CALIFORNIA
ENERGY COMMISSION

Energy Research and Development Division

FINAL PROJECT REPORT

Identifying Effective Demand Response Program Designs for Residential Customers

Gavin Newsom, Governor

November 2020 | CEC-500-2020-072

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Contract Number: EPC-15-073

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PREFACE

The California Energy Commission's (CEC) Energy Research and Development Division supports energy research and development programs to spur innovation in energy efficiency, renewable energy and advanced clean generation, energy-related environmental protection, energy transmission and distribution and transportation.

In 2012, the Electric Program Investment Charge (EPIC) was established by the California Public Utilities Commission to fund public investments in research to create and advance new energy solutions, foster regional innovation and bring ideas from the lab to the marketplace. The CEC and the state's three largest investor-owned utilities—Pacific Gas and Electric Company, San Diego Gas & Electric Company and Southern California Edison Company—were selected to administer the EPIC funds and advance novel technologies, tools, and strategies that provide benefits to their electric ratepayers.

The CEC is committed to ensuring public participation in its research and development programs that promote greater reliability, lower costs, and increase safety for the California electric ratepayer and include:

- Providing societal benefits.
- Reducing greenhouse gas emission in the electricity sector at the lowest possible cost.
- Supporting California's loading order to meet energy needs first with energy efficiency and demand response, next with renewable energy (distributed generation and utility scale), and finally with clean, conventional electricity supply.
- Supporting low-emission vehicles and transportation.
- Providing economic development.
- Using ratepayer funds efficiently.

Identifying Effective Demand Response Program Designs for Residential Customers is the final report for the Load Management Systems That Facilitate Participation as Demand-Side Resources - Group 2 project (Contract Number EPC-15-073) conducted by the UCLA Luskin Center for Innovation. The information from this project contributes to Energy Research and Development Division's EPIC Program.

For more information about the Energy Research and Development Division, please visit the CEC's research website (www.energy.ca.gov/research/) or contact the CEC at 916-327-1551.

ABSTRACT

Demand response encourages electricity customers to reduce their energy consumption at times of high stress on the electrical grid. Utilities notify customers during these critical energy periods, called demand response events, and then measure customer consumption relative to the California Independent System Operator's estimate of their counterfactual consumption, called a baseline. Effective demand response programs reduce the need for peak electricity generation power plants, which are often the most expensive and polluting. To date, empirical studies that evaluate the effectiveness of demand response financial and nonfinancial incentives have been limited.

This project informs residential demand response program designs. Researchers conducted a randomized control trial and analyzed existing demand response data to test the effectiveness of different program designs using two behind-the-meter customer engagement platforms.

Researchers found that demand response events are effective at reducing consumption, but reductions vary by user characteristics and other factors. "Energy engaged" customers or those with solar panels, plug-in electric vehicles, or automation devices had the greatest consumption reductions. Demand response events reduced consumption the most during the spring and summer, especially on hotter days. Offering a financial incentive for participation was critical to inducing consumption reductions, but customers did not respond strongly to changes in marginal incentives. Similarly, messaging emphasizing economic benefits was more effective than health and environmental messaging. Moreover, customers modify the magnitude of their conservation depending on their baseline level, all else equal. Finally, user engagement falls over time. A central challenge to demand response providers is not only attracting customers, but ensuring they remain active long term. Increasing the uptake of automation devices may be one way to address this challenge.

Keywords: Demand response, residential customers, time-of-use, behind-the-meter, financial incentives, nonlinear incentives, critical peak pricing, automation, customer behavior, moral suasion, conservation, consumption behavior

Please use the following citation for this report:

Gattaciecca, Julien, Kelly Trumbull, Samuel Krumholz, Kelley McKanna, and J. R. DeShazo. University of California, Los Angeles. 2020. *Identifying Effective Demand Response Program Designs for Residential Customers.* California Energy Commission. Publication Number: CEC-500-2020-072.

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EXECUTIVE SUMMARY

Introduction

Integrating renewable energy resources like solar increases the need for more grid and load flexibility. Demand response is an important way to achieve such flexibility in California, as it encourages consumers to reduce their energy consumption at times of high stress on the grid.

Demand response events occur when customers are notified to reduce their consumption during critical energy periods. Many demand response providers use behind-the-meter engagement platforms, such as smartphone applications, where customers receive notifications informing them when to reduce consumption. These notifications can also be accompanied by different types of messages and financial incentives, which reward users for reducing their electricity consumption during demand response events.

Project Purpose

The Luskin Center for Innovation at the University of California, Los Angeles (UCLA) partnered with two demand response providers to test the effectiveness of several program designs. To date, empirical studies that evaluate the effectiveness of demand response incentives and, especially, interactions between financial and nonfinancial incentives have been limited.

Specifically, this research aims to identify the most effective demand response messaging content, format, and timing, with an emphasis on identifying differential response by the socioeconomic and energy-use characteristics of targeted populations. This analysis is intended to inform decision makers and help managers of residential demand response programs maximize participation and energy consumption reductions.

Project Approach

This study tested the effectiveness of innovative design strategies for residential demand response programs using behind-the-meter customer engagement platforms. Demand response programs are used to inform and encourage residential electricity customers to reduce or shift their energy consumption during demand response events. This study focuses on four main goals to advance understanding of demand response intervention design. These include (1) evaluating the effectiveness of different timing and format of messages, including economic benefits messages and environmental messages; (2) assessing different fixed and nonlinear financial incentive mechanisms; (3) assessing current baseline methodology and the effect of different baselines level on customers' electricity conservation; (4) anticipating the effectiveness of time of use rates based on the project team's research findings.

These alternative demand response program designs were tested on subsets of customers within Pacific Gas and Electric (PG&E), Southern California Edison (SCE), and San Diego Gas & Electric (SDG&E) service territories. These tests include identifying how customers' responses to alternative demand response strategies differ, depending on their socioeconomic and demographic characteristics.

Researchers partnered with two demand response providers, Chai Energy and OhmConnect, Inc., to test research questions appropriate for the different capabilities of each of the two behind-the-meter customer engagement platforms.

Chai Energy provides users with energy analytics through households' smartphones, alerts users to critical energy periods, and encourages them to shift or reduce consumption. During the first part of this study, researchers performed a randomized control trial to test the effectiveness of demand response program incentives and messages through Chai Energy's smartphone application. Specifically, this analysis included testing the effects of nonfinancial and financial incentives (ranging from $0.05 to $5 per kWh saved) and the effects of cost savings versus environmental messages.

The second half of this study relied on OhmConnect, an internet-based demand response provider with more than 100,000 users in California. OhmConnect challenges them to reduce consumption during critical energy periods called #OhmHours, measures their actual consumption against a calculated historical baseline, and rewards them for the difference.

Researchers used energy consumption data from these customers to perform a variety of nonexperimental statistical analyses. These analyses examined different elements of demand response program designs. Specifically, researchers evaluated (1) streak and status bonus programs that reward users for consistent behavior, (2) the accuracy of user baseline estimations and customer responsiveness to baseline levels, and (3) the ways consumption reductions varied by demographics, which can help inform understanding of the effect of time-of use rates.

Project Results

This study is not a performance evaluation of effective demand response providers. Both OhmConnect and Chai Energy are registered non-utility demand response providers with the California Public Utilities Commission (CPUC). This UCLA analysis is distinct from any performance evaluations or methods required by state agencies like the CPUC or California Energy Commission (CEC) for demand response providers.

Rather, this study aims to further understand the behavioral components of energy conservation. Because demand response is needed when the marginal price of electricity is high, researchers examined if customers respond to marginal price to inform how demand response providers can make it more salient to users. For example, researchers tested responsiveness to changes in marginal prices through OhmConnect's streak and status programs and to different financial incentive levels with Chai Energy.

Effect of Demand Response on Energy Conservation

Researchers found that demand response events are effective at reducing consumption, but reductions vary by user characteristics and other factors. This analysis investigated the differences in the propensity of customers from different demographic and energy-use segments to reduce consumption during critical energy periods. It is important to highlight that the consumption reductions estimated in these analyses are different from those traditionally used to evaluate demand response programs, which calculate savings beneath an California Independent System Operator (California ISO)-estimated baseline, described further in Chapter 4. In this analysis, researchers do not use that baseline because the accuracy of the baseline differs across groups and would lead to bias in the project team's estimations of differing responsiveness. With that caveat in mind**,** researchers estimate the effect of a demand response event on consumption for different types of users. The effect is defined as the amount a user consumes beneath what he or she would have consumed in the absence of the demand response event.

Across all users, researchers found that on average throughout the year, users reduced their energy consumption by 0.15 kilowatt-hours (kWh), or 18 percent, during an OhmConnect demand response event relative to what they would have consumed without an event. Users reduced consumption by similar amounts even when they received demand response events two days in a row; this result suggests that individuals are not merely shifting usage to the next day when an event occurs. Furthermore, users do not increase their consumption in the hours or days before or after a demand response event. This finding provides additional evidence that users are conserving energy in response to demand response events rather than shifting their energy consumption to other times. More importantly, users have larger reductions in energy consumption during demand response events when they first join the demand event platform. Customers reduce energy consumption by 22 percent during their first 20 events relative to 17 percent after. This finding suggests that user engagement falls over time.

Although users reduced consumption during demand response events throughout the year, the greatest consumption reductions occurred in the spring and summer, and especially on hotter days. This conclusion suggests that it is easier for customers to reduce consumption when they have a greater capacity to do so, that is, when they can turn off their air conditioners. On average, customers reduced electricity consumption during demand response events by 21 percent on days hotter than 90 degrees Fahrenheit and only 15 percent on cooler days. Similarly, energy conservation during demand response events is about 1.8 times and 3.5 times greater in absolute terms during spring and summer, respectively, compared to the rest of the year. The time of day that a demand response event began was less important, however, than the time of year. Researchers found that the effectiveness of demand response event timing may be context-specific, and may rely more on messaging or financial incentive than on the time.

Moreover, researchers found customer responsiveness varied by user characteristics. Engaged energy users, or those with solar photovoltaic (PV) panels, plug-in electric vehicles (PEVs), or automation devices (such as smart home, smart thermostats, or smart appliances) or a combination are more likely to reduce consumption during #OhmHours. Specifically, PEV owners reduce consumption 2.5 times more than non-PEV owners, while users who have ever adopted automation reduce three times more relative to never-adopters. Users who have automation devices used 47 percent less energy during a demand response event relative to 13 percent reductions for those who do not. This finding suggests that energy engaged users could be targeted for more focused demand response programs.

There were relatively minor proportional differences among most demographic subgroups. California Alternative Rates for Energy (CARE) customers proportionally conserved less than non-CARE customers, although this difference was driven largely by differences in solar PV, PEV, and automation ownership between those two customer classes. Similarly, when looking at non-energy-engaged customers, time-of-use users reduce less than users on other tariffs. However, these results are inverted when looking at energy-engaged customers. Favoring energy technologies such as automation seems essential to maintain high-demand response efficiency, even as California transitions more customers to time-of-use pricing.

Baseline

Demand response providers typically reward users during a demand response event based on their conservation relative to an assigned baseline. The baseline represents a user's energy consumption in the absence of a demand response event. Baselines are set based on the average of consumption in the same hour of the demand event during the previous 10 non-event, nonholiday weekdays. With OhmConnect, customers receive information about their baseline when they are notified of an event, and how this baseline compares to their electricity consumption for the previous week.

Customers modify the magnitude of their conservation depending on their baseline level. Customers reduce their energy consumption more when their baseline is set lower, all other factors held constant. Customer responsiveness to baseline changes varied by demographics. Only customers without automation respond to changes in baseline, likely because behavioral responses require active engagement by customers. Furthermore, customers in low-income zip codes responded the most to changes in baseline both proportionally and in absolute terms. These findings suggest that in information environments such as OhmConnect where a large emphasis is placed on meeting a goal, the level at which the goal is set may be a useful lever for changing conservation behavior.

Streak and Status Programs

This analysis assesses how nonlinear pricing strategies can influence consumers' willingness to reduce energy consumption during peak periods. OhmConnect employs a novel incentive structure to motivate consumers to conserve electricity during critical energy events (#OhmHours). Here, researchers focused on two of OhmConnect's programs offering nonlinear incentives: streak and status. Individuals build "streaks" by consuming less than their baseline in consecutive demand response events. OhmConnect participants can earn different statuses (silver, gold, or platinum) based on the percentage of energy saved relative to the baseline over their past 10 #OhmHours.

Researchers did not find that maintaining a streak or status (and the corresponding financial bonuses) induced greater energy conservation than missing a streak or status. Researchers found no effect of extending the status or streak when compared to users who lost the status or streak, despite differences in marginal financial incentives. When looking at a user's first 20 events, researchers found that individuals who extend their streak to reduce electricity consumption more than those who lost it, but only if their streak was five events or longer. For status, researchers observed that moving from silver to gold had an effect on consumption and increased the likelihood that a user would invest in automation technology. Those effects were not seen for platinum status.

These results do not find evidence that marginal financial incentives provided by streak and status induce greater conservation behavior in the general population. This finding is consistent with the results from the Chai Energy analysis in this report and in a previous study (Gillan 2017) that found very low additional responsiveness to higher marginal rewards. However, the lack of marginal price effect does not necessarily imply that these programs are not shifting behavior. It could be that the presence of streak or status rewards induces all users to try harder, whether they have an active streak or status. To test this, researchers would need an additional experiment in which only some users had access to the streak and status programs. This experiment is outside the scope of the current study but is an important area of potential future research.

