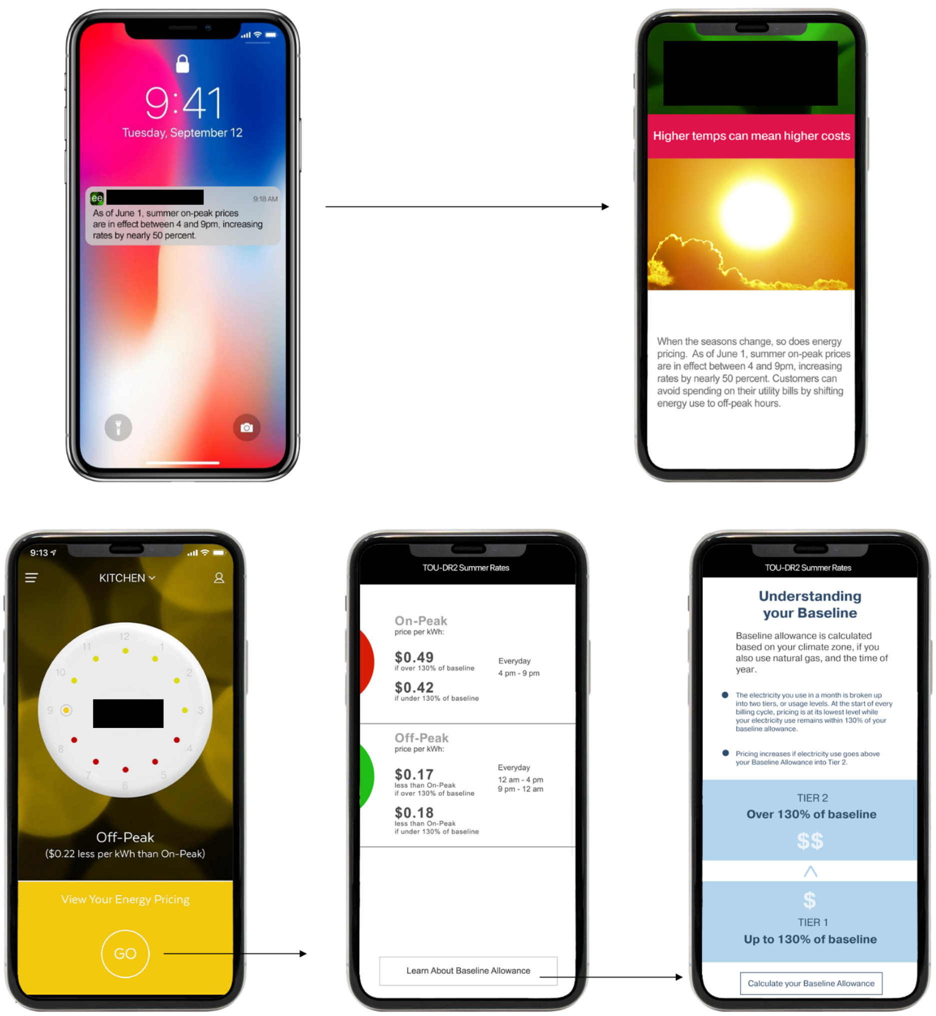
Figure 3: Example Day-Ahead (Left) and Day-Of (Right)

Table 1: Peak Hours (4pm-9pm) Demand Response Event Days

Event	Date	Day of Week	AC Saver Day
1	7/29/2020	Wednesday	Yes
2	8/14/2020	Friday	Yes
3	8/18/2020	Tuesday	Yes
4	8/21/2020	Friday	Yes
5	8/27/2020	Thursday	Yes
6	9/5/2020	Saturday	Yes
7	9/28/2020	Monday	Yes
8	10/6/2020	Tuesday	No
9	10/13/2020	Tuesday	No
10	10/16/2020	Friday	No

The TOU Energy Display Mobile App also reminded customers of the June switch to the summer TOU rate schedule, drawing attention to the steep increase in 4 to 9pm peak-hour rates. Figure 4 features the information delivered to customers from the phone application during June 2020, the start of the summer rate season. The message draws attention to the 50 percent increase in peak-hour rates during the summer season as well as the dramatic intraday changes in electricity pricing, ranging from 17 cents per kWh during non-peak hours to as high as 49 cents per kWh during peak hours. While DR messages encourage energy reductions through persuasion, the seasonal alert draws customer attention to the financial incentives of adapting energy use to TOU rate patterns. Most studies of DR programs and technologies find that persuasive efforts work best when paired with price incentives (Royal, Rustamov 2018; Faruqui, Sergici 2010).

Figure 4: Seasonal Alert Message



The plug-in IHD device pairs with the smartphone app to provide a persistent visual cue, reminding customers of the current TOU rate. The device uses a simple "traffic-light" cue to convey more complicated rate information: red LED lights designate high-rate, on-peak hours and green lights designate low-rate, off-peak hours. The configuration of the colors adapts on-the-fly to the designated rate schedule once activated. It also permits yellow lighting for three-tiered scheduling (e.g., when there is a super-peak rate), but only two colors were required to communicate SDG&E's TOU-DR2 rates. During the designated hours on DR event days, the red lights pulsated to alert the customer.

Figure 5 features one of the devices distributed to customers participating in the project. Each device has an initial cost of $19.77 and an additional $5.42 to drop ship. When active, the device consumes 0.672 watts. The simple design aims to convey rate information clearly at a low cost to the consumer.

Figure 5: In-Home Device (IHD)

3. Low-to-Moderate Income Customers

The Energy Upgrade California initiative recommends that IOUs conduct community outreach to assist with TOU rate introduction (Energy Upgrade California 2020). Low- to moderate-income (LMI) customers face a particular set of challenges with the introduction of TOU rates, including lower margins for energy adjustment, language barriers, and lower incentives to engage in energy saving activities. Some of these challenges are described in the Appendix. The TOU Energy Display IHD can be employed as a tool for improving customers' adaptation to TOU rates and its ease-of-use and low cost makes it particularly suited to address the needs of LMI customers.

4. Assessment Objectives

The evaluation focuses on two distinct treatment effects associated with the TOU Energy Display IHD and smartphone application. First, did TOU Energy Display IHDs drive customers to reduce their typical electricity consumption during peak hours by signaling daily increases in TOU rates during the summer months? The plug-in IHDs offer a regular reminder to customers that rates increase during the 4pm to 9pm "peak hour" window and can therefore motivate sustained reductions in consumption during those hours. Second, did scheduled messages delivered through the TOU Energy Display Mobile App reduce peak consumption during designated DR event calls? The trial included a total of 10 DR event days, seven of which coincided with event days designated by SDG&E's "AC Saver" program.[1] If the smartphone messaging is effective, customers will achieve greater peak-hour electricity reductions on designated event days. To avoid potential customer fatigue, event days were scheduled such that no more than two occurred consecutively, and no more than three occurred within a week.

The treatment effects are estimated using a population NMEC approach to identify demand and energy savings. The cost effectiveness of the energy savings and demand reduction resulting from the device is evaluated using a Total Resource Cost (TRC) test. The TRC test measures the net costs of a program or project based on the total costs, including both participant and utility costs (CPUC, 2001).

The TRC test for energy savings is performed in accordance with the California Standard Practice Manual (SPM). The SPM enumerates costs and benefits required for a TRC test evaluation. Benefits include avoided supply costs; the reduction in transmission, distribution, generation, and capacity costs valued at marginal cost for the periods where there is load reduction. The avoided supply costs are calculated using net energy savings resulting from the device. Costs include that of the equipment and administration (CPUC, 2001).

The DR portion of the project is evaluated in accordance with the 2016 DR Cost Effectiveness Protocols which includes a modified version of the SPM TRC test. This protocol includes additional costs and benefits beyond what is listed in the SPM. For example, additional costs may include increased supply costs and additional benefits may include any revenue the project could have earned in exchange for CAISO market participation (CPUC, 2016).

5. Technology/Product Evaluation

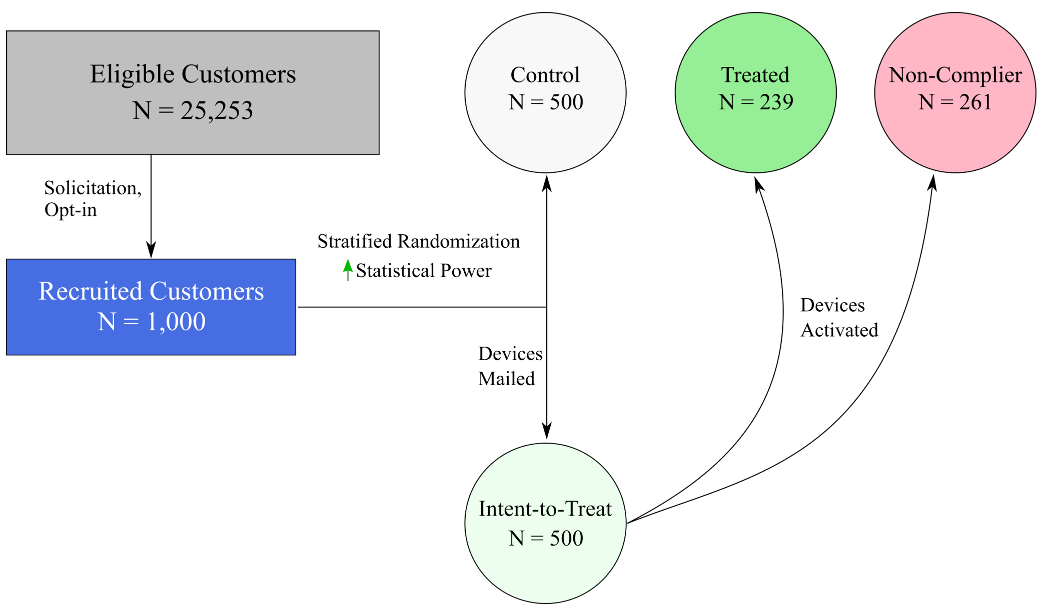
SDG&E coordinated with study authors to implement a randomized controlled trial (RCT) field assessment designed to identify the causal impact of the TOU Energy Display devices on energy

[1] Participants in the AC Saver program receive free direct-installs of a device on their air conditioning system that switches the system off during scheduled hours. The "off hours" fall on 10 hot summer days scheduled between April through October. Program participants receive an annual bill credit as an incentive to participate. More information on the program can be found here: https://www.sdge.com/residential/savings-center/rebates/your-heating-cooling-systems/summer-saver-program.

consumption. An RCT randomizes the assignment of a treatment over a pool of potential subjects, thereby ensuring that any differences observed among treated subjects can be confidently interpreted as a casual effect of the treatment. RCTs are common in behavioral energy efficiency pilots and represent the “gold-standard” (Agnew, Golberg 2017).

As illustrated by Figure 6, the RCT began with a pool of recruited customers who agreed to receive a TOU Energy Display device. A computer program then selected a random subset of customers from the initial pool of volunteers to receive a device in the mail. The remaining customers were assigned to the control group. The RCT randomizes group assignment across only recruited customers to ensure that customers in each group have the same willingness to receive the device. Customers who volunteer to receive the device are likely to possess unobserved (e.g., behavioral) characteristics that differ systematically from non-volunteer customers. Including only volunteer customers in both the treatment and control group ensures that these unobserved differences do not confound the estimated treatment effect.

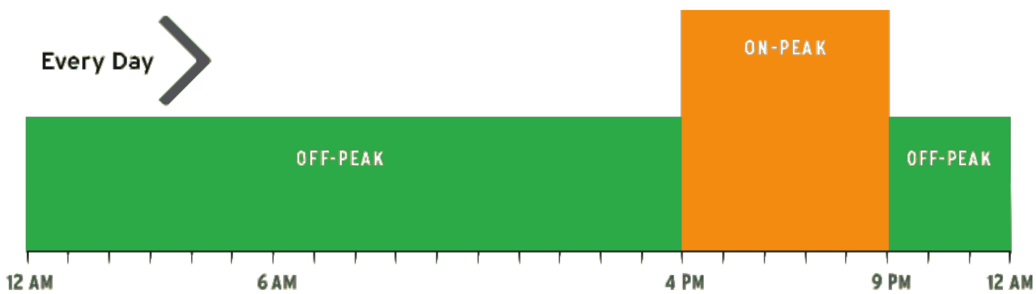
Figure 6: Customer Recruitment Design



Customer Eligibility

Customers were recruited from a pool of eligible SDG&E customers on the SDG&E's TOU-DR2 rate schedule.[2] As illustrated by Figure 7, the TOU-DR2 schedule divides each day into two periods: an on-peak period that spans 4pm to 9pm and is characterized by a higher rate, and an off-peak period in which a lower rate applies. The difference between on-peak and off-peak rates is most dramatic during the summer.