Financial Incentives and Messaging

In the experiment with Chai Energy, researchers uncover how different types of financial incentives and messaging affect consumers' willingness to reduce energy consumption during peak periods. Providing a financial incentive was more effective than not, although the size of the incentive was relatively unimportant.

As a secondary analysis, researchers found that economic benefits messaging emphasizing cost savings was the most effective framing for demand response events, with and without financial incentives. Even on hot days, which saw greater consumption reductions, the moral messages (which emphasized how health and the environment are affected) reduced consumption only by 1 percent to 2 percent compared to the economic benefits message, which reduced consumption by 6 percent.

User Engagement

Finally, user engagement falls over time. Users have larger reductions in energy consumption during demand response events when they first begin participating. Researchers found that users reduced consumption about 30 percent more during their first 20 demand response events relative to later events. Moreover, researchers found that streak length and status level decreased over time, suggesting users were less engaged over time. With Chai Energy, researchers observed high levels of customer attrition after only a few months without receiving demand response event notifications. Users are difficult to recruit in the first place. In order to participate, customers needed to provide demand response providers with access to his or her energy consumption data, through Green Button Data. The process for granting a third-party access to these data was arduous for customers, which resulted in only 24 percent of registered customers successfully providing data. A central challenge of all demand response providers is how to attract customers and ensure that they remain active conservers in the long term. OhmConnect's strategy of emphasizing automation may be an effective way to accomplish this goal.

Technology and Knowledge Transfer – Advancing the Research to Market

This research will help demand response providers to design cost efficient and long lasting demand response programs. This report informs on effective message content, incentives and baseline levels, and the hours at which demand response programs maximize participation and energy reductions from residential customers. This report also provides some policy recommendations, which could be used by a wide variety of stakeholders.

The results and lessons learned from this research are available to the public through communication materials developed by the research team. The research team is preparing to publish this research in academic journals to contribute to the existing demand response literature. Academic journals are a good avenue to disseminate research to other universities and researchers and can result in the identification of opportunities to develop future research. The research team will also disseminate the research through conferences and workshops, as appropriate. Such forums are ways to reach a variety of stakeholders, including key demand response industry players such as representatives from the investor-owned utilities, publicly owned utilities, community choice aggregators, regulatory agencies, and private demand response providers.

Benefits to California

Effective demand response programs result in a variety of economic, health, and environmental benefits for Californians. Demand response is an important way to achieve grid and load flexibility in California, as it encourages consumers to reduce their energy consumption at times of high stress on the grid. In addition, demand response reduces electricity consumption during critical energy periods, when electricity is often generated by the most expensive and polluting power plants. The demand response programs studied over the two years of this research helped electricity customer participants reduce their bills by an estimated total of $34,700, or about $15 per customer. Moreover, a large amount of incentive funds were paid to participating customers. Because demand response happens during critical times, it also likely provides nonparticipants with many other benefits, including reduced greenhouse gas and criteria pollutant emissions, which have environmental and health benefits.

The results of this study can be used to design more effective demand response programs. As this research assists investor-owned utilities (IOUs) and demand response providers in understanding the effectiveness of alternative demand respond messages and strategies across different households, this study also specifically benefits Californian IOU ratepayers with respect to the Electric Program Investment Charge goals of providing greater reliability, lower costs, and increased safety. Furthermore, effective demand response programs directly benefit IOUs' residential customers, the CPUC, CEC, California ISO, California Legislature, and other entities working to modernize California's electricity grid and related infrastructure.

CHAPTER 1: Introduction

Demand response encourages electricity customers to reduce their energy consumption at times of high stress on the electrical grid. Customers are notified during these critical peak periods, called demand response events, and then their consumption is measured relative to their estimated counterfactual consumption, called a baseline. These notifications can also be accompanied by different types of messages and financial incentives, which reward users for reducing their electricity consumption during demand response events. Integrating renewable energy resources increases the need for more flexible demand. Inducing residential consumers to conserve energy during peak periods is a growing component of California's overall electricity demand management strategy.

To date, empirical studies that evaluate the effectiveness of demand response incentives have been limited. Critical peak prices have been shown to work among various populations across the United States.[1,2,3] The effect of these peak time prices appears to be greatest among households in hotter climates and those that possess smart thermostats and other smart appliances.[4] Other studies have compared the use of different incentive structures[5] and the interaction of real-time electricity consumption feedback and peak prices[6] and compared financial incentives with nonfinancial appeals. However, the wealth of new work demonstrating

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[1] Faruqui, Ahmad, and Sanem Sergici. 2011. "Dynamic Pricing of Electricity in the Mid-Atlantic Region: Econometric Results From the Baltimore Gas and Electric Company Experiment." *Journal of Regulatory Economics* 40.1: 82-109.

[2] Faruqui, Ahmad, Sanem Sergici, and Lamine Akaba. 2013. "Dynamic Pricing of Electricity for Residential Customers: The Evidence From Michigan." *Energy Efficiency* 6.3: 571-584.

[3] Faruqui, Ahmad, Sanem Sergici, and Lamine Akaba. 2014. "The Impact of Dynamic Pricing on Residential and Small Commercial and Industrial Usage: New Experimental Evidence from Connecticut." *The Energy Journal* 35.1: 137-160.

[4] Faruqui, Ahmad, and Sanem Sergici. 2013. "Arcturus: International Evidence on Dynamic Pricing." *The Electricity Journal* 26.7: 55-65

[5] Wolak, Frank A. 2011. "Do Residential Customers Respond to Hourly Prices? Evidence from a Dynamic Pricing Experiment." *The American Economic Review:* 83-87.

[6] Jessoe, Katrina, and David Rapson. 2014. "Knowledge Is (Less) Power: Experimental Evidence from Residential Energy Use." *American Economic Review* 104.4: 1417-38

the power of nonfinancial incentives[7,8,9] and the interactions between information and prices[10,11] suggest that there is far more work to be done to identify the most effective approaches to encouraging load shifting among different populations.

This research is intended to identify the most effective demand response message content, format, and timing, depending on the socioeconomic characteristics of the targeted population. This analysis is intended to inform decision makers and help demand response program managers maximize participation and energy consumption reductions for residential customers.

As California's electricity grid becomes more reliant on renewable energy, there is expected to be more intermittency in electricity supply. In order for electricity system operators to maintain reliability, utilities will have to undertake different demand management strategies to encourage greater consumption during periods when intermittency results in misalignment between electricity supply and demand.

This information is highly policy-relevant for two reasons. First, it will inform whether demand response events can be a cost-effective tool within California's greater demand management strategy. Second, even outside demand response events, better understanding of what affects customers' willingness to conserve and how this relationship varies across customer types can allow the creation of a more effective demand strategy. This understanding provides useful evidence for circumstances and customers in which price-based strategies are more effective than nonmarket strategies (such as moral messaging) and vice-versa.

1.1 Overview

This study tested the effectiveness of innovative design strategies, also known as "treatments," for residential demand response programs using behind-the-meter customer engagement platforms. This study focuses on four main goals to advance understanding of demand response intervention design. These include (1) evaluating the effectiveness of different timing and format of messages, including economic benefits messages and environmental messages; (2) assessing different fixed and nonlinear financial incentive mechanisms; (3) assessing current baseline methodology and the effect of different baselines level on customers' electricity conservation; and (4) anticipating the effectiveness of TOU based on the project team's research findings.

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[7] Allcott, Hunt. 2011. "Social Norms and Energy Conservation." *Journal of Public Economics* 95.9: 1082-1095.

[8] Asensio, Omar I., and Magali A. Delmas. 2015. "Nonprice Incentives and Energy Conservation." *Proceedings of the National Academy of Sciences* 112.6: E510-E515

[9] Harding, Matthew, and Alice Hsiaw. 2014. "Goal Setting and Energy Conservation." *Journal of Economic Behavior & Organization* 107: 209-227.

[10] Kahn, M. E., and F. A. Wolak. 2013. *Using Information to Improve the Effectiveness of Nonlinear Pricing: Evidence from a Field Experiment*. California Air Resources Board, Research Division.

[11] Gilbert, Ben, and Joshua Graff Zivin. 2014. "Dynamic Salience with Intermittent Billing: Evidence From Smart Electricity Meters." *Journal of Economic Behavior & Organization* 107: 176-190.

These alternative demand response program designs are tested on subsets of customers within Pacific Gas and Electric, Southern California Edison, and San Diego Gas & Electric service territories. These tests include identifying how customers' responses to alternative demand response strategies differ, depending on their socioeconomic, demographic, and geographic characteristics.

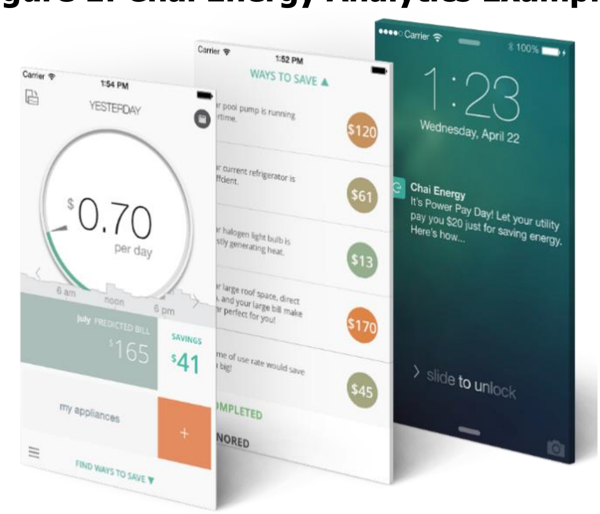
This study used behind-the-meter customer engagement platforms from two demand response providers, Chai Energy and OhmConnect, to test the research questions made possible by the different capabilities of each platform.

1.1.1 Chai Energy

The first half of this study, which took place from August 28, 2017, to October 31, 2017, used a behind-the-meter customer engagement platform developed by Chai Energy. Chai Energy provides a free smartphone application for Android and iOS smartphones. This application had capabilities that allowed researchers to perform a randomized control trial to test the effectiveness of different demand response program incentives and messages. Specifically, this analysis included testing the effects of nonfinancial and financial incentives (ranging from $0.05 to $5.00 per kWh saved) and positive and negative message framing. This analysis also assesses how these effects differ across customers' socioeconomic, demographic, and geographic characteristics.

Chai Energy's customer engagement platform uses smart meter data to provide households with energy analytics through their smartphones, illustrated in Figure 1. There are two levels of service: the Chai Lite energy analytic service is based on 15-minute interval data, and the Chai Pro energy analytic service is based on continuous and appliance-disaggregated data. Customers receiving either service level receive energy analytical insights aimed at increasing awareness of consumption habits and recommendations of ways to save. These insights include energy consumption visualizations, forecasted monthly bills based on rate structure and consumption trends, and periodic emails with cost minimizing advice tailored to specific customer contexts. Customers with Chai Pro also receive appliance-specific information that suggests how to save energy.

Figure 1: Chai Energy Analytics Example



Source: Chai Energy

Chai Energy users have implemented the following methods of saving energy during demand response events:

- Increasing the thermostat setting to a higher temperature or turning off the AC system
- Turning off or unplugging electronics, appliances, lights, or pool pumps or a combination
- Delaying doing laundry or charging electric vehicle.

1.1.2 OhmConnect, Inc.

The second half of this study relied on OhmConnect, Inc., a large San Francisco-based demand response provider with more than 100,000 users in California. OhmConnect encourages users to reduce energy consumption with the goal of reducing residential user demand on the grid using a behind-the-meter engagement platform. OhmConnect provides financial incentives for users of its service to reduce electricity consumption during critical energy periods, called #OhmHours.

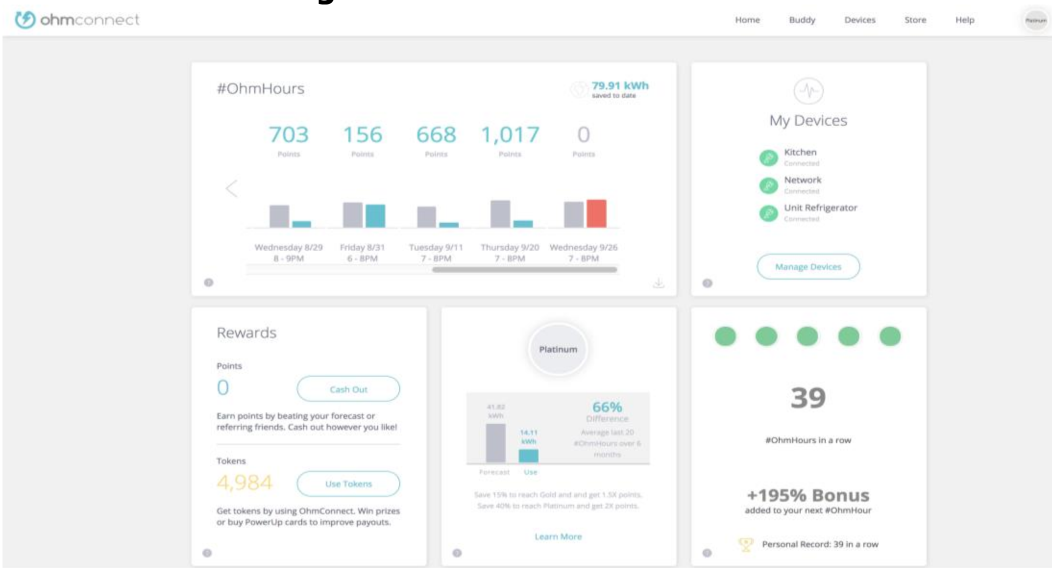
Through OhmConnect, researchers tested several questions made possible by OhmConnect's large user base and its use of nonlinear incentive programs, which provide users with increasing incentives for consistent behavior. Using detailed electricity consumption, event performance, sociodemographic, and geographic data on a random sample of 20,000 users from OhmConnect, the second half of this study focused on three primary research questions examining how to encourage increased participation and improve the cost-effectiveness of demand events. Specifically, researchers used regression discontinuity design[12] methods to test (1) how users responded to demand response program designs like streaks and statuses, (2) How important the baseline calculation is for consumption, and (3) how consumption reductions varied by demographics.