Figure 7: SDG&E's TOU-DR2 Rate Design



Because the trial has a DR component, special attention was given to the eligibility of customers who are currently members of other DR programs. Seven of the trial's 10 DR event days coincided with SDG&E's "AC Saver" program event days. Treatment stratification (see Recruitment section) and regression methods (see Pooled Fixed Effects section) were used as tools to control for the confounding influence of existing DR membership.

Recruitment

Figure 6 depicts a flow diagram of the customer recruitment process along with tabulations of eligible customers, recruited customers and treatment outcomes. SDG&E's marketing team recruited project participants from a pool of 25,253 customers who were eligible for solicitation. Solicitation began on July 26, 2019 when eligible customers received a "Call to Action" flyer by email and postal direct mail. The flyer provided a brief description of the device and notified recipients that they were eligible to receive a device for free in exchange for participating in a study. The flyer included a link to an online submission form that customers filled out if they wished to opt in to the study.

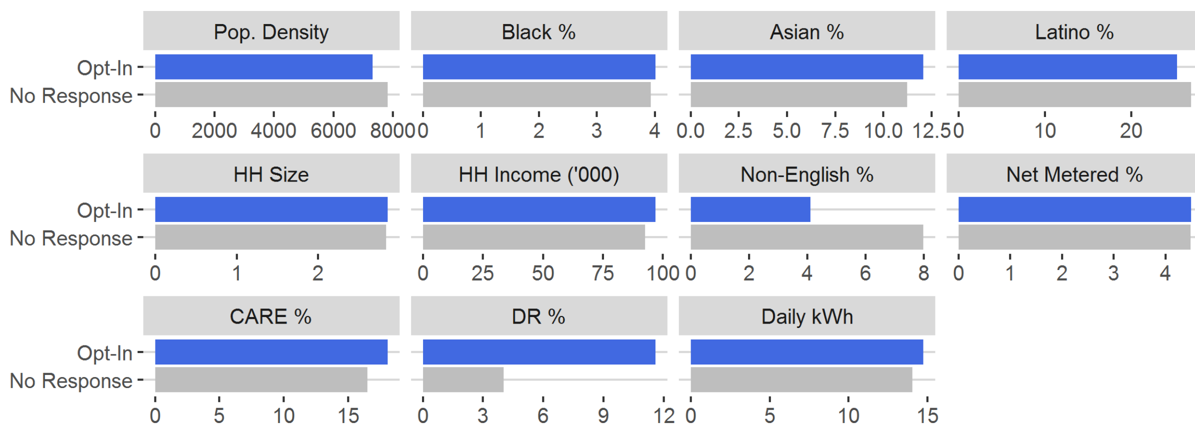
After the initial solicitation, recruitment remained open for several months until the number of customers opting in to the study reached the target threshold of 1,000. Customers who opted into the study were, for the most part, similar to customers who did not respond to the

[2] Participating customers were required to have at least two years of historic hourly data in order to establish savings from the device.

solicitation, according to Figure 8. The charts featured in Figure 8 compare opt-in customers to non-participants along several major characteristics recorded at the block-group level by the US Census and the individual customer level by SDG&E.

The comparison reveals only two major differences: opt-in participants were 50 percent less likely to declare a non-English preferred language and they were nearly four times more likely to have signed up for SDG&E's existing demand response program. The first difference matches the expectation that non-English speaking customers are less likely to respond to opt-in solicitations communicated in English; the second conforms to the expectation that customers are more likely to opt-in to a program or study if they have done so in the past.

Figure 8: Recruited Customer Characteristics*



*Panels 1 through 6 are based on statistics gathered at the census block group level; the remaining panels are based on utility-supplied data at the account level.

Among the customers who had opted into the study, 500 were randomly selected to receive a TOU Energy Display device. These selected customers represent the Intent-to-Treat (ITT), and the stratified randomization procedure ensured that ITT customers did not differ systematically from the remaining 500 opt-in customers assigned to the control group. The *Sample Attributes* section compares the ITT to the control group in detail, verifying that these two groups are identical across key attributes.

Mailing of devices to the ITT group began in October 2019. Once customers received their mailed devices, they had to activate them and connect their devices to the TOU Energy Display Mobile App using a smartphone. Using the vendor's device activations records, it was determined that 239 of the participants activated and began using their device prior to the summer of 2020. Participants with active devices comprise the *Treated* group. The remaining 261 participants who received a device but did not activate it are designated the *Non-Complier* group.

Figure 9 depicts the rate at which devices were activated after being shipped to treated customers. Device activations increase steeply in the first three weeks after shipment: the activation rate reached 20 percent during the first four days after shipment and climbed to 40 percent after about three weeks. From there activations occurred at a much slower pace, reaching a peak of 48 percent after 341 days. A reminder message sent to treated customers on April 27 2020 may have encouraged some of these later activations but it does not coincide with a significant jump in the overall activation rate.

The possibility of non-compliance with the treatment (failure to activate the device) implies that that there is some degree of self-selection into the treatment. For instance, Figure 10 shows that Treated participants (those who activated their devices) are more than twice as likely to be enrolled in SDGE's demand response program when compared to Non-Compliers. In the statistical evaluation, this self-selection problem was addressed using two approaches: (1) assessing the treatment effects among the entire ITT group, ignoring non-compliance, and (2) assessing the treatment effect among active devices while adjusting for self-selection using instrumental variable methods. Both approaches are cited by CPUC guidelines as valid ways to adjust for self-selection effects (Agnew, Goldberg 2017).

Figure 9: Device Activations

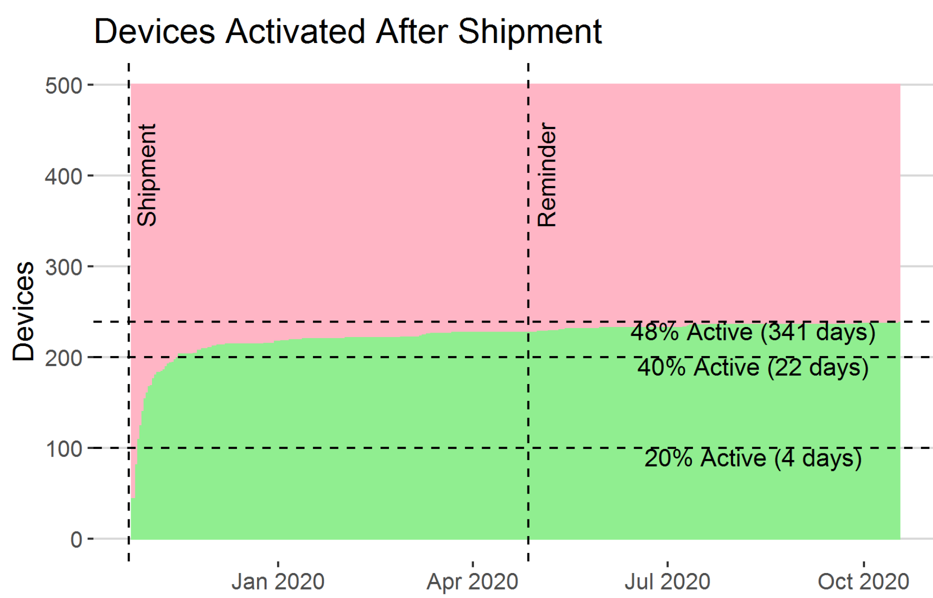
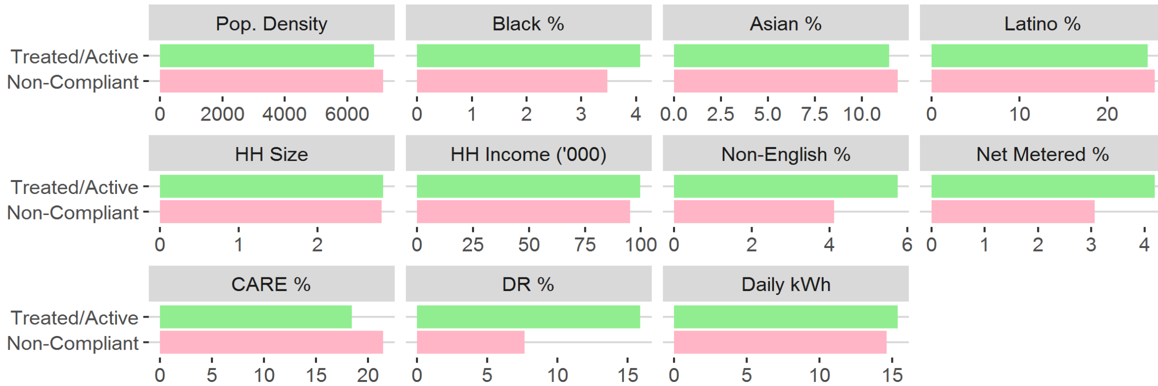


Figure 10: Treated Customer Characteristics*



*Panels 1 through 6 are based on statistics gathered at the census block group level; the remaining panels are based on utility-supplied data at the account level.

6. Technical Approach/Test Methodology

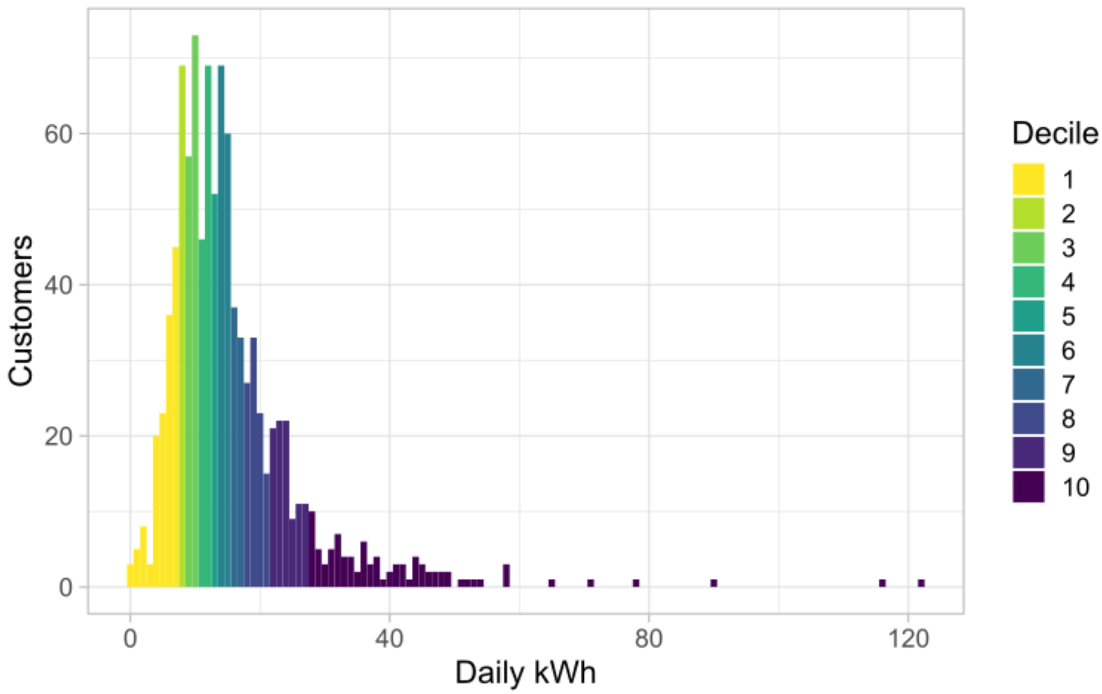
One of the primary goals of the TOU Energy Display Emerging Technology project is to determine the causal effects of the TOU Energy Display device on residential customer electricity usage patterns. To make causal claims about the "treatment" group that received the device, one needs a valid comparison group of customers who have not received it. Randomization of the device assignment ensures that customers in the comparison group are qualitatively similar to those of the treatment group – customers receiving devices. It also eliminates the influence of self-selection on treatment group outcomes, a prerequisite for measuring net savings caused by TOU Energy Display device assignment (Violette, Rathbun 2017). This section describes the method for treatment randomization and compares the attributes of customers assigned to either the treatment or comparison group.