Figure 2 shows the OhmConnect engagement online platform, which is used by residential electricity customers to receive information about demand response events. During #OhmHours, users earn points for each kWh reduced relative to what their estimated consumption would have been without a demand response event, known as a baseline. Users can cash out points (on PayPal, Amazon, Target, and the OhmConnect store), donate points to a charity, or send them to another OhmConnect user at any time. Users can also use their points to purchase items at the OhmConnect store, including automation devices that can be used during #OhmHours such as smart thermostats or smart appliances.

OhmConnect users also can receive engagement bonuses. Examples include payments for reaching certain levels within the platform, responding proactively to others on forums, connecting additional devices for automation, and referring others. OhmConnect works to keep users engaged with the platform to reduce their energy consumption regularly, including by using gamified features, such as streaks and status levels.

[12] Regression discontinuity design allows researchers to non-experimentally test differences between groups that fall above and below a threshold.

Figure 2: OhmConnect Platform



Source: OhmConnect, Inc.

During #OhmHours, users receive points by reducing energy consumption through 'behavioral' or 'automated' responses. Based on a dispatch signal, OhmConnect dispatches users either via behavioral notifications or device automation or both. 'Behavioral' responses are when users take actions in response to #OhmHours by turning off lights, waiting to do laundry until after the #OhmHour event, or any other direct, energy-saving activity.

OhmConnect users can also automate their participation by using their smart home, smart appliances, or smart thermostats. Users that "connect" their devices to the OhmConnect platform allow OhmConnect to turn off or change the temperature level of the thermostat during #OhmHours. Across all OhmConnect users, more than 30,000 smart devices (smart plugs, smart thermostats, and smart appliances) are turned off during each energy-saving event and turned back on when the #OhmHour is over. OhmConnect observes that users with automation devices reduce their energy usage 100-300 percent more than users without devices. In addition, users with automation devices typically continue to reduce electricity consumption during #OhmHours over time for longer than users that do not connect devices. OhmConnect notes that device saturation has increased among OhmConnect users over time, and its users adopt additional devices over time.

CHAPTER 2: Project Approach

This study used behind-the-meter customer engagement platforms from two demand response providers: OhmConnect, Inc. and Chai Energy. These platforms allowed researchers to test two sets of research questions made possible by the different capabilities of each platform. OhmConnect's large user base and multiple incentive designs were used for most of the nonexperimental analyses, and Chai Energy's smartphone application has capabilities that allowed researchers to perform a randomized control trial. To conduct this study, a sufficient number of customers needed to be recruited to each customer engagement platform. These customers needed to be representative of different household characteristics – including income, household structure, climate zone, and utility[13] – to study the effect of different demand response strategies across California. This section describes the methods used to recruit users. For information on how data were gathered from these users and transferred to researchers to be used in the analysis, see Appendix A.

2.1 OhmConnect Engagement Platform

2.1.1 Study Participant Recruitment for OhmConnect

To conduct the identified analyses identified in this report, the research team needed access to energy consumption data for a large sample of users. OhmConnect provided the UCLA team with detailed data on energy consumption, event performance, and sociodemographic and geographic characteristics for 20,000 OhmConnect users. All analyses were carried out nonexperimentally on already-performed #OhmHours using nonpersonally identifiable information (non-PII) energy-related information for OhmConnect users across California. This section describes OhmConnect's strategies for user acquisition.[14]

User acquisition refers to getting users to sign up for the OhmConnect service. Demand response programs naturally have greater potential to reduce energy consumption during demand response events with more participants. Moreover, OhmConnect user acquisition ensured UCLA has adequate data to perform analysis on demand response behavioral patterns and general engagement. The sample of customers used in this study were recruited by OhmConnect using three user acquisition methods related to paid channels: social media campaigns, third-party paid leads, and, direct mail marketing.

Social media campaigns: Social media forums allow companies to buy advertising campaigns so that their marketing targets a specific demographic. Specifically, OhmConnect used

[13] Customers were from each of the three major investor-owned utility (IOU) territories: Pacific Gas and Electric, Southern California Edison, and San Diego Gas & Electric.

[14] The user acquisition strategies discussed in this memo are tailored specifically to this study. Therefore, these strategies are independent of OhmConnect's business and consequently not reflective of how OhmConnect scales the number of its users. Moreover, the results highlighted should not be used as reference points for the OhmConnect, Inc. business.

Facebook and Nextdoor, a community-based email newsletter and online posting network. The Facebook advertisements explained that participants could get paid for saving energy while helping the environment, while the Nextdoor ads emphasized earning money.

Third-party paid leads: OhmConnect uses third-party marketing organizations to generate paid customer leads, which target promising customers. Paid leads help identify potential users via social media tools, and the marketing service provides data analytics to help focus advertising campaign efforts in channels that have higher user acquisition rates, making recruitment more cost-effective. These ads focused predominantly on the financial aspect of OhmConnect and targeted potential new users interested in ways to earn money or to become more financially savvy.

Direct mail marketing: OhmConnect also acquired users using coupon mailers. One example using this method used the Valpak coupon book. This coupon book contains a variety of coupons from many different companies and is mailed directly to people's homes based on a propriety list curated by Valpak. OhmConnect described its service within the coupon. Most coupons were combined with other financial incentives, such as a $20 gift card to Target upon signup. The "coupon" encouraged IOU users to use the URL to sign up for OhmConnect.

Based on overall cost of acquisition, social media was the most expensive user acquisition method, followed by mail marketing. Third-party paid leads were the least expensive. The average cost of recruitment by customer for each of these methods is summarized in Table 1.

Table 1: OhmConnect Costs of Acquisition

Method of Recruitment	Cost per Customer
Facebook	$89
Nextdoor	$34
Direct Mail Marketing	$15
Third-party Paid Leads	$5

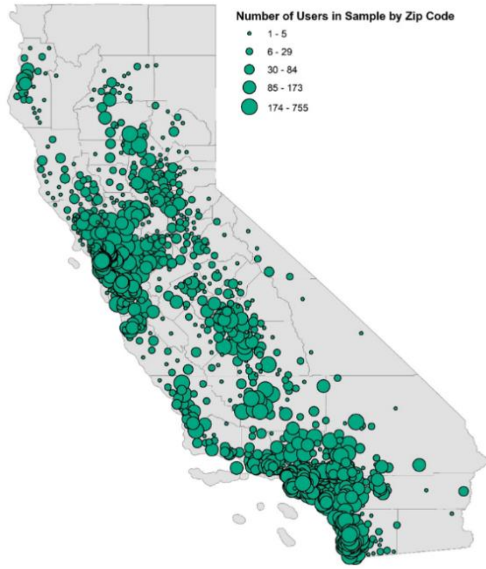
Source: OhmConnect, Inc.

2.1.2 Study Participant Demographics for OhmConnect Sample

In this study, UCLA used a randomly drawn sample of 20,000 OhmConnect users.[15] These customers represent a variety of sociodemographic characteristics and geographic locations. Figure 3 shows the geographic distribution of OhmConnect customers across the state.

[15] The demographics and trends are for the sample of 20,000 users and not for the entire OhmConnect platform. Because these users were randomly selected, the trends should be representative of the trends in total Ohm users, but the levels will be off by some scalar factor.

Figure 3: Geographic Distribution of OhmConnect Customers



Source: UCLA Luskin Center for Innovation.

Table 2 shows the average sociodemographic characteristics of the study sample compared to the California population. To protect customer privacy, the demographics of each customer in the sample was unknown to researchers. This table, therefore, represents the average demographics based on the zip code in which each user is located.

This table summarizes five key demographic variables by the average demographics of the zip code in which the users in the sample are located: percent white, percent homeowner, median income, proportion of California Alternative Rates for Energy (CARE) customers, and percent single-family home. Among represented zip codes in the sample, the mean is 44 percent white, and 81 percent single-family home ownership, both above the California mean of 38 percent and 58 percent, respectively. The average median annual household income of represented zip codes is slightly above the California median of $67,739.

Table 2: Demographics of OhmConnect Sample

Demographic	Sample	California
Home Ownership	55%	55%
Median Income	$73,246	$67,739
Single-Family Home Share	81%	58%
Average Annual Energy Use (kWh)	5,798	7,266

Source: Sample statistics from UCLA and OhmConnect. California population statistics from United States Census Bureau and American Community Survey as of January 2019.

In the OhmConnect sample, 12 percent are CARE customers, 8 percent are on a TOU rate, 15 percent own a PEV, 8 percent have solar PV panels, and 25 percent own automation devices.[16] Solar PV customers, PEV owners, users with automation devices, and TOU customers make up a minority of the overall sample. One major goal of the analysis in this report is to observe if these "energy-engaged" customers behave differently in response to events than less-engaged customers. About 4 percent of users adopt automation devices immediately upon joining, and about 14 percent adopt automation after 18 months. Finally, there is a large variation in customers' average consumption during an event. Although mean consumption is around 1 kWh, the median is 0.74 kWh, suggesting there are outlier high-energy users. Consumption during an event also varies dramatically by season. In summer, usage is closer to 1.5 kWh per event, while in winter consumption falls to 0.5 kWh per event.

2.2 Chai Energy: Randomized Control Trial

Chai Energy's smartphone application provides participants with energy analytics and feedback that enables them to participate in demand response events. Researchers used this engagement platform to implement a multitreatment randomized control trial to identify the most effective demand response incentives and messaging for different customer classes.

2.2.1 Adaptation of Chai Energy's Platform and Implementation

For this study, Chai Energy upgraded and modified its application to support the functionalities necessary to run a randomized control trial on thousands of customers. As described in more detail in Chapter 3, each demand response event delivers different types of messages, incentives, and formatting to different groups of study participants to test the identified strategies. Chai Energy developed its smartphone application capabilities to support the delivery of different financial incentives, messaging, and messaging times depending on a study participant's assigned treatment group for this study. Chai Energy developed a system to allow alternative treatments to be distributed simultaneously and at different times to understand how the timing of messages could affect customer's behavior, depending on the study participant's assigned treatment group. Moreover, each demand response event has several event-specific push notifications at preset times. Chai Energy developed the capability of the application to send notifications to study participants at various times and for the various treatments.

Furthermore, in support of this study, the Chai Energy team incorporated the ability to distribute financial incentives to study participants, when applicable. Chai Energy also developed a researcher portal specifically for this study to allow researchers to view and export anonymized data from the different treatments and events at the study participant level. Researchers also manage and adjust the different treatments and groups through this portal.

[16] Researchers do not observe solar PV or PEV ownership directly; instead researchers must proxy for it using individuals' energy-use patterns. Researchers define a user as having solar PV if he or she ever consumed negative energy in an hour. Researchers define a user as having a PEV if his or her maximum hourly usage is at least 5 kWh greater than mean usage (representing a PEV charge).

2.2.2 Study Participant Recruitment and Attrition for Chai Energy

The project team recruited 2,989 participants for the Chai Energy study. The goal of recruitment was to have a large enough sample to (1) have sufficient power to determine with statistical significance the expected effects of each treatment group and (2) be representative of different household characteristics, including income, household structure, climate zone, and investor-owned utility (IOU) territory, to study the effect of different demand response signals across California.

Chai Energy used several strategies to recruit study participants: targeted advertisements on Facebook and Google, advertisements on multiple radio channels, and advertisements on local media: KTLA (the local television news station in Los Angeles). About 9,500 users downloaded the application on their smartphones, but only 6,100 users registered for Chai Energy during the study recruitment period between December 2016 and August 2017. The average cost of recruitment per customer who registered for Chai Energy was roughly $7, which is lower than the market benchmark.[17] However, to be enrolled in the study, each registered customer needed to provide Chai Energy with access to his or her energy consumption data, through Green Button Data. Green Button Data allows residential customers to access their 15-minute interval energy consumption information. The process for granting a third-party access to these data was arduous for customers, which resulted in only 24 percent of registered customers successfully providing data. This low registration rate increased the cost of customer recruitment to about $29 per customer. The Green Button Data presented an obstacle to Chai Energy, who lost several thousand customers when it was forced to migrate its existing customers toward the Green Button Data registration process, affecting the sample size of the study. The California Public Utilities Commission (CPUC) has since improved the process to make it simpler for customers to share their data with third parties, like demand response providers, which is discussed more in a later section.

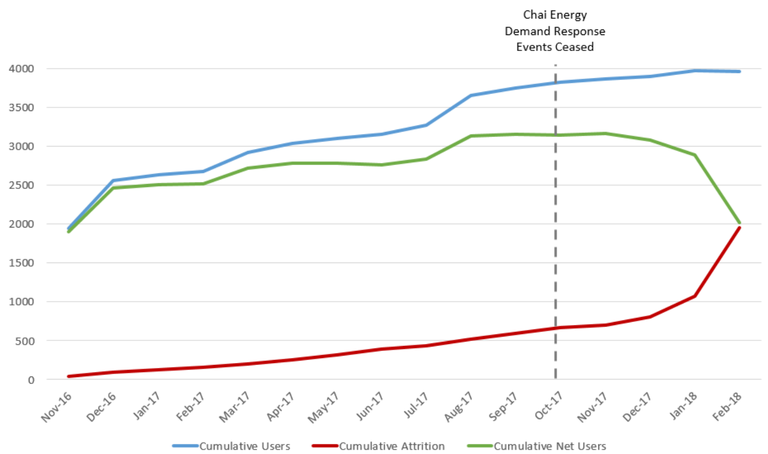
Customer recruitment faced unanticipated challenges, especially regarding the cost and method of recruitment. For example, because of the way the Facebook marketing platform is designed, Chai Energy reported that these advertisements seem to reach saturation rapidly (where people repeatedly see the same advertisement), diminishing the effectiveness of recruitment. Chai Energy used a slow to moderate rate of advertisements to address market saturation. However, this action limited daily customer recruitment. Some other marketing channels such as third-party paid leads have brought down the cost per acquisition but also potentially resulted in a biased customer sample. In terms of the success of the digital advertisements, only about a quarter of clicks resulted in registrations. While the advertisements may have been enough to pique a potential customer's interest, it may have been insufficient to motivate action.

A large number of participants were lost to attrition over the recruitment and study period because of a lack of engagement, illustrated in Figure 4. During months that researchers were administering demand response events, customer attrition averaged 2 percent per month. After demand response events ceased in October 2017, attrition increased rapidly. Forty-three

[17] The UCLA Luskin Center contacted several marketing firms and paid leads, which all reflected a cost of acquisition of around $20 per customer.

percent of users left the platform after four months of inactivity. The main reason for attrition is likely associated with a lack of demand response events during the winter.

Figure 4: Chai Energy Customer Recruitment and Attrition over Time



Source: UCLA Luskin Center for Innovation.

2.2.3 Study Participant Demographics for Chai Energy Sample

This section summarizes the demographics of the Chai Energy user sample. To protect customer privacy, identifying characteristics of participants are unavailable to researchers. Demographic and economic estimates are therefore based on a user's zip code of residence. This means that a customer is assigned the 'mean' demographics of the zip code. Table 3 shows the average demographic, economic, and energy-use characteristics for the customers in this sample compared to the California average.

The marketing campaign resulted in a sample that was over representative of white populations and under representative of Hispanic and African American populations relative to the California population as a whole. On average, the customers in the sample live in zip codes that are well-off, with median incomes above $80,000 and median home values above $500,000.

Finally, participants are heavy adopters of solar PV; about 20 percent have solar PV panels installed on their homes. This large share of solar PV customers suggests that study participants may be more energy-conscious than the average California consumer.[18] It is likely that these customers who enrolled through the general marketing campaign may be representative of those who are early adopters of other technologies. As such, some populations may need to be targeted specifically to promote future demand response or energy conservation programs. These populations may not be as accessible through general marketing campaigns, and additional resources may be needed to recruit these underrepresented populations more directly.

[18] Data on solar PV ownership were imputed by whether a user ever had an hour with less than 0 kWh energy use. All other data came from the 2012-2016 American Community Survey (ACS).

Participants recruited from the general marketing strategy could also be a reflection of those who are more likely live in zip codes with higher proportions of single-family homes or own a smartphone. For example, participating with Chai Energy necessitates that customers own a smartphone to download the application and have internet access. As of 2016, an estimated 77 percent of adults in the United States owned a smartphone, and 64 percent of lower-income adults owned a smartphone.[19]

Chai Energy's customer recruitment relied primarily on digital advertisements through Facebook and Google. Social media advertising algorithms could also affect the sample. If this is the case, other recruitment strategies or media need to target those that may be underrepresented as a result of a more general marketing strategy. One solution could be reducing the need to have a smartphone to participate. For example, OhmConnect's service requires only access to the internet and does not necessitate the use of its smartphone application, which makes it more accessible to a wider audience.

Table 3: Chai Energy Sample Energy Characteristics and Demographics

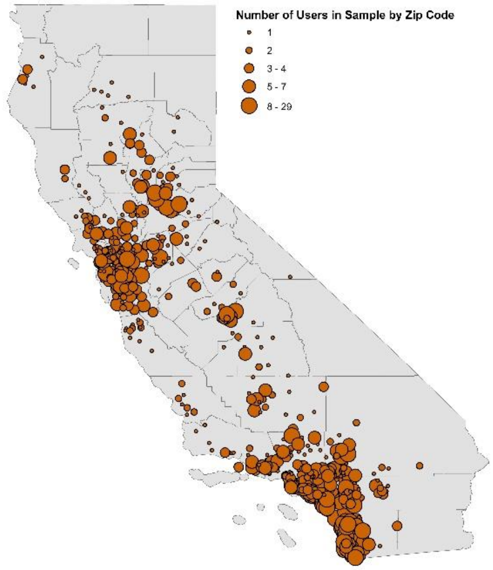
Demographic	Sample	California
White	52%	38%
Hispanic	26%	39%
African American	4%	6.5%
Home Ownership	62%	55%
Median Income (by Zip Code)	$81,802	$67,739
Single Family Home Share	63%	58%
Average Annual Energy Use (kWh)	7,469	7,266
Has Solar PV Panels	20%	-
Has Automation Device(s)	10%	-

Source: Sample statistics from UCLA and Chai Energy. California population statistics from the United States Census Bureau as of January 2019. Average annual energy use (kWh) estimated based on the most recently available (2017) California Energy Commission "Electricity consumption by County" for all residential customers and the United States Census Bureau's estimate for occupied housing units.

The study sample is geographically representative of the state, shown in Figure 5. While there are concentrations of customers in Los Angeles County, San Diego County, Orange County, and the San Francisco Bay Area, the concentrations of the study participants fall similarly to the population density of California. Forty-three of the 58 counties in California have at least one customer included in this sample. The eight most represented counties are Los Angeles, San Diego, Orange, Santa Clara, Riverside, San Bernardino, Alameda, and Contra Costa.

[19] Pew Research Center. 2017. "Record Shares of Americans Now Own Smartphones, Have Home Broadband."

Figure 5: Geographic Distribution of Chai Energy Customers



Source: UCLA Luskin Center for Innovation.

CHAPTER 3: Effect of Demand Response on Energy Conservation

By 2020, most California investor-owned utility (IOU) customers are expected to switch to time-of-use (TOU) pricing. To understand how TOU pricing will change consumer behavior and electricity demand, it is important to know how customers from different demographic and energy-use segments may react to higher prices during peak periods. This section provides estimates of these response rates using differential responses during critical energy periods, also known as *demand response events*. Although TOU pricing differs from demand response events on several dimensions (daily versus occasionally), responses to both require individuals to modify their typical consumption behavior during a predefined period. It is, therefore, likely that there is a correlation between the ability of customers to change consumption habits in the face of demand response events and TOU pricing. As such, these estimates can be of use to regulators designing policy.

This analysis investigated customers' propensity to reduce consumption during demand response events, on average and by relevant customer subgroup. This analysis could inform how TOU pricing affects future behavior. Moreover, if demand response providers are able to target events toward customer segments with higher levels of responsiveness, demand events will be a more effective tool for energy reductions during peak periods, which can lower the overall price of reducing electricity demand.

3.1 Treatment Design

To estimate the causal effect of a critical-peak-pricing event on customer energy use, it is necessary to identify a counterfactual: the amount a customer would have used had there been no event. By taking the difference between true usage and the counterfactual, researchers identified the true causal effect of the demand response event. As it is not possible to know a customer's true counterfactual usage if the event had not occurred, researchers approximated this through the construction of an appropriate comparison group.

A counterfactual was constructed by performing a difference-in-difference regression analysis. First, individuals' event-hour usage was compared with their own usage in the same hour on other similar-temperature days when no event occurred. Then, the energy consumption of nonparticipants[20] in the same zip code in the event hour was compared to their own consumption during the same hour on other same-temperature days. The difference in usage for nonparticipants between event and non-event days was then used to estimate the counterfactual change in usage for the participants on event and non-event days (in the same zip code). The average difference from the counterfactual is the non-experimental estimate of the effect of the event. For more information on the controls applied, see Appendix B.

[20] *Nonparticipants* typically are individuals who had not yet joined the OhmConnect platform at the time of the event but provided their historical consumption data when they joined.

In this analysis, researchers estimate the effect of a demand response event on consumption for different types of users. The effect is defined as the amount a user consumes beneath what he or she would have consumed in the absence of the demand response event. It is important to highlight that this is a different definition from those traditionally used to evaluate demand response programs, which estimate savings beneath an estimated baseline. In this analysis, researchers do not use that baseline because its accuracy differs across groups, which means that there would be bias in comparing responsiveness among these groups. As such, the consumption reduction estimates here should be compared only to other reports that examine reductions relative to baseline with caution, as they are measuring consumption reductions by different methods.

The relative differences in electricity consumption behavior are not causal; the dimensions of heterogeneity may be correlated with other user characteristics that influence use. However, these differences among types of users nevertheless provide a suggestive guidepost for what types of users are more likely to be induced by #OhmHours to conserve energy.

3.1.1 Discussion Around Treatment Design

A potential method of estimating the effect of demand response events is a randomized controlled experiment, as in Gillan (2017) and as in Chapter 6 "Project Results: Financial Incentives and Messaging" in this report. The advantage of this approach is that it estimates an unbiased effect of the event for the population studied. However, there are two primary disadvantages of an experimental approach. First, unless OhmConnect was willing to run an experiment during each of its events, the sample of experimental events would be limited. This would make it difficult to have the statistical power necessary to examine heterogeneity in responsiveness, especially for phenomenon like demand events where the effect is already relatively small. Second, in many experiments, the sample is recruited specifically for participation in the experiment. As a result, study participants may be at their most engaged during this period, and their behavior may change in the long-run. In this section, researchers instead took a different approach for estimating responsiveness to #OhmHours.

3.2 Results

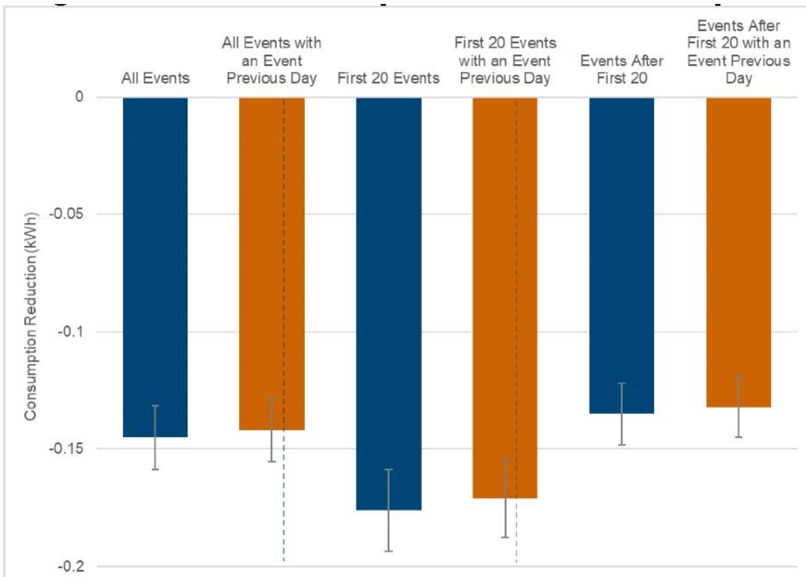
3.2.1 Spillover Effects of Demand Response

This section presents the effect of demand response on consumption relative to what a user would have consumed in the absence of the event, rather than what they consumed relative to their baseline. This analysis included only weekday events, which make up the vast majority of all #OhmHours. With these caveats in mind, researchers found that exposure to an #OhmHour demand response event led to a 0.145 kWh reduction in usage, or a 18 percent reduction, relative to what they would have consumed in the absence of the event. This result is robust to an increasingly strict set of controls. For detailed information regarding statistical results and controls used, see regression tables in Appendix B.

Researchers then estimated whether event behavior changed if a user also had an event the day before, which reflects a situation more closely related to a TOU setting. Importantly, it appears that having an event the previous day does not have a large effect on consumption reduction during the demand response event in the following day (shown in the orange bars in Figure 6). This finding suggests that individuals are not merely shifting usage to the next day when an event occurs, which increases confidence that these findings may also apply to a TOU setting.

Next, researchers repeated the same analysis as above but restricted the event sample to only users' first 20 events. Figure 6 shows a user's average consumption reduction in all events compared to the reduction in his or her first 20 events and events after the first 20.[21] The effect sizes were around 30 percent larger during a user's first 20 events than all events after. This finding implies that users had larger reductions in consumption during demand response events when they joined the platform, suggesting that user engagement falls over time.

Figure 6: Demand Response Event Consumption



Source: UCLA Luskin Center for Innovation.

Researchers also examined spillover effects from demand response events by examining changes in energy consumption in the hours and days prior to and following a demand response event. The effect during the event is an order of magnitude larger than the effects in the hours and the days surrounding the event. These results suggest that demand response event energy consumption reductions were not offset by increases in surrounding hours or days, providing evidence that demand response events lead to overall reductions in energy and not shifting consumption to either the surrounding hours or the following days. For quantified results, see Appendix B.