Sample Attributes

The quality of treatment randomization can be measured by the overall similarity between treatment and comparison groups across attributes that are relevant to the study outcomes. When there are strong similarities across important attributes, the comparison group represents a more plausible counterfactual to the treatment group. Regression methods can be used to control for dissimilarities in observable characteristics, but these methods often require (linear) extrapolation of the effects of customer attributes on behavior following the treatment, and therefore should be viewed as a second-best solution. The preferrable solution is to produce a comparison group that closely resembles the treatment group.

The most relevant attribute for this study is a customer's typical electricity consumption. Figure 11 plots the distribution of average daily kWh consumption during the year prior to the pilot start date, ending shortly before the devices were shipped. Each customer was assigned to one of ten deciles, which classify customers by their typical level of consumption. Consumption averages were taken over the entire year for all but 9 percent of customers who did not have a full year of data. For these customers, only average consumption during the most recent month was observed, which is a strong predictor of average consumption across the entire year (ρ=0.93).

Figure 11: Customer Average Daily Consumption



Customers are characterized by several other important attributes, summarized in Table 2. According to the statistics reported on the table, customers are unevenly distributed across California climate zones (CZ), with zones 7 and 10 accounting for a combined 99 percent of participants and zone 14 accounting for the remaining one percent.[3] The multi-family attribute (MF) indicates whether a customer resides in a multi-family (or condo) development, as indicated by the existence of a unit number on the customer address. The majority (77 percent) of participating customers did not live in a multi-family development.

The remaining attributes reported in Table 2 could predict behavior of customers either directly or indirectly. A minority of participants are enrolled in an existing demand response program. Additionally, a minority of participants have discounted rates on the basis of financial need

[3] The California Energy Commision (CEC) has established 16 climate zones throughout the state based on energy use, temperature, weather, and other variables. See https://cecgis-caenergy.opendata.arcgis.com/documents/CAEnergy::building-climate-zones/about for more detail.

(CARE and FERA), medical conditions (MED) or employment status (Emp_Discount).[4] Lastly, the majority (76 percent) of participants are signed up to their account's online portal (My Account).

Table 2: Customer Attributes (Bolded Attributes are Used for Stratification)

Attribute	Value	Customers	Percent
Climate Zone (CZ)	7	572	57
	14	7	1
	10	421	42
Multi-Family (MF)	N	772	77
	Y	228	23
Demand Response (DR)	N	884	88
	Y	116	12
Net Metered	N	955	96
	Y	45	4
CARE	N	819	82
	Y	181	18
FERA	N	993	99
	Y	7	1
MED	N	973	97
	Y	27	3
Emp_Discount	N	994	99
	Y	6	1
My_Account	N	241	24
	Y	759	76

[4] The California Alternative Rate (CARE) offers a 30 percent or greater discount on rates based on a customer's participation in public assistance programs, while the Family Electric Rate Assistance (FERA) program provides 18 percent discounts to qualifying families. The Medical Baseline Allowance program (MED) provides lower rates to customers with qualifying medical conditions and equipment.

Stratified Randomization

The treatment was assigned by stratified randomization across all participating customers. Stratified randomization ensures that treatment assignment is locally random across circumscribed regions in the distribution of customer attributes. It achieves *local* randomness by randomly assigning a fixed number of treatments (without replacement) within each pre-determined strata, defined as a group of individuals who share similar attributes. The attributes used to define strata include:

- Daily kWh consumption,
- Climate Zone (CZ), and
- Multi-family residence.

Stratified randomization ensures an even assignment of the treatment within all subgroups defined for daily consumption (deciles), climate zone (7/14/10) and multi-family residence (Yes/No). Pure randomization guarantees a balance of attributes across treatment and control groups when applied to large samples. However, stratified randomization ensures balance even when dealing with a small sample (1,000 customers) or subgroup.

Table 3: Strata Summary

Stratum	Climate Zone	Daily kWh	MFR	Treated	Control	Treated %
1	7	0:7	N	27	29	48
2	7	0:7	Y	22	23	49
3	7	7:8	N	13	13	50
4	7	7:8	Y	10	9	53
5	7	8:10	N	23	23	50
6	7	8:10	Y	16	15	52
7	7	10:12	N	26	26	50
8	7	10:12	Y	6	6	50
9	7	12:13	N	10	9	53
10	7	12:13	Y	3	3	50
11	7	13:15	N	27	27	50
12	7	13:15	Y	5	5	50
13	7	15:17	N	18	17	51
14	7	15:17	Y	2	1	67
15	7	17:21	N	27	28	49
16	7	17:21	Y	2	3	40
17	7	21:27	N	18	19	49
18	7	21:27	Y	2	1	67

19	7	27:122	N	28	30	48
20	14			4	3	57
21	10	0:7	N	14	13	52
22	10	0:7	Y	8	7	53
23	10	7:8	N	6	7	46
24	10	7:8	Y	6	5	55
25	10	8:10	N	18	19	49
26	10	8:10	Y	8	8	50
27	10	10:12	N	20	20	50
28	10	10:12	Y	6	5	55
29	10	12:13	N	10	11	48
30	10	12:13	Y	3	3	50
31	10	13:15	N	26	28	48
32	10	13:15	Y	6	5	55
33	10	15:17	N	10	11	48
34	10	15:17	Y	6	5	55
35	10	17:21	N	16	15	52
36	10	17:21	Y	4	3	57
37	10	21:27	N	25	25	50
38	10	21:27	Y	3	3	50
39	10	27:122	N	16	17	48

Table 3 lists the characteristics and treatment assignment distribution for each of the 39 strata. The maximum number of strata is equal to the product of the number of divisions within each variable (2×3×10 = 60 for the three variables included); however, given that there were only seven customers in CZ-14, these customers were assigned to a single stratum. Additionally, there were not any multi-family customers in the top consumption decile in CZ-7, further reducing the strata count. Assignment to the treatment group follows a 50-50 split on average to ensure a total 500 of 1,000 participants received a TOU Energy Display device. The rightmost column on Table 2 shows that each stratum approximates a 50 percent treatment rate.

Evaluating Random Assignment

The balance of customer characteristics across groups is verified by comparing sample averages across each attribute. Columns two and three of Table 4 list averages for the Treatment and Control Group, and the fourth column lists the *normalized* differences between these values, defined as the difference in averages divided by the standard deviation in the underlying value. Differences in customer attributes never exceeded 0.1 standard deviations and were typically far less. The greatest difference is in the percent of customers with subsidized CARE rates, totaling 20 percent among the treatment group and 16 percent among the control.

Table 4: Attribute Comparison

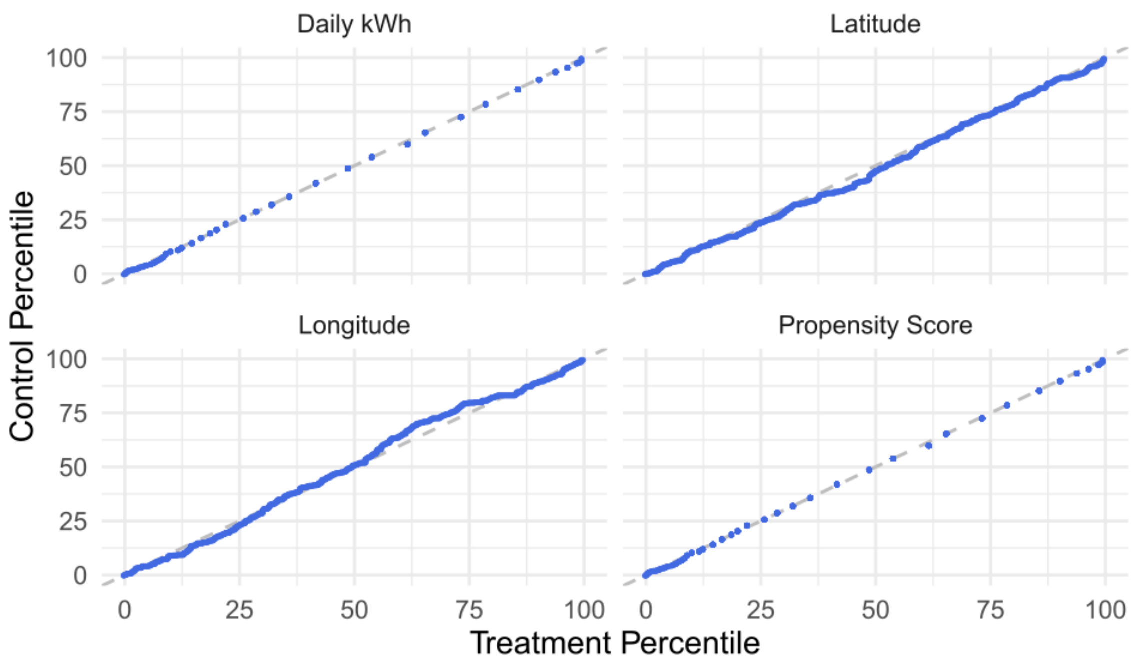
Attribute	Treatment Average	Control Average	Normalized Difference	Qt	Qc
Net_Metered	0.04	0.05	-0.09		
Emp_Discount	0	0.01	-0.05		
CARE	0.2	0.16	0.1		
MED	0.03	0.02	0.09		
FERA	0.01	0.01	0.02		
My_Account	0.76	0.76	0		
DR	0.12	0.12	0		
Latitude	32.98	32.97	0.04	0.96	0.94
Longitude	-117.19	-117.19	0	0.96	0.94
Daily kWh	15.72	15.6	0.01	0.96	0.95
CZ == 7	0.57	0.57	-0.01		
CZ == 14	0.01	0.01	0.02		
CZ == 10	0.42	0.42	0		
Propensity Score	0.5	0.5	0.01	0.96	0.95

The Qt and Qc terms listed in the fifth and sixth columns measure the overlap in the distribution of attributes that contain continuous values. In particular, Qt represents the share of the control group values that fall within the treatment value distribution after removing the top and bottom tails. The tails are evaluated at the 2nd percentile and the 98th percentile, so a value of 96 indicates a perfect overlap in control and treatment distributions. The value Qc represents the same measurement but reverses the role of treatment and control group. Both columns show that distributions of latitude, longitude and daily kWh were nearly identical, as estimates of Qc and Qt ranged from 0.94 to 0.96. This finding verifies that the distributions of characteristics share a common support.

The final row of Table 3 summarizes differences in propensity score. The propensity score represents a modeled probability of receiving the treatment, where the model is estimated from the sample using a methodology described in Imbens & Rubin (2015). The average propensity score is equal to 0.5 for both groups, indicating that there are no systematic differences in the attributes predicting treatment assignment. Propensity score also shares a common support across groups.

Figure 12 illustrates Q-Q plots for each of the customer attributes that have continuous values. The Q-Q plot compares the cumulative distribution functions of the treatment and control groups evaluated for each observation. The gray dashed line indicates the point of equality for each distribution function, while the blue dots represent the evaluated observations. For each attribute, daily kWh, longitude, latitude and propensity score, the blue dots closely track the dashed line, indicating that there are no significant inequalities in the distributions.

Figure 12: Comparison of Attribute Distribution (Q-Q Plots)



Testing of Technology

The impacts of the TOU Energy Display device were evaluated along two dimensions: (1) the effectiveness of the app and device in reducing consumption during 10 demand response messaging days and (2) the effectiveness of the device in managing peak-hour (4pm-9pm) consumption during the five summer rate months, when peak TOU rates dramatically increase. Changes in customer energy usage are evaluated using over two years of hourly advanced metering infrastructure (AMI) data for each of the 1,000 customers participating in the study. The statistical evaluation follows a 2-stage approach: first, individual baseline models for each customer were constructed and then the prediction residuals from these models were inputted into a fixed effects regression.[5] This approach is recommended by CPUC guidelines and reflects the state-of-the-art in population NMEC evaluation (Agnew, Goldberg 2013).

[5] In general, the analysis is unable to control for customer installations of electric vehicle chargers, solar panels, or other technologies coinciding with event days. However, individual baseline modeling can partially account for these potentially confounding factors.

Stage 1: Customer Level Models

First, 1,000 baseline energy consumption models were estimated, one for each customer in the study. The data used to estimate the baseline model are drawn from a *baseline period* spanning the year prior to the TOU Energy Display device mailing date, from October 2018 to September 2019. A gradient boost machine is fitted to the baseline data for each customer and then used to predict customer-level hourly electricity consumption for the entire period of the trial. Gradient boost machines are effective tools for AMI modeling (Touzani et al. 2018), and a more in-depth description of these models is provided in the Appendix.

Table 5 summarizes the performance of customer-level models in predicting hourly energy consumption. It is generally difficult to attain a high level of accuracy when modeling hourly residential electricity usage for a single household. The models, however, perform reasonably well, only rarely explaining less than 20 percent of the variation in hourly energy use; 95 percent of the models achieve an R^2 above 0.22. The coefficient of variation of the root-mean-squared error (CVRMSE) typically exceeds the recommended values for site-level evaluation (30 to 35). Though the CVRMSE for most models is below 100, making them adequate for population-level evaluation.

Table 5: Customer Baseline Model Performance

	COEFFICIENT OF DETERMINATION R^2	CVRMSE
5th percentile	0.22	28
25th percentile	0.35	40
Median	0.48	53
75th percentile	0.6	71
95th percentile	0.77	107

Stage 2: Pooled Effects

The second stage of the procedure collects values from the customer-level analysis and incorporates them in a *pooled fixed effects regression* that tests the overall effect of the treatment. The pooled regression evaluates the treatment effect using the residuals of the customer-level models, defined as $\tilde{y}_i : \tilde{y}_i = \hat{y}_i - y_i$ where $\hat{y}_i$ is predicted kWh consumption for customer i and y_i is the customer's actual consumption.[6] The regression analysis includes all peak-hour intervals $h: h \in 1, \ldots H$, from January through October 2020, and a fixed-effect term λ_i that controls for each customer's average prediction residual. The following equation is used to estimate the effect of event-day messaging on a customer's peak-hour consumption:

[6] This approach is also taken in Burlig et al. (2019) and described in Agnew, Goldberg (2013).

$$\tilde{y}_{i,h} = \beta_1 Event_h + \beta_2 Device_i \times Event_h + \lambda_\text{i} + \varepsilon_{i,h} \qquad (1)$$

where the $Event_h$ term equals one if the hour falls within one of the 10 scheduled DR windows and zero otherwise. The coefficient β_1 therefore represents the average change in hourly kWh observed during peak-hours on event days. The coefficient β_2 measures the interaction between event days and treatment status: $Device_i$ equals one if the participant received or activated a TOU Energy Display device and zero otherwise. In other words, β_2 is the effect that the device and application have on consumption during scheduled event days. Lastly, ε is the model error term.

Another important outcome is the effect that the device and application have on customer's responses to TOU rates. The IHD and messaging protocol were designed to draw customer attention to steep increases in peak-hour rates during the summer. The following equation measures the effect of the device and application on overall peak-hour consumption during the summer:

$$\tilde{y}_{i,h} = \beta_1 Summer_h + \beta_2 Device_i \times Summer_h + \lambda_\text{i} + \varepsilon_{i,h} \qquad (2)$$

where the $Summer_h$ term equals one if the hour falls within SDGE's summer-rate season, from July through October, and zero otherwise. The coefficient β_1 measures the average seasonal change in peak-hour hourly consumption observed during the designated summer months. The coefficient β_2 measures the effect that receiving or activating the TOU Energy Display device has on hourly peak consumption during the summer rate season.

Adjusting for Self-Selection

Because control and treatment groups are both drawn randomly from the set of opt-in customers, there is no possibility of self-selection in treatment *assignment* (i.e., selection into the ITT group). However, customers who received a device could still decide whether to activate it; and indeed 261 ITT customers did not activate their devices. This poses a measurement problem because the full treatment effect can be measured only from customers who activated their devices, but these $Active$ customers represent a self-selected sub-sample of the ITT group.

To address this issue, three different versions of regressions (1) and (2) were estimated, with the goal of determining whether treatment effects persist even after adjusting for self-selection effects. The first specification substitutes $Device_i$ with $Active_i$, which equals one for the 239 customers who activated their devices and zero for all others. This specification has the advantage of directly measuring the impact of an activated device, but it is potentially subject to self-selection bias. The second specification substitutes $Device_i$ with $Treated_i$, which equals one for all 500 ITT customers and zero otherwise. This specification provides an unbiased estimate of a treatment effect, though the estimated effect is attenuated in proportion to the non-compliance rate ($261/500$). Lastly, an instrumental variable (IV) specification measures the treatment effect through a two-stage regression that substitutes $Peak_i$ with $\widehat{Active}_i$, the predicted activation status generated by a first-stage regression. The IV specification adjusts for self-selection effects without attenuating the estimated impact of the device.

Table 6 summarizes each of the three regression specifications. As described in the results below, there were not any large quantitative differences between the estimates yielded by each specification; nor do the small differences that do exist suggest that self-selection has inflated the treatment effect. The cost benefit analysis therefore draws from the more straightforward first (SS) specification that compares customers who activated their devices to all other customers.

Table 6: Regression Specifications

Symbol	TOU Energy Display Regression Term	Specification	Description
SS	$Active_i$	Self-Selected	Compares customers who activated their peak devices (a self-selected sample) to all other customers.
ITT	$Treated_i$	Intent-to-Treat	Compares customers who received the device (the intended treatment group) to all other customers.
IV	$\widehat{Active}_i$	Instrumental Variable	Compares customers who activated their peak devices (a self-selected sample) to all other customers, while correcting for self-selection.

7. Results

The three statistical regressions specifications converge on similar findings. First, there is consistent evidence that the TOU Energy Display device and messaging did not cause any significant energy-use reductions on designated event days. Second, the activation of the device is associated with a *seasonal reduction* in peak-hour electricity-use. According to all three regression specifications, device users reduce hourly electricity use by about 0.1 kWh during peak hours on hot summer days, equal to about 8 percent of the average customer baseload. Additionally, among device users:

1. Reductions in energy consumption were realized primarily by customers with higher baseload consumption.
2. Customers enrolled in CARE did not significantly reduce energy usage.
3. Some of the device users were also participants in SDG&E's demand response program. These users reduced peak energy use at a rate similar to other users. In other words, when looking at energy reductions, there were not any strong complementarities observed between the program enrollment and the device.

Data Analysis

Tables and Figures

Table 7 reports coefficients for the three regression specifications used to estimate the TOU Energy Display device impact on event days, corresponding to equation (1). The three model specifications yield similar findings: the estimated reductions in kWh are statistically insignificant on event days. The magnitude of the effects is on the order of 0.012 to 0.043 kW per hour, which represents a 1 to 4 percent reduction. The initial power tests conducted at the start of the pilot indicated that an effect this small would likely go undetected, so it is not surprising that the coefficients are statistically insignificant. The coefficient for the SS (treatment group) is substantially larger than the other two groups.

Table 7: Event Regression Coefficients

	Δ kWh		
	SS	ITT	IV
$Event$	0.243***	0.236***	0.236***
	(0.018)	(0.021)	(0.021)
$Active \times Event$	−0.043		
	(0.032)		
$Treated \times Event$		−0.006	
		(0.030)	
$\widehat{Active} \times Event$			−0.012
			(0.064)
Observations	1,371,215	1,371,215	1,371,215
R^2	0.098	0.098	0.098
Adjusted R^2	0.098	0.098	0.098
Residual Std. Error (df = 1370263)	0.708	0.708	0.708
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 8 reports the results of a regression designed to estimate seasonal reductions in peak hour consumption during the summer of 2020. The *Summer* term in this regression is assigned to all peak hours from June to October, not just those hours that coincided with events. The SS specification yields a statistically significant finding that the group of customers with active devices reduced peak hourly consumption by 0.038 kWh on average during the months of June through October 2020. This change amounts to roughly 3 percent reduction in average peak consumption. The IV specification, however, fails to confirm this finding at a statistically significant level. Though the IV coefficient is statistically insignificant, it has a similar magnitude as the SS model coefficient, and therefore suggests that the SS result is not inflated.

Table 8: Summer Peak Regression Coefficients

	$\Delta\ kWh$		
	SS	ITT	IV
$Summer$	0.089^{***}	0.091^{***}	0.091^{***}
	(0.011)	(0.013)	(0.013)
$Active \times Summer$	-0.038^{*}		
	(0.020)		
$Treated \times Summer$		-0.022	
		(0.019)	
$\widehat{Active} \times Summer$			-0.047
			(0.040)
Observations	1,371,215	1,371,215	1,371,215
R^2	0.099	0.099	0.099
Adjusted R^2	0.099	0.099	0.099
Residual Std. Error (df = 1370263)	0.708	0.708	0.708
Note:	*p<0.1; **p<0.05; ***p<0.01		

Table 9 reports the results of a regression designed to estimate seasonal reductions in peak period hourly kWh during the 15 days in the summer of 2020 in which temperatures at San Diego International Airport exceeded 85 degrees F. All specifications confirm statistically significant reductions in peak kWh consumption among customers with devices during hot summer days. Reductions among customers with active devices average 0.1 to 0.12 kWh per hour, representing a roughly 8 percent decline in consumption during those hours.

Table 9: Hot Summer Peak Regression Coefficients (Daily High > 85)

	$\Delta\ kWh$		
	SS	ITT	IV
$Summer$	0.212***	0.216***	0.216***
	(0.019)	(0.023)	(0.023)
$Active \times Summer$	−0.105***		
	(0.037)		
$Treated \times Summer$		−0.057*	
		(0.032)	
$\widehat{Active} \times Summer$			−0.122*
			(0.069)
Observations	1,371,215	1,371,215	1,371,215
R^2	0.099	0.099	0.099
Adjusted R^2	0.099	0.099	0.099
Residual Std. Error (df = 1370263)	0.708	0.708	0.708
Note:			*p<0.1; **p<0.05; ***p<0.01

Figure 13 illustrates the hourly effects of the device on active customers with 95 percent confidence intervals in gray. Statistically significant reductions in electricity use occur at points where the gray region drops below zero, denoted by the dashed horizontal line. The bottom row of three graphs shows significant reductions occurred in the early peak hours between 4 to 6 pm and that these reductions are were realized on the hottest summer days (>85 degrees). There does not appear to be statistically significant evidence of a "snapback" phenomenon, where use increases after peak hours.

Figure 13: Hourly Effects of Device

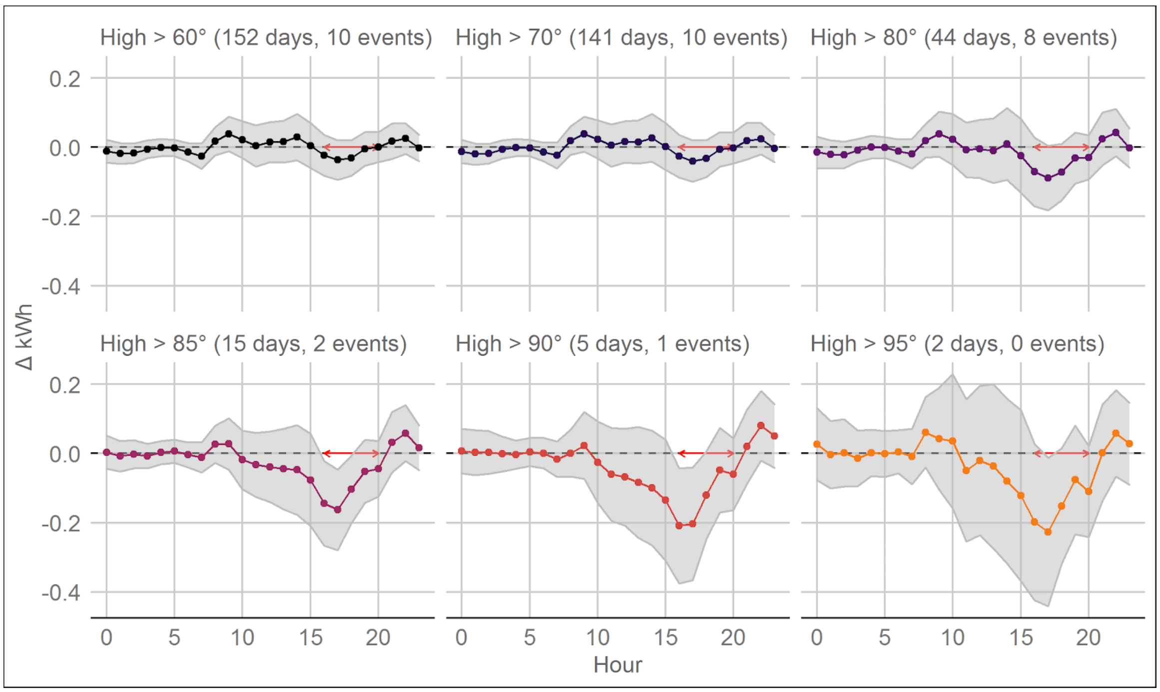


Figure 14 approximates maximum hourly savings at the daily level by subtracting active customer model residuals from the residuals of all other customers. Plotting the daily maximum of peak savings among customers with active devices confirms that kWh reductions were greatest on the hottest days of the year. The white labels on the plot denote event days in which customers received reminders to reduce the peak hour consumption. Savings on event days seem to only have been realized when the event coincided with a hot summer day. Customers appear to have been more responsive to event days over time, suggesting that fatigue was likely not an issue.