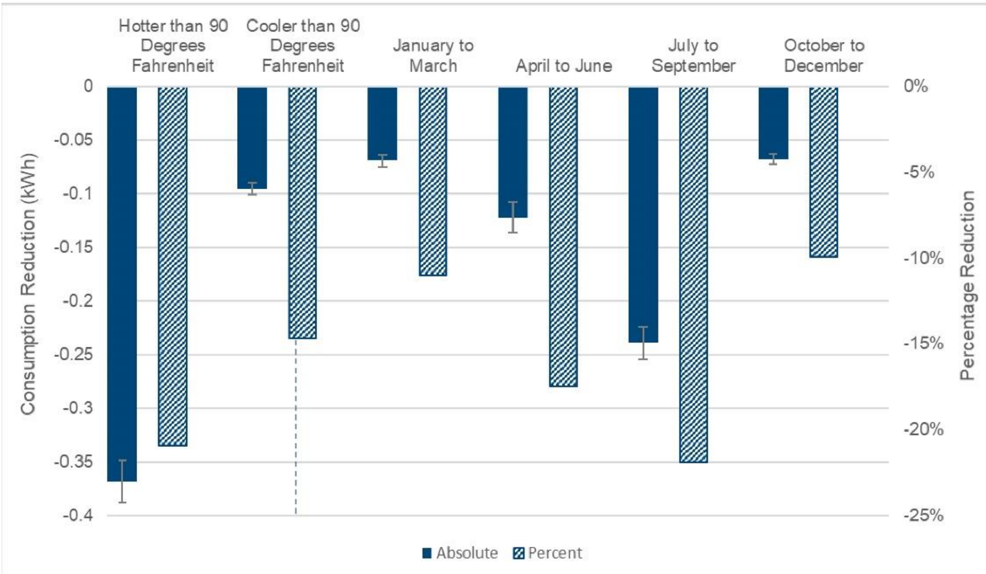
3.2.2 Effect of Demand Response by Temperature, Season, and Timing

Researchers analyzed how responsiveness to demand response events differs by event temperature and season. Event responsiveness is larger during the summer season and on hot days throughout the year (when temperatures are above 90 degrees Fahrenheit), as shown in Figure 7. In summer, usage is closer to 1.5 kWh per event, while in winter consumption falls to 0.5 kWh per event. As mean consumption also increases during these times, the differences

[21] Results shown for the researchers' preferred specification.

are less extreme when viewed as proportions[22] but are still higher in spring and especially summer (17 percent and 22 percent consumption reduction, respectively) than fall and winter (10 percent and 11 percent consumption reduction, respectively). These differences are likely driven by the use of air conditioning (AC) in the summer and on hot days. Users' have a greater capacity to reduce consumption when they can turn of their AC.

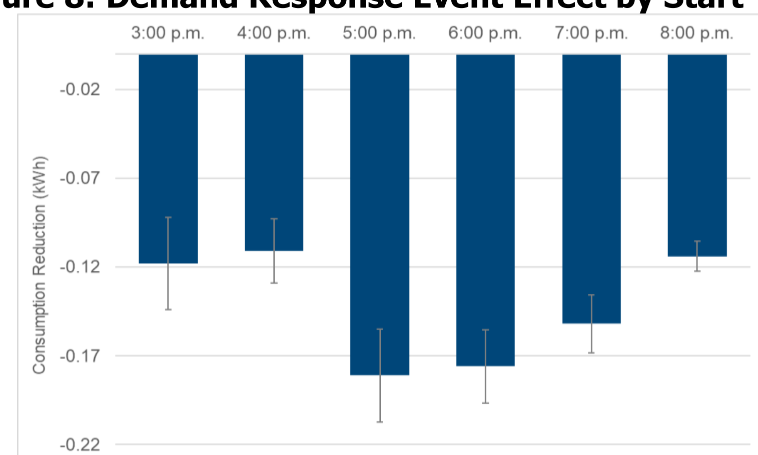
Figure 7: Demand Response Event Consumption by Temperature and Season



Source: UCLA Luskin Center for Innovation.

Finally, researchers examined how consumption reductions varied by the hour a demand response event started, shown in Figure 8. The largest consumption reductions occurred for events that started at 5:00 p.m. or 6:00 p.m. Because usage also increased during the evening, the largest proportional response was for events starting at 5:00 p.m., with a reduction of more than 20 percent (compared to 15 percent to 17 percent in other hours).

Figure 8: Demand Response Event Effect by Start Time



Source: UCLA Luskin Center for Innovation.

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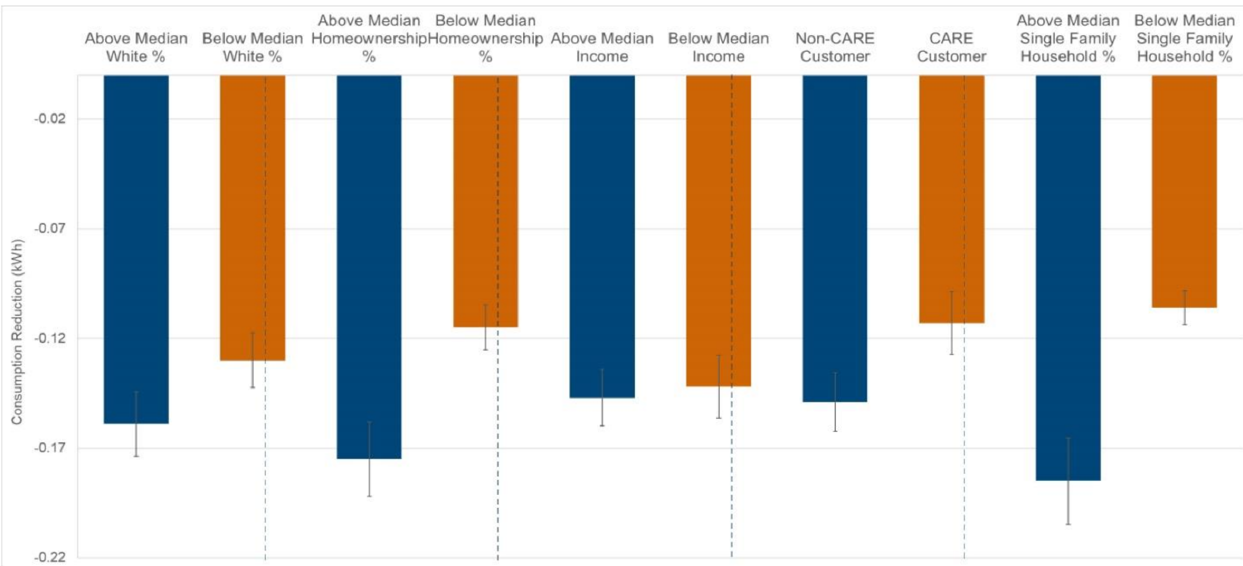
[22] Proportions are calculated by dividing the effect size by the mean usage.

3.2.3 Effect of Demand Response by Demographics

This analysis examined how responsiveness to events varies across different demographic subgroups. Researchers ran the same model separately for each demographic subgroup, the results of which are shown in Figure 9. There were not large absolute or proportional differences across most subgroups. Differences in consumption reductions ranged from 0.01 to 0.08 kWh, or about 2 to 4 percentage points, between users living in zip codes above versus below the median for income, percentage white population, and home ownership. The largest absolute difference was seen when comparing users living in zip codes above the median for single-family homes: those above the median reduced by 0.08 kWh more, although this is only a 2 percentage point difference. The largest proportional difference was between non-CARE and CARE users, with non-CARE users reducing by 7 percentage points more.

Figure 9: Demand Response Event Load Reduction by Demographic Subgroup

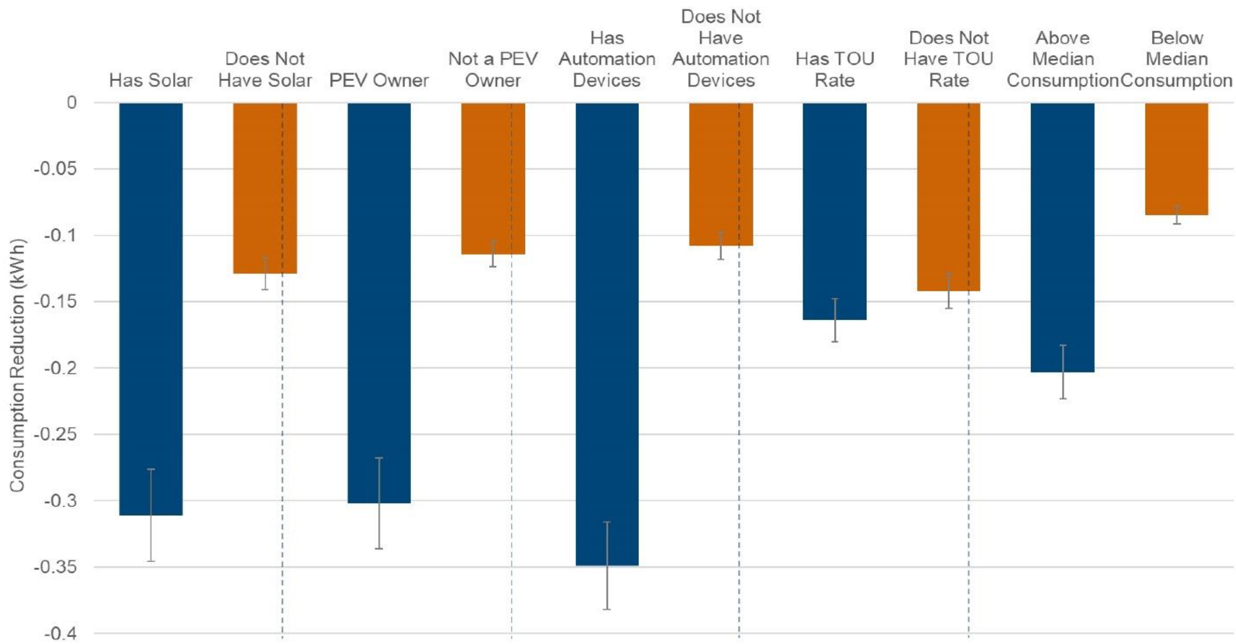


Source: UCLA Luskin Center for Innovation.

3.2.4 Effect of Demand Response by Energy Profile

Researchers examined whether users with different energy profiles had different reactions to OhmConnect events. Figure 10 shows the results. Users with solar PV, PEVs and automation were more likely to reduce consumption during #OhmHours. The most noticeable differences were seen between users with and without automation devices. Users who have automation devices used 47 percent less energy during an event relative to 13 percent reductions for those who do not. Among other energy-engaged users, PEV owners reduced their consumption by 25 percent during demand response events, while non-PEV owners reduced consumption by only 16 percent. It is difficult to do a similar comparison for solar because customers' mean usage does not reflect the actual amount of energy used in the household but instead represents their net energy consumption (electricity consumed minus electricity produced), making the scaling factor unclear. In absolute terms, however, users with solar PV reduced energy consumption almost 2.5 times more than users without solar PV. Researchers cannot identify users with solar PV or PEV directly but instead estimate adopters based on their energy profiles.[23] Two possible explanations for these results are that users who have a more sophisticated understanding about their energy use save more during #OhmHours, or users who care more about the environment (and by extension adopted green-friendly technologies like solar PV and PEVs) are more willing to save during Ohm events.[24]

Figure 10: Demand Response Event Consumption by Energy Profile



Source: UCLA Luskin Center for Innovation.

As shown in the previous figure, users on a TOU rate reduce slightly more than those not on a TOU. However, when researchers isolate users who are not energy engaged, users on a TOU rate reduce energy consumption by less than those on other rate schedules. This finding is important to consider as more customers switch to TOU, demand response events could become less effective. Conversely, when looking at energy-engaged customers, those enrolled in TOU actually reduce more. Figure 11 illustrates these results.

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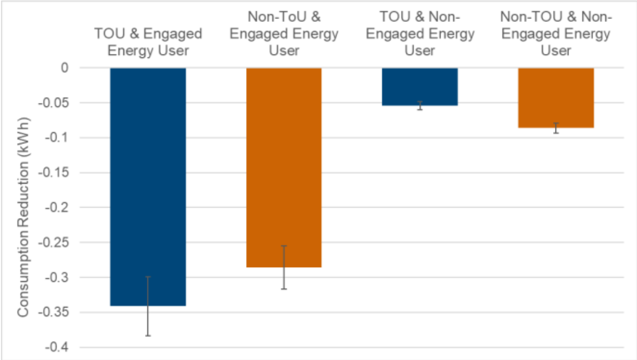
[23] Solar PV adopters are identified by anyone who ever experiences negative usage in an hour. PEV adopters are identified by anyone whose maximum hourly energy use is at least 5 kWh greater than their mean usage. (This represents the usage shocks from charging.)

[24] Standard errors on these estimates are larger than the estimates for non-PEV, nonsolar, and nonautomated users because the number of users who have these items is smaller.

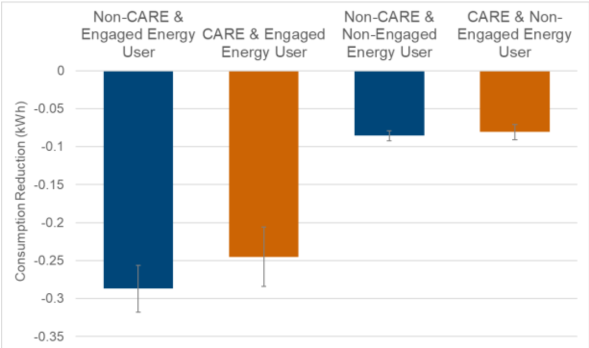
Figure 11: Demand Response Event Consumption by Rate Schedule and Energy Profile



Source: UCLA Luskin Center for Innovation.