Figure 14: Maximum Hourly Savings by Day

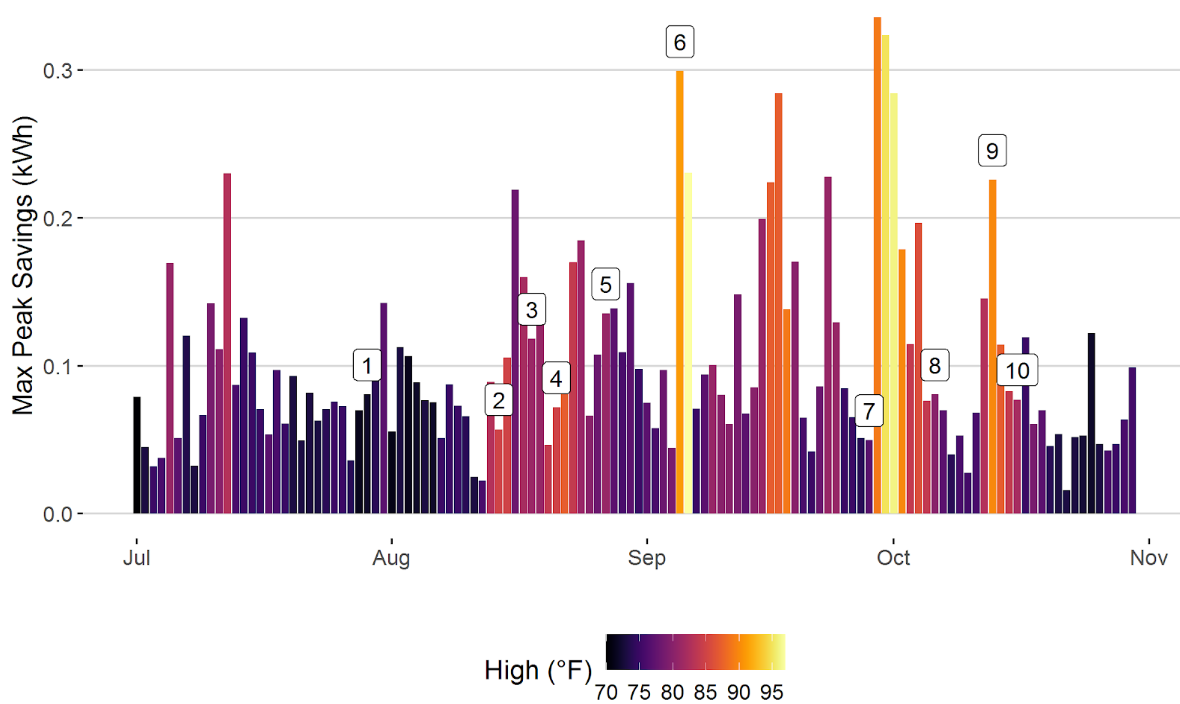


Figure 15 shows that savings from the device were driven primarily by those customers who had high baseloads, exceeding a daily average of 12 kWh. The fact that high-baseload users account for the majority of kWh reductions conforms to the intuition that these customers have a higher margin of adjustment and is consistent with previous findings in the literature.

Figure 15: Peak Reductions by Baseload

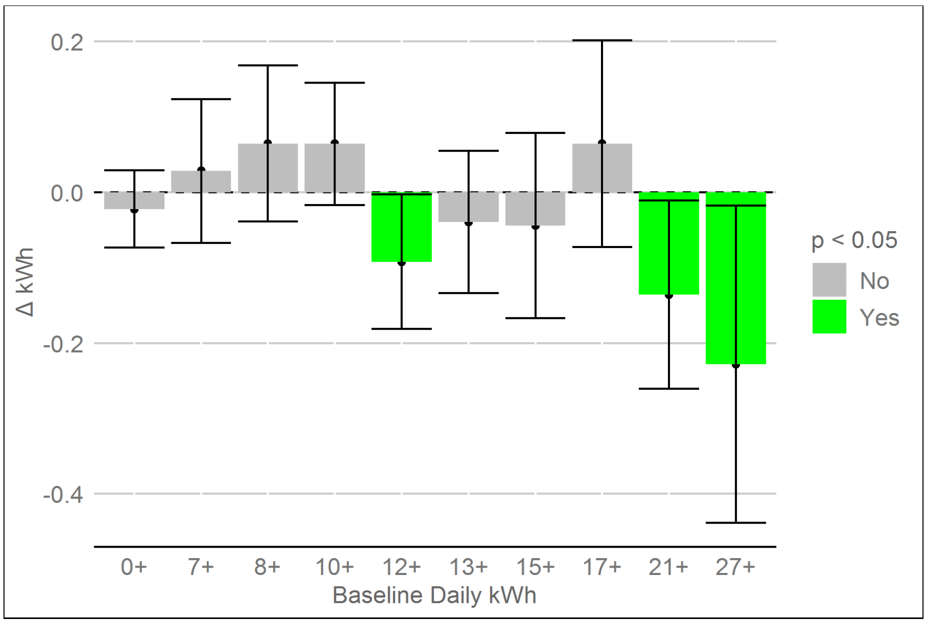
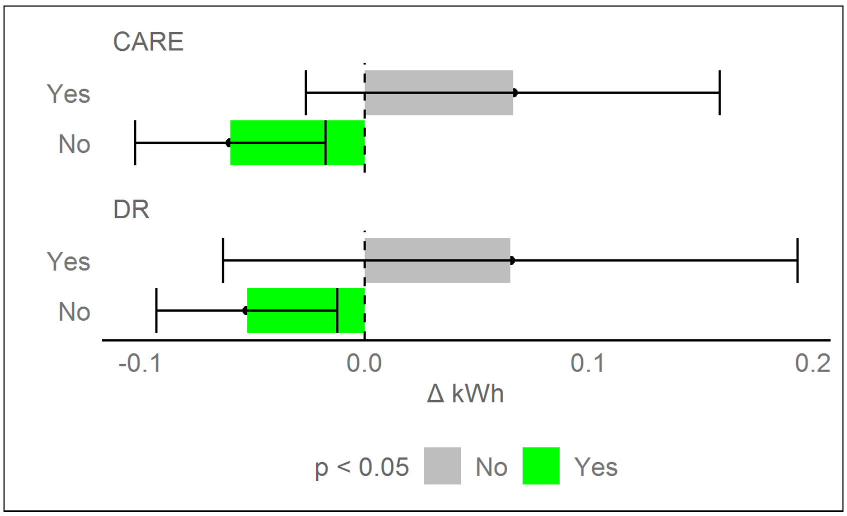


Figure 16 compares savings among those enrolled in CARE and the demand response program (DR) with those who are not enrolled in these programs. CARE participants did not achieve statistically significant savings during peak hours as demonstrated by the fact that the error band for the coefficient estimate includes zero. Similarly, the roughly 10 percent of TOU Energy Display customers enrolled in SDG&E's demand response program also did not achieve statistically significant savings. This second finding is somewhat surprising given that DR enrollment was a significant, positive predictor of trial enrollment and device activation (see *Recruitment* section). The counterintuitive result is perhaps a symptom of the relatively small sample size of DR enrollees with active TOU Energy Display devices, totaling only 38 customers.

Figure 16: Peak Reductions by Program Participation



Cost Effectiveness Analysis

To support the evaluation of the TOU Energy Display device, the total resource cost and the cost benefits ratio (CBR) of the energy savings and demand reduction were estimated for the TOU Energy Display device using the 2016 DR Cost Effectiveness Calculator as well as the Energy Efficiency Cost-Effectiveness Tool, both developed by Energy and Environmental Economics, Inc. (E3).

DR Cost Effectiveness Overview

This section provides an introduction to the CBR test methodology, an explanation of its results, and conclusions and recommendations for the client to inform their evaluation for SDG&E's pilot TOU Energy Display device program.

As part of the TOU Energy Display Pilot program, SDG&E distributed the TOU Energy Display device to 500 customers on time-of-use (TOU) rates. The DR analysis focuses on the cost effectiveness of the device in managing peak-hour (4pm-9pm) consumption during the five summer rate months, when peak TOU rates dramatically increase.

Cost-effectiveness tests capture the net costs of a demand-side management (DSM) load management program based on the total program costs and benefits.[7] There are various types of cost effectiveness tests beyond the total resource cost test, including the ratepayer impact measure test, the utility cost test, and the participant cost test. These different tests vary in what the impacted group is considered to be, and thus what classes of costs and benefits are included. The total resource cost test is designed to compare DSM program impacts to more traditional utility system investments, such as new generation capacity. Benefits are the avoided supply costs captured at load reduction times, which are calculated using net program savings. In other words, the benefits are costs that may/would have occurred in the absence of the energy-saving/load reduction program. Costs include the total program costs borne by both the customer and the utility, in addition to the costs incurred during a period of higher demand. The evaluation team calculated the CBR of the TOU Energy Display device in accordance with the 2016 DR Cost Effectiveness Protocol.[8]

Demand Response Reporting Tool

The DR reporting tool has three sources of inputs: avoided costs calculator (ACC) inputs for distributed energy resources (DER) inputs, California Public Utilities Commission (CPUC) inputs, and utility- and program-specific data that are user inputs. The program-specific inputs for the one-year and three-year CBR iterations included the following (references are to the Inputs tab of the calculator):

- T&D right time-right place adjustment (row 43): SDG&E currently does not claim any T&D benefit for demand response (0%).
- Load impacts (row 56): The evaluation team calculated the load impacts (MW) of the TOU Energy Display device program assuming 239 active devices and used the regression model results that reported the overall reduction among active TOU Energy Display device users during the summer peak hours (0.038 kWh, on average) during the summer months (June-October). The evaluation team assumed that each of the 239 participants saved 0.038 kWh per day in the summer months. The DR reporting tool does not account for negative load values in its load impact calculations, so the electric consumption of the TOU Energy Display device was not included in calculating the load impact. No information was provided about when the 15 hottest days of the summer months occurred, therefore the regression results that reported the estimate of the overall

[7] https://www.cpuc.ca.gov/-/media/cpuc-website/files/uploadedfiles/cpuc_public_website/content/utilities_and_industries/energy_-_electricity_and_natural_gas/cpuc-standard-practice-manual.pdf.

[8] https://www.cpuc.ca.gov/WorkArea/DownloadAsset.aspx?id=11573

impact of the device on peak period (4pm-9pm) hourly kWh consumption during the 15 hottest days in summer 2020 were not used.

- Energy savings (row 57): The evaluation team calculated the energy savings (MWh) of the TOU Energy Display device program assuming 239 active devices and used the regression model results that reported the overall reduction among active device users during the summer peak hours (0.038 kWh, on average) during the summer months (June-October). The 0.038 kWh savings from the regression model in Table 8 above were assumed to last for the five-hour peak period (4pm-9pm) for the length of the month across the 239 customers. The energy consumption of the device for the non-summer months (November-May) was calculated using the device's energy consumption (0.672 W) multiplied by the 15-hour duty cycle a day across the duration of the month and the 239 customers.
- Program administrative costs (row 61): The evaluation team relied on the Emerging Technology (ET) program recommendation to use ~4 percent of the EM&V vendor budget for the administrative costs. No SDG&E program administration costs were included. All administrative costs were included in the device O&M costs.
- Equipment costs (rows 70, 74, and 80): TOU Energy Display device cost ($19.77, one-time, 239 devices total), drop ship to consumer cost ($5.42, one-time, 239 devices total), and operations, maintenance, messaging, events costs ($.69 per month, 239 devices total). The TOU Energy Display device power consumption is equal to 0.672 watts at a 15-hour duty cycle (hours on per day), with a total of 239 active devices. The device is assumed to have an effective useful lifetime (EUL) of five years. These inputs were provided to the evaluation team by the client and were used to calculate annual benefits and expenses for the 2020 program year and a three-year program (2020-2022).
- CAISO Market Participation (rows 94-99): The 2016 DR Cost Effectiveness Protocol[9] includes additional costs and benefits beyond what is listed in SPM, including CAISO Market Participation Revenue. This is revenue that the project could earn for CAISO market participation and therefore is counted as a benefit in the CBR. The TOU Energy Display device provides benefits for bidding 6.45 MWh into the CAISO market for the first year at $2.25/MWh value assumed in the DR Tool.