As noted, energy-engaged users are more likely to reduce consumption during #OhmHours. Non-CARE users are 9 percentage points more likely to have solar PV, PEV, or automation than CARE users. Researchers tested the idea that because non-CARE users, homeowners, and those living in single-family households are more likely to have solar PV, PEV, and automation, this drives their higher responsiveness. Figure 12 shows these results by comparing responsiveness among users in four categories: CARE customer and active energy user (solar PV, PEV, or automation); non-CARE customer and active user; CARE customer and non-active energy user; and non-CARE customer and non-active energy user. Researchers found that higher response rates in some demographic subgroups are driven partially by differential take-up of solar PV, PEV, and automation. For non-energy-engaged customers, CARE and non-CARE customers reduce by roughly the same amount. Among energy-engaged customers, non-CARE customers still reduce more.

Figure 12: Demand Response Event Consumption by CARE Status and Energy Profile



Source: UCLA Luskin Center for Innovation.

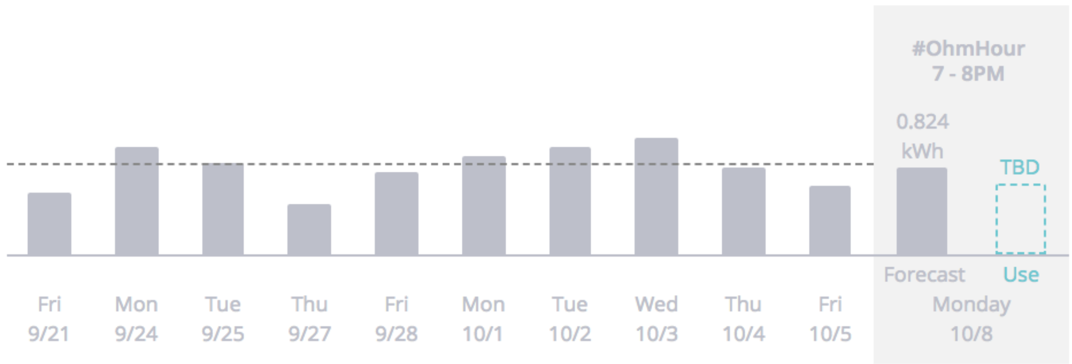
CHAPTER 4: Baseline Effects Project Results

To maximize the effectiveness of conservation during critical periods, it is important to know how various aspects of demand events affect user-responsiveness. This analysis examined how the baseline set by demand response providers affect users' conservation behavior.

Demand response providers reward users during a demand response event based on their energy conservation relative to an assigned baseline. The baseline is the providers' best guess for users' consumption in the absence of an event. If customers consumed more energy than their baseline, they lost points, and if they consumed less than their baseline, they gained points. Points can be converted into cash rewards. Baselines are set based on the average of consumption in the same hour of the demand response event during the previous 10 nonevent, nonholiday weekdays for weekday events and the previous four non-event, non-holiday weekends for weekend events.

The baseline level assigned to a user may affect his or her actual consumption decisions for several reasons. Most significantly, users may use their baseline value as a cue of how much they should reduce consumption. When OhmConnect users receive a notification about an event, they also receive information about what their baseline is and how it compares with their use over previous days. An example of what users see is in Figure 13. The 'forecast' communicates the user's baseline in kWh. The figure also shows the user's consumption over the previous ten days. Users can see how their consumption compares to their baseline by using the dashed line provided in the figure. If their baseline value is higher than their consumption from the previous day, they may not think that much conservation behavior is necessary. They could behave in the same way as the day before and still consume less than their baseline. Conversely, if users' baseline value is set much lower than their consumption was in recent days, they may take this as a signal that greater behavioral action is necessary. This theory is known as *information targeting*. It is important to note that this is specific to how OhmConnect communicates information to its users; if a demand response provider did not provide information comparing baseline level and previous consumption, then it is less likely to see a large response.

Figure 13: Baseline and Consumption Information OhmConnect Users Receive



Source: OhmConnect, Inc.

Additionally, there is a robust experimental economics literature on the existence of loss aversion[25], which suggests that people are generally more motivated to prevent losses than accumulate gains. Loss aversion may affect a user's consumption behavior. When the baseline is set higher than a user's theoretical true counterfactual use, a user would likely earn points without changing their conservation behavior. Any conservation behavior in this case will result in additional point gains. When a baseline is set lower than a user's theoretical true counterfactual use, a user would likely not consume less than their baseline if they did not change their behavior. Therefore, any conservation behavior in this case will reduce the overall level of point losses. Thus, if loss aversion is affects behavior, researchers would expect user conservation behavior to respond to changes in the baseline even if the marginal price remains constant. Furthermore, users have a financial incentive to conserve under the baseline because OhmConnect users receive a larger financial reward when they accumulate 'streaks' - the number of events in a row in which a user consumes below their baseline. . Users may therefore choose to conserve more when baseline levels are set lower in order to ensure they maintain their increased financial incentive.

This analysis quantifies whether user baselines have a causal effect on energy consumption during events using an econometric approach, called an *instrumental variables strategy*. Then, additional analyses disentangle what mechanisms may be driving this effect. Understanding how the event baseline affects user behavior is important because if baselines have a strong effect on conservation behavior, changing them is a relatively costless way to induce more conservation from a given event.

4.1 Background

For #OhmHours, individuals typically receive an alert that a demand event will occur the night before an event is scheduled to start. The user sees the baseline value beneath which he or she must conserve but is provided no information about the total number of points they will receive. Points vary across events but typically are worth about $1.50 for each kWh conserved.

Individuals accumulated points by conserving energy below their baseline. Conditional on having a positive point balance, individuals' marginal incentives were about the same regardless of whether they conserve below the baseline; the only difference was that if they consumed less than the baseline, they earned points, and if they consumed more than the baseline, they lost points. Because this analysis focused on individuals that face this constant marginal price, any individuals who started an event with a balance fewer than 100 points were excluded (about 15 percent of demand events in the sample).[26]OhmConnect baselines were set using California Independent System Operator's (California ISO) 10-in-10 method,

[25] Tversky, Amos, and Daniel Kahneman. "Loss aversion in riskless choice: A reference-dependent model." The quarterly journal of economics 106.4 (1991): 1039-1061.

[26] One hundred points is the cutoff because only 25 percent of events end with a user earning or losing more than 100 points (and of course even if a user earns more than 100 points, he or she will still lose points for the first 100 points (equivalent to 0.65 kWh on average) that he or she is above the baseline.

which calculates a baseline using the average of a user's energy use in the same hour of the event during their previous 10 non-event, nonholiday weekdays.[27] [28]

4.2 Treatment Design

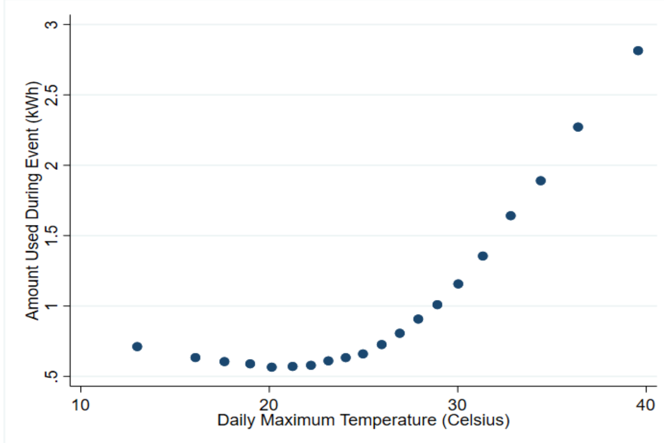
This analysis estimates how different baselines affect user behavior during demand events. A naïve analysis may simply correlate energy consumption during demand response events with the baseline of the event. The problem with this approach is that because of the way baselines are calculated, they are likely correlated with other factors affecting a household's recent level of energy use that may affect consumption, such as if a household recently purchased an air conditioner (AC). In this case, because this household is now operating an AC, its consumption during event days may increase, as would its baseline (because recent non-event weekdays would also have higher electricity consumption due to AC use). However, the relationship between these two variables would be spurious; the higher baselines are not causing the higher level of electricity use.

Accordingly, in order to estimate how varying the baseline affects consumption, researchers would ideally randomize baselines across individuals. Unfortunately, such an experiment is not feasible within the current OhmConnect architecture. Instead, researchers used a feature of the baseline calculation that can produce an as-good-as-random variation in the baseline, approximating the necessary randomization for this experiment: temperature on the ninth and tenth days of the baseline.

The idea behind this empirical strategy is that temperature is strongly correlated with energy consumption, shown in Figure 14. As such, if there are more high-temperature days included in a customer's baseline calculation, he or she is more likely to face a higher baseline. High-temperature days in the non-event, nonholiday weekdays just before an event influence the baseline calculation and are also likely to be correlated with event-day temperature. However, temperatures on non-event days that make up the ninth or tenth non-event weekday in the baseline calculation are typically multiple weeks in the past and, therefore, unlikely to be correlated with either energy consumption or event-day temperature, especially conditional on controls for lagged temperature as included in our analysis.

[27] This is for weekday events. Weekend events were excluded from the sample.

Figure 14: Relationship Between Temperature and KWh Consumed During an Event

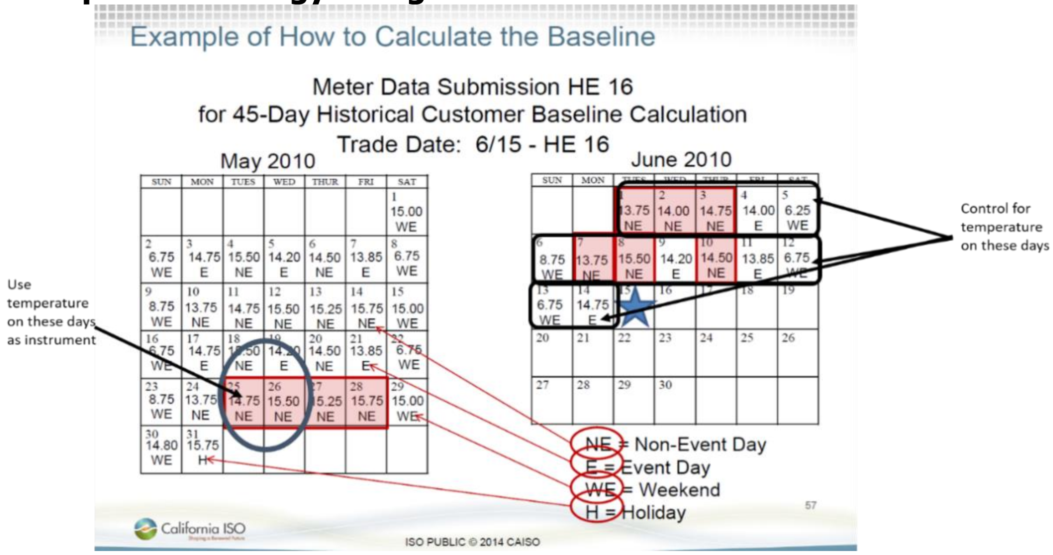


Source: UCLA Luskin Center for Innovation.

Researchers implemented an instrumental variables strategy using the maximum temperature on the ninth and tenth previous non-event nonholiday weekdays to instrument for the baseline a customer faces on a given event. The goal of the instrumental variables strategy was to isolate the random component of the baseline (that is, the component that is uncorrelated with other factors that might influence the outcome variable) and test whether changes in this random component affect the outcome variable. Since the random component of the baseline can affect only the outcome variable through the effect on the baseline itself, any effect observed must be caused by the baseline. Researchers used the temperature during the previous week as a way of isolating "random" variation in the baseline level during a given demand response event.

In practice, this means researchers predict what a customer's baseline will be for a given event using the temperature on the ninth and tenth previous non-event nonholiday weekdays on event consumption. Researchers controlled for high temperatures in the two weeks before the event and consumption in the week before the event. Researchers then estimated the effect of this predicted baseline level on actual consumption the day of the event. The assumption was that the high temperature on these ninth and tenth previous non-event nonholiday weekdays can affect consumption only on the event day through the related effect on the customer's baseline. If this is true, then the relationship between the predicted baseline and actual usage would be the causal effect of changes in baseline on event consumption. The only other way that the previous week's temperature might plausibly affect consumption on these days is through event-day temperature. Researchers found that empirically that there is no such relationship. Figure 15 shows how this empirical strategy leveraged the existing baseline calculation in more detail using a sample baseline calculation provided by California ISO.

Figure 15: Empirical Strategy Using California ISO's Baseline Calculation Method



Source: Underlying image by California ISO. Edited by UCLA to illustrate method.

As an example of how this works in practice, one can imagine two #OhmHours that occur on identical 90 degree Fahrenheit days. Two weeks before one #OhmHour was unseasonably cool, leading to lower-than-average energy use. Two weeks before the other #OhmHour was unseasonably warm, leading to higher-than-average energy use. As a result of the previous weeks' energy use, customers participating in the first #OhmHour will have a much lower baseline than customers participating in the second #OhmHour, even though conditions on the days of both #OhmHours are the same. Thus, if researchers saw differences in customer responsiveness between these two types of events, they could reasonably be attributed to changes in the baseline, as it is unlikely that the temperature more than seven days ago has large effects on contemporaneous consumption. This assumption holds empirically in this analysis, as the predicted baseline is uncorrelated with either temperature on the day of the event or consumption on the day following the event.

In this analysis, all estimates controlled for high temperature in the two weeks prior to the demand response event, baseline usage in the week before the event, user fixed effects, and day fixed effects.[29] In essence, these variables helped hold all other factors that might have affected consumption during a demand response event constant, ensuring that any changes seen must be due to a user receiving a higher or lower baseline. Researchers showed that conditional on the controls, high temperatures two weeks before the event are uncorrelated with both temperature on the day of the event and usage on the next non-event day following the event, which provides additional support that any observed changes on the event day are caused by changes in the baseline.