DR Results

In order to provide both specific results from the 2020 pilot and a more general view of benefits under other sets of costs, the CBR was calculated using both a single year set of inputs, as well as a set of inputs assuming that the costs of the inactivated devices are included in the CBR. Another set of results (not shown) were estimated with the same set of costs over a three-year period (2020-2022).

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[9] https://www.cpuc.ca.gov/WorkArea/DownloadAsset.aspx?id=11573.

Table 10 shows the summary of energy savings and demand reductions from the DR Reporting Tool.

Table 10: Summary of Energy Savings and Demand Reductions

	Annual Energy Consumption (kWh/yr)	Annual Energy Savings (kWh/yr)	Peak Demand (kW)	Peak Demand Reduction (kW)
Baseline	-	-	-	-
New Technology	864	6,450	.24	1,450

Table 11 shows the results of the CBR calculations for the 2020 program year, with 239 active devices, along with the PAC, RIM, and PCT results. Table 12 shows the results of the CBR calculations for the 2020 program year, with 239 active devices, but shows the fixed costs for all 500 devices purchased and shipped.

Table 11: CBR Base Case Results for TOU Energy Display Device 2020

2020 Dollars	Benefits	Costs	Net Benefits	Net $/kW-Yr.	CBR	PAC	RIM	PCT
TRC	$50,999	$7,859	$43,139	$32	6.49	10.81	10.81	0.00

Table 12: CBR Results for TOU Energy Display Device with Costs for 500 Devices (Only 239 Activated)

2020 Dollars	Benefits	Costs	Net Benefits	Net $/kW-Yr.	CBR	PAC	RIM	PCT
TRC	$51,554	$11,637	$39,916	$29	4.43	10.18	10.18	0.00

The benefit-cost ratio is the ratio of discounted total benefits of the program and gives an indication of the rate of return of the TOU Energy Display device program to the utility and its ratepayers. The 2020 baseline and 500 Device scenarios ratios (6.4 and 4.4) signify that the program provides 4-6 times as many benefits to the utility and its ratepayers as it incurs costs. The positive net benefits for the 2020 scenarios indicate that the program is a less expensive resource than the supply option upon which the marginal costs of the program are based.[10]

Caveats

The latest update of the data in the Avoid Cost Calculator (ACC) was in 2016. E3 staff are currently in conversations about a contract to update the DR cost-effectiveness tool with an updated ACC but are awaiting authorization. Therefore, the evaluation team recommends updating the results of the DR cost-effectiveness tool once the ACC is updated.

[10] ftp://ftp.cpuc.ca.gov/gopher-data/energy_division/DR/2020/SDGE_Nov_2020.pdf.

The CBR iterations described in this evaluation reflect a pilot program with 239 active devices, with the same assumptions used for a one-year and three-year program. If the program is scaled up or lasts several years, program costs and benefits will change. Therefore, the evaluation team recommends the client run several iterations of the CBR when thinking about expanding the program to understand how assumptions, costs, and benefits are affected with more participants or a multi-year program.

Energy Efficiency Cost-Effectiveness Tests

The Cost-Effectiveness Test (CET) tool is used to estimate the energy efficiency benefits from the TOU Energy Display device. The CET is available online here: https://cedars.sound-data.com/cet_ui/. Most of the inputs and assumptions for the CET tool are the same as those of the DR reporting tool described above. Additionally, the CET analysis of the device uses inputs from a previous smart thermostat CET analysis. This assumption is made based on the device's similarities to a smart thermostat. The CET also utilizes single-family and multi-family building types. The 239 active users were split into 184 units (77%) for single-family and 55 units (23%) for multi-family buildings.

The key difference in inputs between the two tools is the estimated kWh savings. Recall that the energy savings from the TOU Energy Display device were found to occur during summer peak periods (0.038 kWh from Table 8). To calculate annual device EE savings for the CET, the 6,450 kWh savings from the DR calculator (Table 10) was used and then divided by 239 devices. This yielded an average annual savings of 26.97 kWh per device.

Next, the energy efficiency benefits were calculated using the CET tool for active device users. These results are shown in Table 13 below.

Table 13: CET Results for TOU Energy Display Device 2020

2020 Dollars	Benefits	Costs	Net Benefits	Net $/kWh-Yr.	CBR	PAC
TRC	$2,871	$13,185	-$10,315	-$1.60	0.22	0.51

The benefit-cost ratio (0.22) from the cost-effectiveness test of the TOU Energy Display device indicates that the total discounted benefits from the program are roughly 22 percent of the size of the program's costs.

Non-Energy Benefits

These tests do not provide a quantitative analysis of the non-energy benefits (NEBs) and non-monetary benefits associated with the TOU Energy Display device. However, the potential of these should be noted and include social NEBs, utility NEBs, and participant NEBs. The social NEBs include the potential health-related benefits from the avoided greenhouse gas emissions from lower demand on the load during peak events. Utility NEBs include fewer customer calls to engage in DR activities and potentially improved customer relations. Participant NEBs include the "warm glow" effect customers receive from lowering their energy demand during peak events.[11] NEBs are difficult to quantify as they do not have an inherent monetary value attached to them however, when discussing a DR program's cost effectiveness, they should be acknowledged.

Cost Effectiveness Tests Conclusions and Recommendations

The TOU Energy Display device did not show year round energy efficiency savings under current cost-effectiveness assumptions. However, the evaluation team's findings show the device does provide cost-effective demand response for SDG&E and its ratepayers under current assumption of costs. Further analysis of the cost effectiveness implications of the device at a more granular level could add additional insight, with the CBR results showing promising potential for the TOU Energy Display device program in SDG&E's ET program.

8. Conclusions

The TOU Energy Display Pilot Program provided an opportunity to assess customer interest and engagement with a low-cost IHD and smartphone application designed to draw attention to seasonal TOU rates. There are several criteria that can be used to measure the success of the TOU Energy Display device, including (1) customer demand for the device, (2) interaction with the device among those customers who receive it and (3) the extent to which the device causes behavioral changes among device users, evidenced by reductions in peak-hour or event day energy usage. In reference to these criteria, the pilot program delivered the following insights:

1. There is demonstrated interest in an IHD to aid with TOU pricing among SDG&E's customers: over 1,000 out of a pool of 25,253 customers requested a device within 3 months of the initial solicitation. Customers who requested the device were nearly four times more likely to be enrolled in SDG&E's demand response program.

2. The TOU Energy Display IHD achieved lower take-up among non-English speaking customers.

3. A large portion of customers who acquire an IHD fail to activate it. In the trial, 52 percent (261 out of 500) of customers who requested and received a device failed to activate it. A post-trial survey of customers who failed to activate their devices found that only 14 percent of these customers had changed their mind about using the device and another 14 percent simply did not want to install a phone app. The remaining 72 percent of

[11] https://www.cpuc.ca.gov/WorkArea/DownloadAsset.aspx?id=11573.

surveyed customer cited difficulties such as not understanding the product (26 percent), forgetting to activate it (14 percent) and having difficulty finding an outlet for the device (12 percent).

4. The IHD and smartphone application promote seasonal reductions of peak-hour energy usage on the order of 3 to 5 percent of typical use. These reductions are concentrated on the hottest days of the summer, where temperatures at San Diego International Airport exceed 85 degrees F.

5. Savings in peak-hour energy use are realized primarily by high-end energy users and those not enrolled in the CARE low-income program. This suggests that the TOU Energy Display IHD had less success in affecting the behaviors of LMI customers.

6. Customers enrolled in SDG&E's demand response program were not any more likely to reduce energy usage after receiving the device.

7. The event-day messaging from the TOU Energy Display Mobile App and device did not cause any additional reductions in energy usage on event days. In contrast, 91 percent of surveyed customers claimed that they took action in response to messaging on at least one of the scheduled event days (see Figure A.1).

8. The TOU Energy Display IHD and smartphone applications provide cost-effective demand reductions for SDG&E and its ratepayers under current assumption of costs.

9. Recommendations

The following recommendations are offered based on the findings from the TOU Energy Display Pilot Program evaluation:

1. The TOU Energy Display IHD can be used as a cost-effective demand-side management tool for reducing peak-hour consumption during the summer rate season.

2. The device's cost effectiveness can be improved by increasing its ease-of-installation and addressing difficulties expressed by surveyed customers who failed to activate it. These difficulties include insufficient understanding of the device's purpose and inability to find an appropriate outlet for the device.

3. Device marketing campaigns that target customers enrolled in SDG&E's demand response program should achieve higher conversion rates, as evidenced by the greater device request and activation rates among these customers.

4. The TOU Energy Display device might have greater success when messaging for customers who have super-peak rate schedules that align with additional event messaging. Prior research suggests event-day messaging is more effective when paired with super-peak or critical peak period pricing, which are not rate elements in the TOU-

DR2 schedule but are in the TOU-DR1, TOU-SES, TOU-EV rate schedules (Royal, Rustamov 2018; Faruqi, Sergici 2010).

5. As management of the energy grid and utilities shifts away from a unidirectional, linear service delivery structure and into a multi-directional service model, residential customers must become active participants in energy load management (Rocky Mountain Institute 2017). Widespread adoption of integrated demand side management devices, such as the TOU Energy Display IHD, have the potential to help TOU customers understand and respond in real time to price changes. These messages can be tailored to key customer characteristics such as LMI status, occupancy (renter vs. owner), native language, labor force participation and employment status (e.g. whether a customer works multiple jobs).

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Appendices

TOU Energy Display Customer Survey

This section shows the overview of the survey responses performed as part of the pilot project.

Survey Background

The TOU Energy Display Device Customer Survey was sent to 1,000 SDG&E customers over a 10-day time frame in January 2021. The first survey was sent on January 11th. A reminder email was sent on January 14th and one final reminder email was sent on January 21st (all sent at 11:00 AM PST). The customers are divided into three testing groups: control, intent to treat, and treated.

Treated Group

Respondents in the “treated” group were sent and activated the TOU Energy Display device. The survey was sent to 239 SDG&E customers with 100 customers completing the survey resulting in a 40 percent response rate.

Intent to Treat Group

Respondents in the “intent to treat” group were sent the TOU Energy Display device but did not activate it. The survey was sent to 261 SDG&E customers with 63 customers completing the survey resulting in a 24.1 percent response rate.

Control Group

Respondents in the “control” group were not sent the TOU Energy Display device. The survey was sent to 500 SDG&E customers with 187 customers completing the survey resulting in a 37.4 percent response rate. 98 percent of those who responded to the survey completed the entire survey.

The average response rate between all three groups was 37 percent.