4.3 Results

Using this empirical approach, researchers found evidence that when users receive lower baselines holding all else equal energy consumption declines and vice-versa. On average, a 0.1

[29] Fixed effects control for nontime-varying characteristics of each variable (i.e. control for the fact that different users may have different average propensities to consume).

kWh decrease in a user's baseline led to an additional 0.017 decrease in actual consumption during an event. For the average user in this sample, a 0.017 kWh decrease is about 1.9 percent of hourly use. For detailed tables showing the results of all statistical regressions, see Appendix C.

Next, researchers tested whether these effects vary across two major covariates: income and having automation. Figure 16 shows the results. Only customers without automation responded to changes in baseline, though because of the relatively small number of automated customers, the effects were relatively imprecise. If customers with automation had programmed their homes to respond automatically to an event notification, then there would be no scope for them to make behavioral changes when a baseline is high or low relative to true counterfactual use. This finding provides increased support that the observed differences above in consumption by baseline level are indeed caused by reactions to the baseline and not some other omitted factor affecting demand (as researchers would expect this would affect the automated customers as well).

Next, researchers analyzed the differential effect of response to baseline changes by whether the household's zip code's income is above or below the sample median. The effects were driven largely by customers in below median income zip codes who reduced their consumption by an additional 0.022 kWh on average for every 0.1 kWh decrease in their baseline. This result suggests that these types of households may be more reliant on information targeting than those with higher incomes. Those above the median income reduced their usage by an additional 0.0076 kWh when their baseline decreased by 0.1 kWh, although this result is not statistically significant.

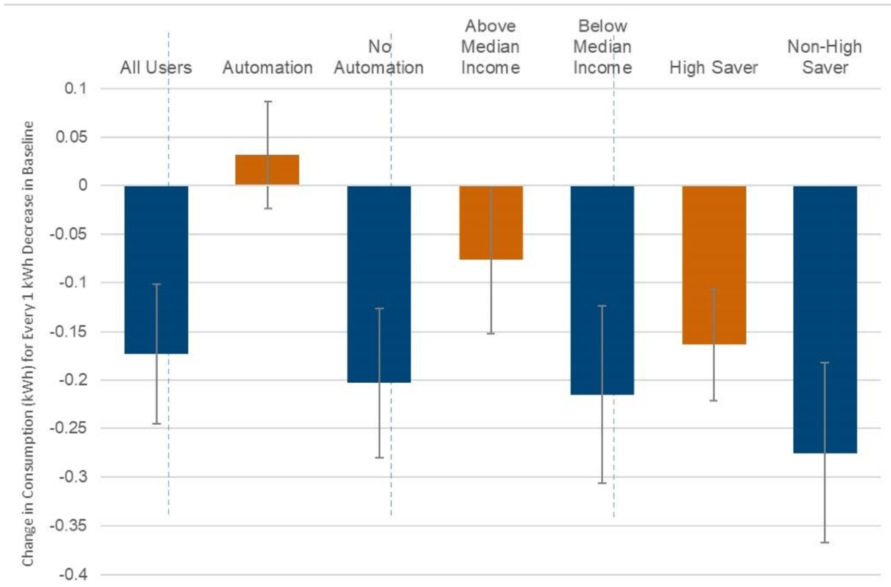
These results suggest that baseline values have large effects on individuals' conservation behavior during demand events. Researchers identified three hypotheses for why this might be the case in the introduction: (1) dynamic incentives to maintain streaks motivate reductions in usage below baseline, (2) the baseline provides valuable information for consumers about when to target conservation behavior, or (3) there is loss-aversion, where customers are motivated by minimizing losses that could occur. Next, researchers tried to distinguish among these hypotheses by looking at how different types of users react to baseline changes. Specifically, researchers tested whether "high savers" or people who conserve on average 0.2 kWh under the baseline, were more or less likely to change behavior in response to their baseline. This analysis could help distinguish between hypotheses because high savers were more likely to have long streaks, increasing the value of maintaining streaks. High savers were also more likely to be gold or platinum status members. These statuses increased the amount of points a user gained if he or she consumed less than the baseline (or lost if he or she consumed more than the baseline). As a result, they are expected to amplify loss aversion as the potential losses are much higher. Consequentially, if either dynamic incentives to maintain streaks or loss aversion are driving the results, one might expect to see high-savers have larger reactions to streaks. Conversely, if the results are driven by information targeting, one might expect non-high savers to have larger reactions to baseline changes as these users were likely to be less informed and therefore more likely to rely on heuristics.

As seen in Figure 16, non-high savers responded more strongly to changes in baseline than high savers. For every 0.1 kWh decrease in the baseline, non-high savers reduced consumption by an additional 0.028 and high savers reduced by 0.016, or 2.8 percent and 2.2

percent, respectively. Although certainly not determinative, this result suggests that the observed results were more likely driven by information targeting than by dynamic incentives to maintain streaks or by loss aversion.

Together, these results suggest that for demand response providers like OhmConnect that provide users with information about their baseline relative to past usage, baseline levels can have an important effect on overall consumption. This finding highlights the potential importance of non-price factors in determining user responsiveness to demand events.

Figure 16: Change in Consumption for Every 1 KWh Decrease in Baseline



Source: UCLA Luskin Center for Innovation.

CHAPTER 5: Nonlinear Incentives: Streaks and Statuses Project Results

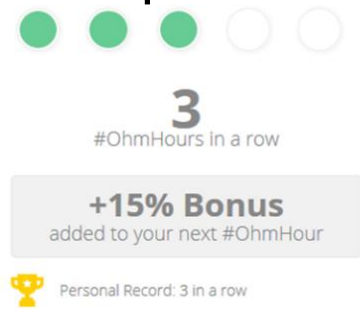
OhmConnect employs novel incentive structures to motivate users to conserve electricity during critical energy periods called #OhmHours. This analysis focused on OhmConnect’s programs offering nonlinear incentives: streaks and statuses. These programs offer nonlinear bonus incentives for conserving over an extended period or repeatedly conserving beneath a goal, respectively. The research team estimates the effect of the marginal incentive on willingness to conserve under OhmConnect's nonlinear incentives.

To identify the effect of these additional incentives on overall consumption, the research team needed an appropriate control group to assess counterfactual conservation. However, given the structure of the data, researchers were not able to test whether those who receive a bonus used less electricity during events than they would have if they had not received a bonus. While not allowing a definitive assessment of the cost-efficacy of the bonus structure, this analysis provides insights into the role of marginal rewards in energy conservation.

5.1 Background

In addition to the base rate, participants can earn bonuses for consistent savings (streak) and for consistently saving significant amounts of electricity (status). Users can build streaks by consuming less than their baseline in consecutive demand response events. For every event an individual successfully consumes less than his or her baseline, he or she maintains any existing streak and extends it by one. If he or she consumes more than his or her baseline, his or her streak returns to zero. Each extension of the streak is rewarded with an additional 5 percent points. For example, if the base rate is 100 points per kWh and the participant beats his or her baseline for the first time, the user would have a streak of one (5 percent bonus) and would be awarded 105 points per kWh saved. If his or her streak is five and he or she beats the baseline again, he or she would be awarded 130 points per kWh conserved as new streaks are immediately applied to point calculation. Consuming more than the baseline or opting out of an event or consuming more than the baseline, break a streak, and everything goes back to zero. Customers do not see their negative points amplified by the streak level they were in. Figure 17 shows an example of how a user’s streak and associated rewards are communicated.

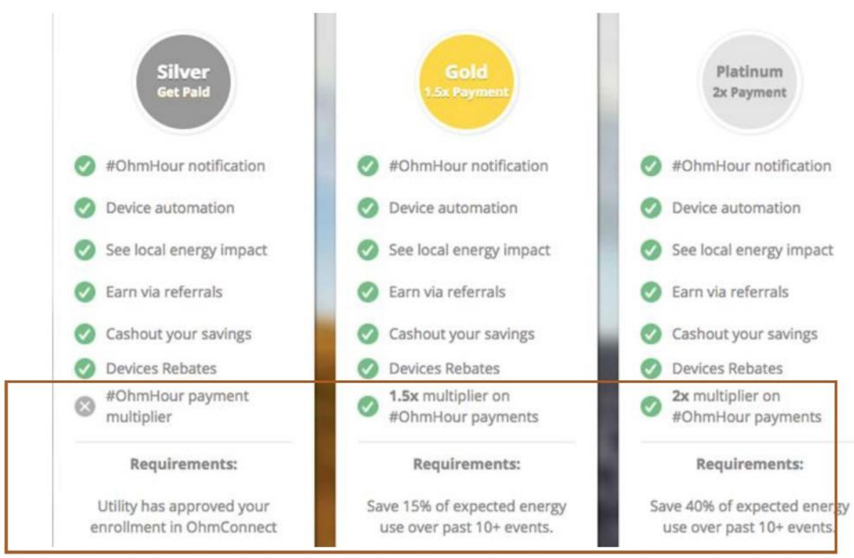
Figure 17: Example of Streaks Reward



Source: OhmConnect, Inc.

OhmConnect participants can also earn status bonuses. At the time of this study, OhmConnect assigned active members into three status levels: silver, gold, and platinum. Assignment to a status is based upon the amount of energy saved relative to their baseline over the past 10 or more #OhmHours. To qualify as an Ohm gold member, a customer must save 15 percent beneath baseline on average for the previous ten events. To qualify as a platinum member, the customer must save 40 percent beneath baseline over the same period. Ohm gold members receive 1.5 times more points per #OhmHour, and Ohm platinum members receive 2 times more points. In the event a customer consumes more than his or her baseline, the status level multiplier amplifies the negative points received. However, customers' points cannot go below zero. Figure 18 provides more details about the status levels.

Figure 18: Description of Status Levels



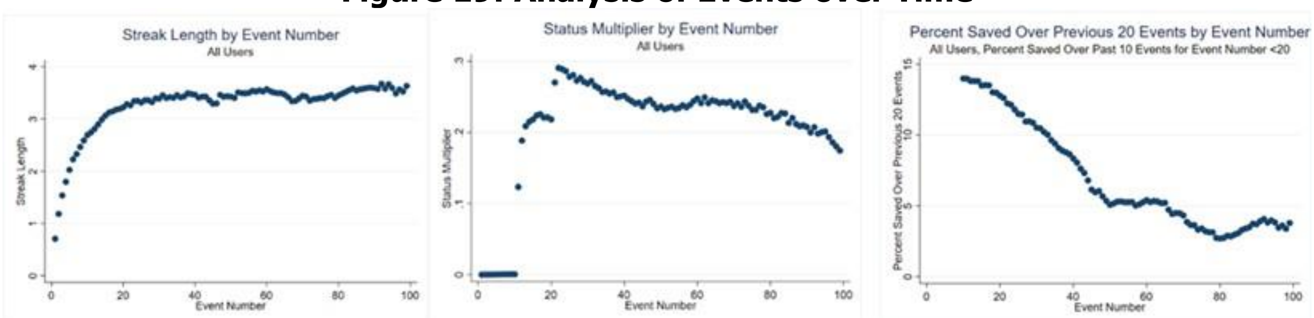
Source: OhmConnect, Inc.

5.1.1 Descriptive Analysis of Streaks and Statuses

This section examines how streaks and status vary across customers to provide context about what types of customers benefit from these programs.

Figure 19 shows the average streak length, status multiplier, and percentage electricity saved over the previous 20 events by a user's event number. There are two important takeaways from these plots. First, as individuals get more experience with OhmConnect, they have longer streaks and higher status. This is in some part mechanical; long streaks require a user to participate over a long period, and a user does not become eligible for higher status until having participated in at least 10 events. However, this improvement in streaks and status stagnates after about 20 events. For streaks, average length remains roughly constant after a user's twentieth event at about a streak length of 3.5. For status, the average multiplier and average savings of users decline over time. These findings suggest that over time users may be learning how to do the minimum necessary to maintain streaks while not further reducing consumption. Indeed, the reductions over time in average percentage saved per event suggest that any learning about total conservation that takes place with long-run experience with OhmConnect appears to be outweighed by increasing apathy or disengagement.[30] Another explanation could be that some conservation strategies become permanent. To combat this stagnation, a solution could be to make streaks harder to maintain at longer streak lengths. In light of the results in this analysis, OhmConnect has limited the length of a streak one customer can accumulate to 20.

Figure 19: Analysis of Events over Time



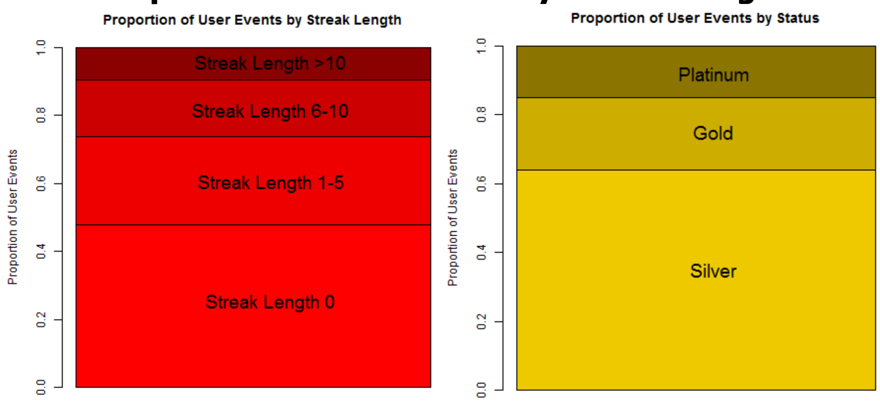
Source: Figures created by UCLA Luskin Center for Innovation. Data from OhmConnect, Inc.