Survey Results for Treated Group

Figure A - 1: Number of Times Acting on Scheduled Event Days

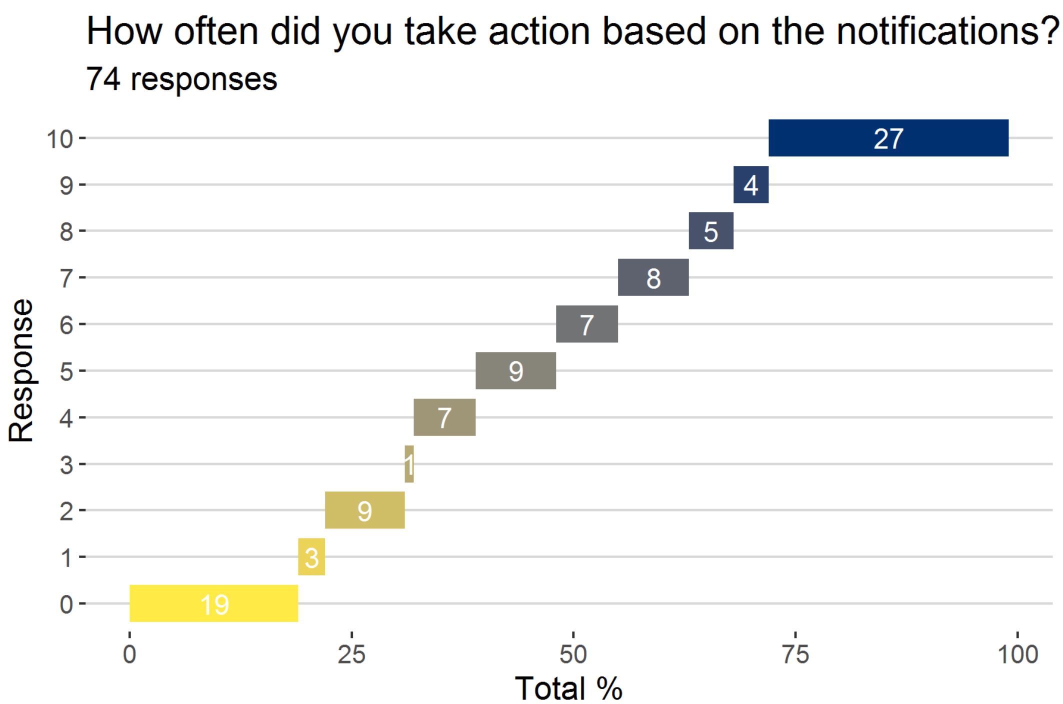
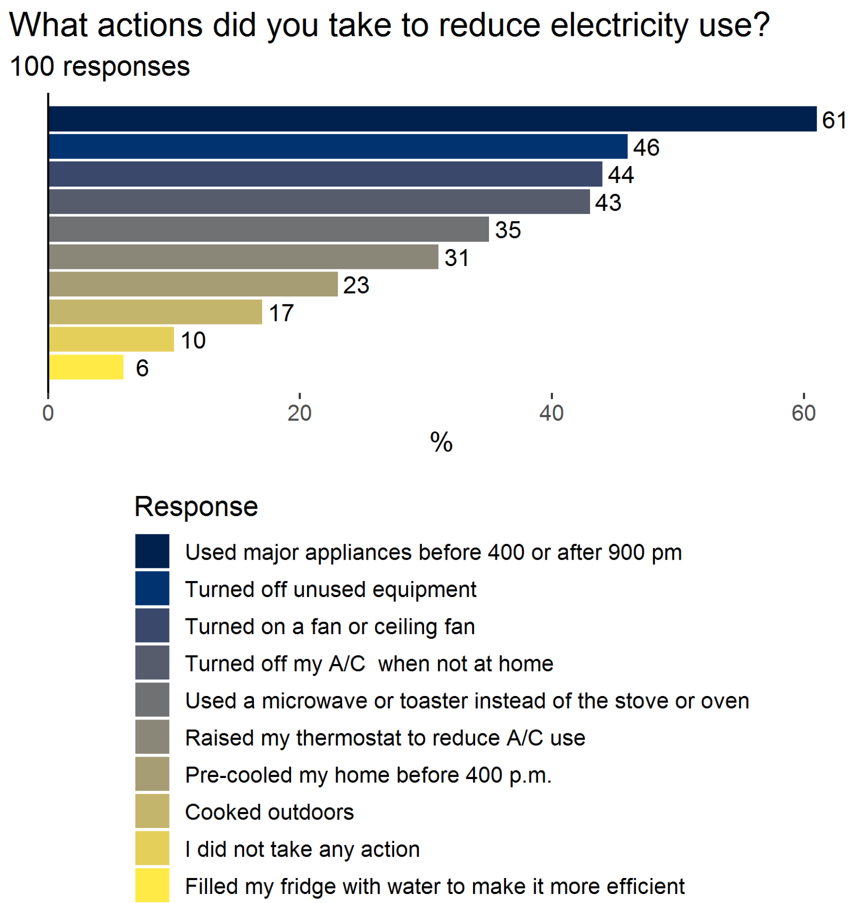
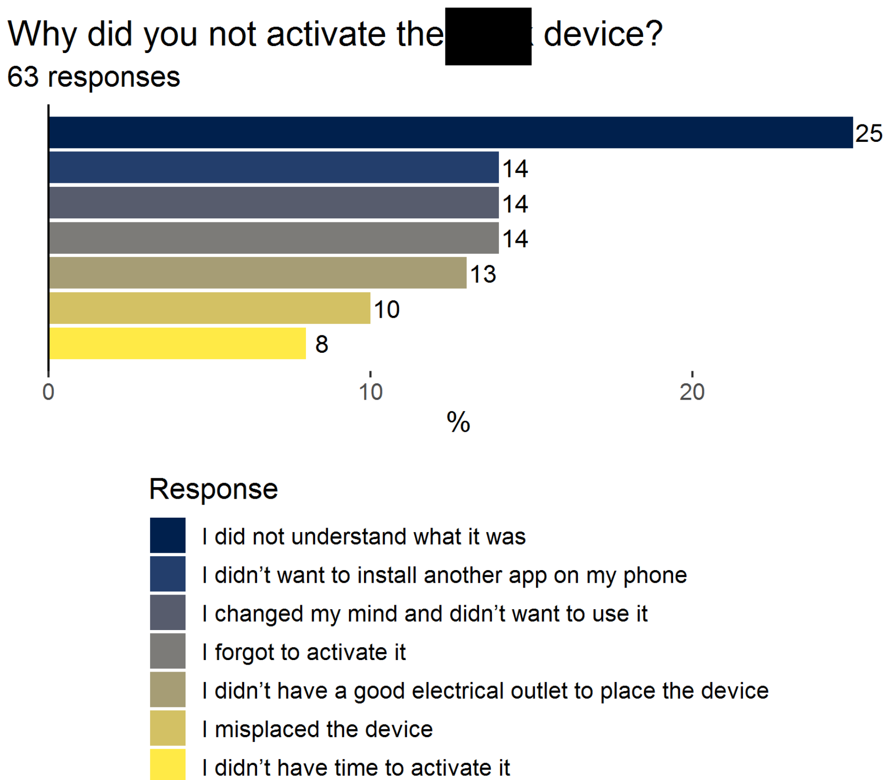


Figure A - 2: Actions Taken to Reduce Use



Survey Results for Intent to Treat Group

Figure A - 3: Reasons for Failing to Activate



Survey Results All Groups

Figure A - 4: Thermostat Type

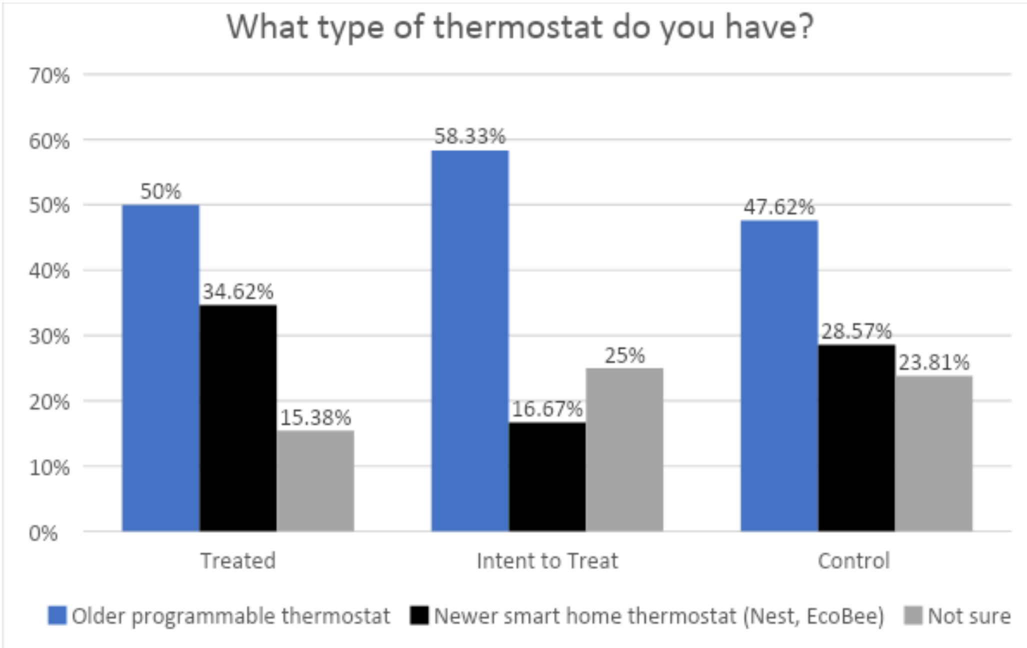


Figure A - 5: Knowledge of Blackouts

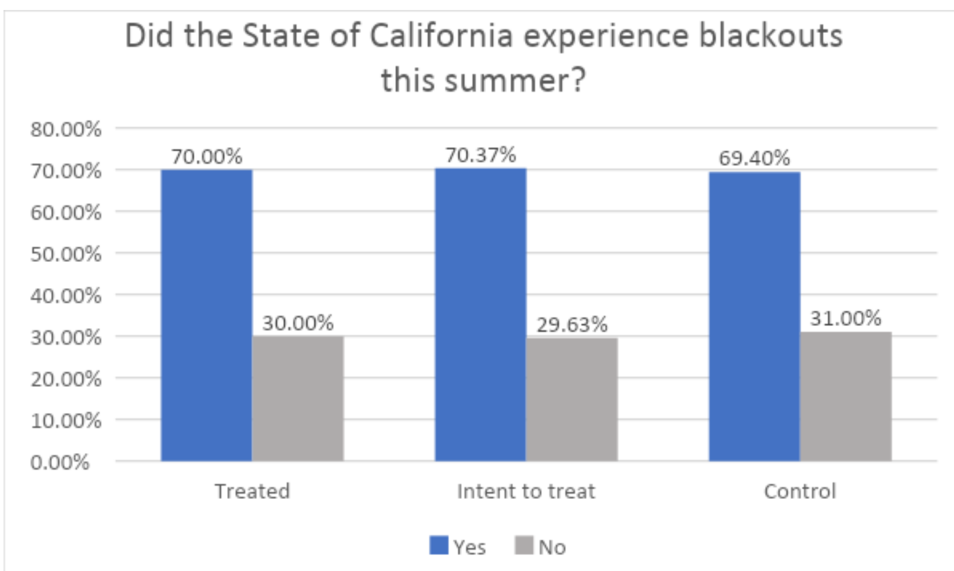
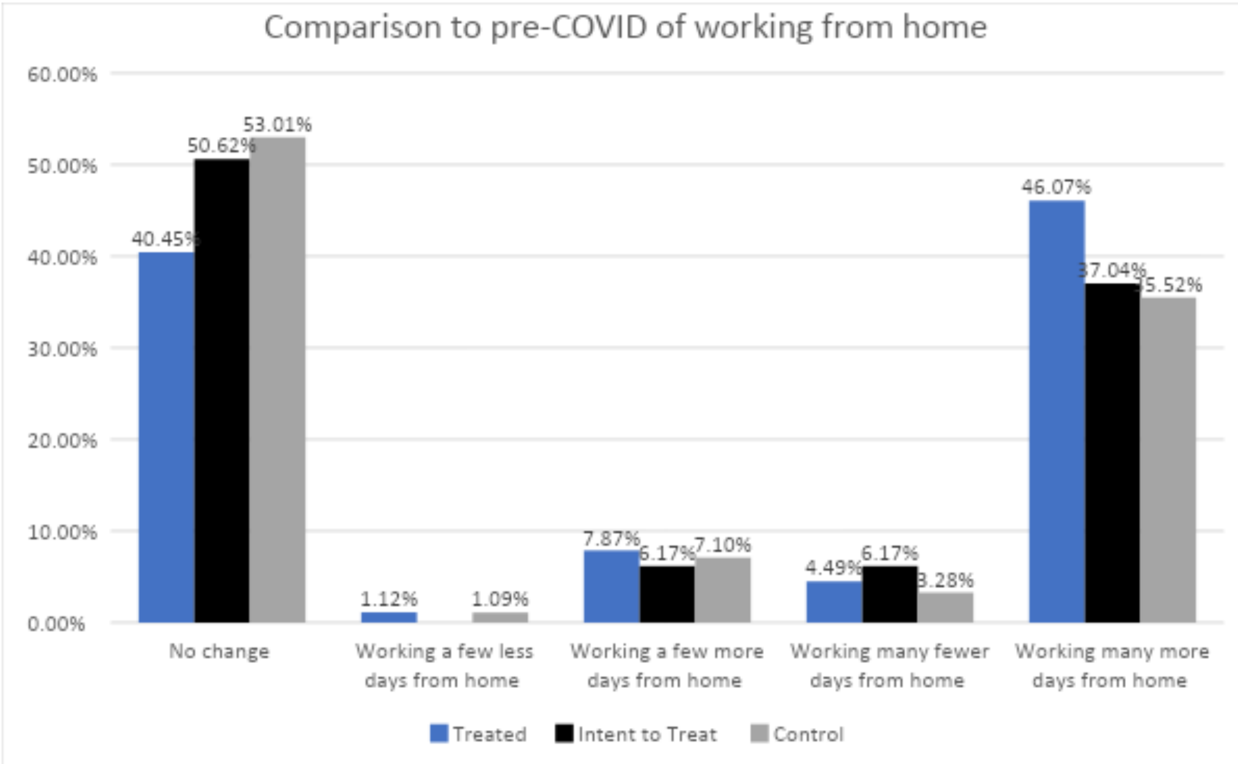


Figure A - 6: Working from Home Comparison



Challenges Among LMI Customers

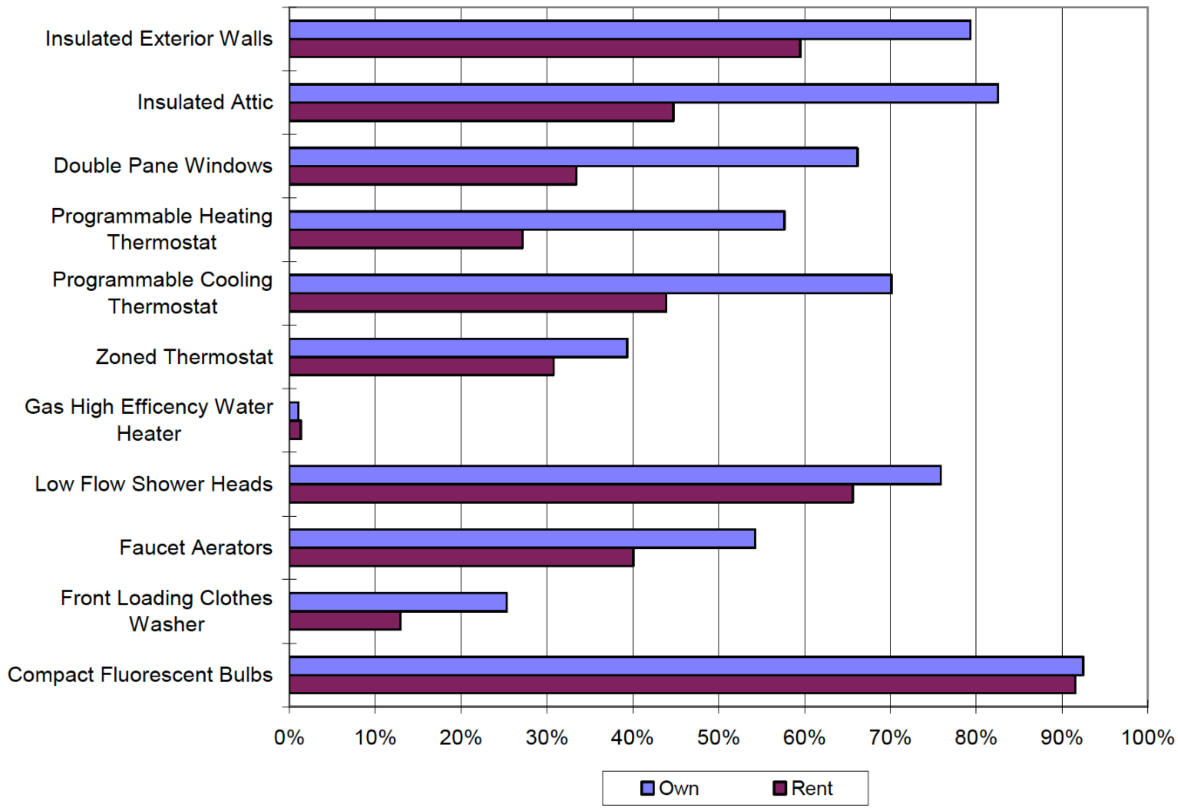
Common assumptions behind TOU rates are that they empower customers, send price signals to reduce demand when energy usage is carbon intensive, and are better reflective of the changes in external costs of energy generation and distribution throughout the day (Trabish 2019). For low to moderate income (LMI) customers, however, some of the common adaptations for reducing TOU rate impacts and keeping energy bills low can be cost prohibitive or counter to health and comfort.

A key measure suggested by the Energy Upgrade California effort by IOUs to conduct community outreach on TOU rate introduction is to precool or prewarm homes during off peak hours (Energy Upgrade California 2020). This entails cooling or heating homes beyond the normal threshold and allowing the building envelope to maintain a comfortable temperature. This can be counterproductive for LMI customers who tend to be renters at high rates, and live in older, less insulated homes, and whose landlords have little to no incentive to invest in energy efficiency upgrades while their tenants bear the cost of the energy bill (Nelson and Gebbia 2018). In these energy-burdened homes, energy expenditures can consume anywhere between 6 percent and 10 percent of household income (Drehobl, Ross and Ayala 2020), forcing difficult decisions about remaining household expenses, such as food and education as household budgets are squeezed (Nelson and Gebbia 2018). Additional research has found that renters have 27 percent less attic insulation than homeowners, which compromises the efficacy of building envelopes to accommodate pre-cooling or pre-heating efforts (Nelson and Gebbia 2018). Energy efficiency improvements like insulation, smart thermostats, and new appliances are also typically not within renters' control; these decisions are made by the property owners. Figure ES-1 shows the much lower penetration of energy efficient measures for renters versus owner-occupied households.

Furthermore, LMI customers that are also renters may not, for a multitude of reasons, wish to request energy efficiency upgrades from their landlord or property manager (Falls and Salgado 2021). This can stem from something as simple as avoiding confrontation with landlords, to not seeking improvements that will increase property value and therefore rental prices (Im, et al. 2017).

Proactively adjusting climate control also requires someone to be in the home if temperatures need to be adjusted manually, or the use of a smart thermostat or programmable thermostat for setback temperatures, an additional requirement that can pose a barrier to LMI customers. Customers are also often encouraged to purchase smart thermostats, either through messaging or rebate mechanisms. These are primarily found in higher income households making over $100,000 per year, and due to the complexity and cost of installation have little to no market penetration in LMI households, especially in those households that are renters (PWC 2017). Assuming that these and other energy efficiency measures are readily accessible for LMI customers is unrealistic, given high capital costs (Trabish 2019) and low adoption rates in rental housing.

Figure A - 7: Energy Efficiency Measures by Ownership, Source: (Palmgren, et al. 2010)



Source*: 2010 California Residential Appliance Saturation Survey*

Additional social factors that can pose challenges for subsets of LMI customers including language barriers and customers that work multiple jobs, which are common characteristics in LMI households (Brown 2020). Language barriers and non-English fluency can make messaging difficult to convey and challenge resident understanding of language around programs and changing energy bills. Vulnerable populations need specific, targeted messaging, including BIPOC communities and fixed-income senior citizens (Brown 2020). Household characteristics such as having multiple jobs can pose a challenge for behavioral changes and these circumstances require their own set of solutions and communications strategies for equitable implementation. When residents work during the day and during the evening, they are not home to take advantage of non-peak hours for energy intensive household chores or manually adjust their thermostat (Brown 2020) (Falls and Salgado 2021). These same factors can impact low wage workers that work night shifts – energy usage patterns will be substantially different, and communications such as phone calls and texts may go unanswered in the evenings while people sleep (Tappero 2011).

Implementation of TOU rates cannot make assumptions about affordability and ease of installation of thermostats, energy efficient appliances, and additional weatherization measures, given the existing financial constraints of LMI customers. If not combined with education, access to energy efficiency measures, and targeted communication, TOU rate implementation could pose a costly shift for some of California's already energy-burdened households. As management of the energy grid and utilities shifts away from a unidirectional, linear service delivery structure and into a multi-directional service model, the customer has to go from being a passive consumer to an active participant in load management and their own energy usage (Rocky Mountain Institute 2017). Pilot programs have demonstrated that LMI households have an equal interest in engaging as non-LMI customers and that LMI households stand to benefit financially from TOU rate implementation, given the right tools and conditions (Falls and Salgado 2021), (Sergici, et al. 2020).

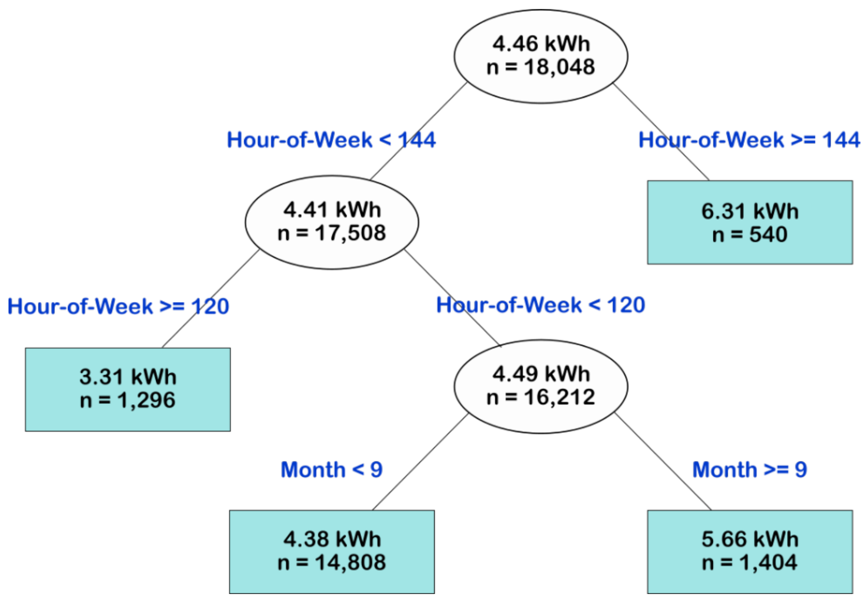
A clear thread throughout conversations around equitable implementation of TOU rates has emerged across the nation (Trabish 2019). For energy customers, and especially LMI customers, the key is to market and educate well in advance of TOU rate implementation. Energy bills are not user-friendly documents, and the added complexity of variable rates throughout the day can result in customers unknowingly running up prohibitive monthly expenses. In order to enhance understanding and equitable policy adoption, customers must have cost-effective measures that enhance transparency quickly and surmount language barriers. Widespread adoption of integrated demand side management devices, such as the TOU Energy Display IHD, have the potential to help TOU customers understand and respond in real time to price changes. The TOU Energy Display IHD overcomes a multitude of complex communication barriers and simplifies a very complex concept into a simple, visual cue.

Gradient Boost Machine

The Gradient Boost Machine (GBM) is a machine learning model that predicts consumption based on time-of-week, month and temperature. The fundamental component of the GBM is the decision-tree model. The GBM combines predictions from multiple decision trees to generate a single prediction for consumption during a given time interval.

In simple terms, a tree model predicts consumption based on what bin an hour or day falls into, where bins are determined by a series of conditions on the explanatory variables (time-of-week, month, temperature). These conditions can be expressed as a sequence of splits, forming a decision tree, as illustrated on Figure A.8.

Figure A - 8: Tree Example



The tree begins at the top node, reporting average consumption (4.46 kWh) across all hours (18,048) recorded by the meter. The tree then determines the series of splits in the data that produce the greatest reduction in prediction error, and the terminal nodes in the tree contain the tree's final predictions. For example, this tree predicts 6.3 kWh hourly consumption for any hour in the last day of the week ("Hour of Week > 144"), and it predicts 5.66 kWh for the first five days of the week in months September to December.

The GBM relies on predictions from an *ensemble* of tree models $T_0, T_1 \ldots T_J$. These tree models are generated using the following sequential algorithm:

1. $Initialize\ T_0$
2. $For\ j = 1\ to\ J$:
    a. $Compute\ residuals$: $r_t = c_t - T_{j-1}\ \forall\ t.$
    b. $Fit\ regression\ tree\ to\ \{r_t\}$:
    $$T_j(\Theta) = argmin_{\Theta} \sum \left(r_t - T_j(\Theta)\right)$$
    c. $Update\ T_j = T_j + T_{j-1}$
3. $Output\ \hat{c} = T_J$

The GBM requires setting some additional *hyper*-parameters including the number of trees (J), the *scale* parameter and the maximum depth of each tree. These parameters are estimated using a cross-validation procedure. Setting the correct hyper-parameters is critical to ensuring that the model does not *overfit* the data and thereby underperform when predicting out-of-sample.

The preceding is a very brief explanation of the GBM and the reader may wish to refer to Touzani et al. (2018) for a more detailed summary of the GBM and its application to NMEC. They show that the GBM offers considerable improvements in accuracy and performance compared to linear regression models.