One concern with the above graphs is that they may reflect purely compositional changes. For instance, imagine most users join in the beginning of the summer, when consumption reductions are higher. If that were the case, one would expect to see large reductions early in a user's OhmConnect career and more moderate reductions later. To control for this, researchers performed a regression analysis controlling for temperature, invariant user effects, and average zip code performance on an event. Differences observed here by event number are more plausibly caused by longer experience with OhmConnect itself. The results are consistent; as OhmConnect users have more events, they reduce their consumption by less, have shorter streaks, and have lower statuses. For instance, after a user's fiftieth event, he or she reduces consumption by 0.05 kWh less electricity on average compared to his or her first demand response events. Similarly, users are 3 percentage points more likely to have a streak length of zero. They are also 6.7 percentage more likely to not have a gold or platinum streak compared to events 10 through 30. This suggests that users become disengaged over time. A detailed table showing these results is included in Appendix D.

[30] One concern with this analysis might be that only long-time users could have up to 100 events, while most users have only 10 events. As a result, the effects could be compositional. To account for this, researchers make the same graphs restricting the sample to only users with at least 100 events and find strikingly similar patterns.

Figure 20 shows the proportion of demand response events a user receives that they spend at various streak and status lengths.[31] On average, nearly half of a user's #OhmHours result in a streak length of zero, meaning they gain no additional incentives for consumption reductions. Around 25 percent of all of a user's #OhmHours have streak length of six or higher, suggesting that a meaningful number of #OhmHours are paying out high streak bonuses. Similarly, roughly 60 percent of user #OhmHours have silver status, which has no reward multipliers. Together, these suggest that the majority of events are unaffected directly by the streak and status reward programs (although they may still have dynamic effects), while an important minority of these events result in the user receiving increased incentives for reductions.

Figure 20: Proportion of User Events by Streak Length and Status

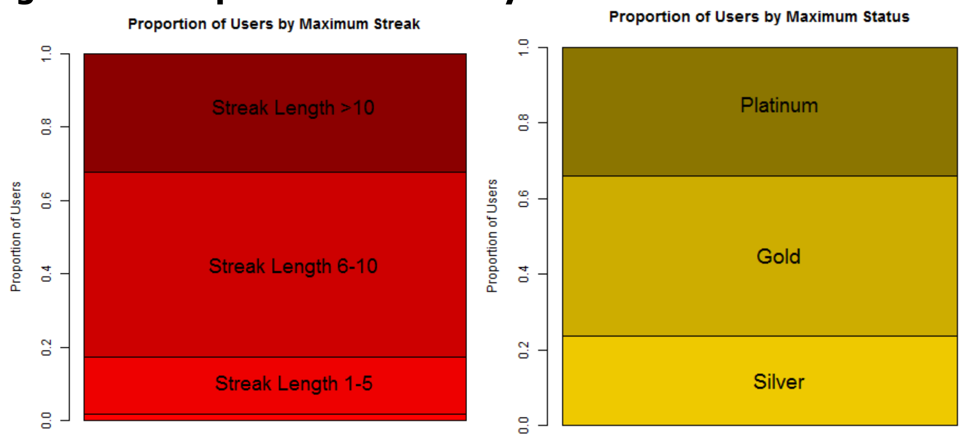


Source: UCLA Luskin Center for Innovation.

Figure 21 shows the same breakdown but by a user's maximum streak or maximum status. Even though almost half of an average user's events result in a streak length of zero, most users have at least one streak length of six or more. Only a small proportion of users have a maximum streak length of 0. More than 30 percent of users have at least one streak length greater than 10. Only 15 percent of users never have a streak longer than five. A similar pattern exists for status. Even though more than 60 percent of a user's events have a status level of silver, nearly 80 percent of users reach gold or platinum status for at least one event. These results suggest that although most users do not consistently access streak or status bonuses, most have reached such rewards at least once. Since these events, in theory, provide strong incentives to conserve more, it is somewhat puzzling why users with the ability to reach higher streak and status levels do not remain at these levels consistently. These results suggest that most users do have the capacity to make large consumption reductions in response to events but choose not to do so as time progresses. Increases in long-run user engagement could lead to larger gains in user responsiveness.

[31] This excludes all individuals' first 10 events as it is impossible to gain a status above silver during this time frame.

Figure 21: Proportion of Users by Maximum Streak and Status



Source: UCLA Luskin Center for Innovation.

Finally, researchers examined if some demographic or energy-use subgroups were more likely to have higher streak or status levels than others. As with the previous analyses, the demographics of each customer was unknown to researchers. A user is therefore considered to represent the average demographics based on the zip code in which the user is located. Table 4 shows summary statistics about user streak and status performance by demographic group, again excluding users' first 10 events.

Table 4: Proportion of Events by Streak and Status for Each Demographic Subgroup

Subgroups	Streak Length				Status		
	0	1-5	6-10	>10	Silver	Gold	Platinum
Zips Above Median Share White Residents	47%	26%	17%	10%	62%	22%	16%
Zips Below Median Share White Residents	49%	26%	16%	9%	66%	20%	14%
Zips Above Median Own Home	47%	25%	17%	11%	63%	21%	16%
Zips Below Median Own Home	49%	26%	16%	9%	65%	21%	14%
Zips Above Median Income	47%	26%	18%	10%	**61%**	**23%**	**16%**
Zips Below Median Income	49%	26%	16%	9%	**67%**	**19%**	**14%**
Non-CARE Customer	**47%**	**26%**	**17%**	**10%**	**62%**	**22%**	**16%**
CARE customer	**53%**	**26%**	**14%**	**7%**	**75%**	**16%**	**9%**
Zips Above Median Single Family Home Share	48%	25%	16%	10%	64%	20%	16%
Zips Below Median Single Family Home Share	47%	27%	17%	9%	64%	22%	14%

Source: UCLA Luskin Center for Innovation.

The number in each column represents the proportion of events that falls into a given category for the average user. For instance, for individuals who live in a zip code above the median for proportion of white residents, 46.8 percent of events have a streak length of zero. There are no large differences in status across most demographic groups. The major exception is income. Users in zip codes that are above the median in household income are five percentage points more likely to have events that begin in gold or platinum status, suggesting that these users save more consistently over time. Even more dramatically, users with CARE, an electricity rate assistance program for low-income households, are 12 percentage points less likely to have gold or platinum status for a given event and 6 percentage points more likely to be at a streak length of zero for a given event. There are three potential explanations for this result. One, lower-income households may conserve less electricity than high-income households. However, this explanation appears unlikely because in Chapter 3 researchers find that users living in zip codes both above and below median income save similarly in response to an event. Two, CARE customers are less able to save consistently and occasionally have days where they far exceed their baseline. This explanation makes sense intuitively; low-income households may have a lower ability to smooth energy shocks. Three, it is possible that the way baselines are calculated systematically provides lower-income households with higher baselines.

Table 5 shows these same statistics for different energy-use subgroups.[32] There are much bigger differences among energy-use subgroups than demographic subgroups. Differences between customers with and without automation are particularly striking. Customers with automation are 17 percentage points more likely to have an event with a streak length above zero, and nearly 30 percentage points more likely to have a status better than silver. These types of engaged customers are much more likely to access the streak and status bonuses provided by OhmConnect. Customers with solar PV and customers that have below-median baselines are more likely to have gold or silver statuses.

Table 5: Proportion of Events by Streak and Status for Each Energy-use Subgroup

Subgroups	Streak Length				Status		
	0	1-5	6-10	>10	Silver	Gold	Platinum
Has Solar PV	46%	24%	17%	12%	**57%**	**21%**	**22%**
No Solar PV	48%	26%	17%	9%	**65%**	**21%**	**15%**
Has PEV	47%	25%	17%	11%	62%	20%	18%
No PEV	48%	26%	17%	9%	64%	21%	15%
Has Automation	**33%**	**19%**	**22%**	**26%**	**39%**	**25%**	**36%**
No Automation	**50%**	**27%**	**16%**	**7%**	**68%**	**20%**	**12%**
TOU Customer	47%	25%	17%	11%	62%	22%	17%
Non-TOU Customer	48%	26%	17%	10%	64%	21%	15%
> Median Baseline	49%	25%	16%	10%	**67%**	**18%**	**15%**
< Median Baseline	47%	27%	17%	9%	**61%**	**24%**	**15%**

Source: UCLA Luskin Center for Innovation.

[32] Researchers exclude a user's first 10 events.

5.2 Treatment Design

Researchers examined how extensions in a user's streak or an increase in their status affect consumption reductions in future events. The analysis compared responses to #OhmHours among customers of different streak length and status levels. However, customers likely differed across a number of unobservable characteristics, which made it difficult to know if any observed differences were due to differences in streak or status or in other characteristics. Randomization into different streak length and status levels was not feasible for this study, so the research team could not simply compare between customers across groups.

UCLA, therefore, evaluated the effect of earning higher rewards in OhmConnect's streak and status programs by using nonexperimental regression discontinuity design methods. That is, comparing the performance of individuals whose performance on their last #OhmHour was either just above or below the threshold level necessary for receiving the associated streak and/or status reward.

Since customers, especially those who do not use automation, cannot precisely control energy use, it is somewhat random whether a customer's electricity conservation during an #OhmHour event is just above or just below his or her baseline. This means it is somewhat random whether a customer just misses or just maintains his or her streak or status. For the streak analysis, the research team compared the consumption of customers just above to the consumption of those just below the streak continuation threshold on future #OhmHour events. For the status analysis, the research team compared the behavior of customers just above or just below the status threshold on future #OhmHour events. This comparison allowed the research team to estimate how streaks and status affect a customer's future conservation.

For example, imagine that a customer needs to save more than 0.1 kWh relative to the baseline value during an #OhmHour to qualify for increased rewards on the next event. Some customers will happen to save 0.099 kWh and miss qualifying for additional savings, while others will save 0.101 kilowatt hours and just qualify. In this analysis, researchers assumed that random chance led some customers to consume electricity just below the threshold and others to consume electricity just above the threshold. Using this assumption, researchers then compared energy consumption and energy-saving investments from OhmConnect among customers who just qualified and just missed qualifying for each program in each event. Researchers attributed any differences between the two sets of customers to the effect of qualifying for either the streak or status program.

Researchers estimated the effect of treatment by estimating how the relationship between x and y changes at the discontinuity.[33] This estimation was done by estimating the shape of the function on either side of the discontinuity. For the analysis, researchers excluded users whose consumption was in the top and bottom deciles so that those outliers did not skew results.

OhmConnect streak and status incentives could increase event conservation in two ways. First, the existence of these rewards may motivate all users to conserve more electricity. Because there is no variation across users in this motivation, researchers could not test this proposition

[33] Specifically, researchers estimated the local polynomial at the discontinuity using the MLE optimal bandwidth and robust standard errors.

empirically, but this is an important area for future research. Second, streak and status programs increase the marginal incentive for conservation and so individuals would be expected to save more. Researchers investigated this idea.

5.2.1 Streak Method

The streak rewards program is a unique incentive design that has not been evaluated in the context of electricity consumption and has received little attention in other domains.[34,35] The goal of this analysis was to use available data to assess the marginal effect of maintaining and extending a streak on an individual's performance in the next event.

Researchers thus used the previously described regression discontinuity approach to estimate the marginal effect of maintaining a streak relative to losing it (and the associated bonus) on energy consumption reductions. Researchers used statistical tools to estimate how average consumption changes across the discontinuity, where the baseline was equal to actual consumption.[36] To increase precision, the regression discontinuity analysis included covariates controlling for baseline, temperature, the individual's event number, and his or her OhmConnect status before the event.

This approach had several limitations. As a result, it is possible that researchers failed to detect a treatment effect even though the incentive design might be effective relative to the traditional flat incentive or a tiered incentive without a streak framing. First, there are many ways in which the treatment could affect motivation, and individuals might be affected differently. As a result, these effects might mask each other if individuals respond differently to the loss of the streak. Second, the design could plausibly increase consumer engagement over time or increase motivation generally, but if it does not lead to a marked change in motivation when individuals lose their streak, researchers cannot detect an effect.

Researchers hypothesized several potential mechanisms through which streak maintenance and extension could affect subsequent consumption, including marginal financial incentive, medium maximization, moral licensing and compensation,[37] and learning, described in detail below. While it would ultimately be interesting to estimate the relative efficacy of the streak incentive in comparison to a more traditional incentive structure, this estimation was not

[34] Renfree, I., D. Harrison, D., P. Marshall, P., K. Stawarz, K., and &A. Cox, A. 2016. "Don't Kick the Habit: The Role of Dependency in Habit Formation Apps." In *Proceedings of the 2016 CHI Conference Extended Abstracts on Human Factors in Computing Systems* (pp. 2932-2939). ACM.

[35] Huynh, Duy, and Hiroyuki Iida. (2017). *An Analysis of Winning Streak's Effects in Language Course of "Duolingo."*

[36] Estimation was done using the rdrobust package in R. For detailed description of the estimation assumptions and procedures, see "Cattaneo, M. D., N. Idrobo, and R. Titiunik. 2018. *A Practical Introduction to Regression Discontinuity Designs: Volume I.* or Calonico, S., M. D. Cattaneo, and R. Titiunik. 2015. "Rdrobust: An R Package for Robust Nonparametric Inference in Regression-Discontinuity Designs." *R Journal*, *7*(1), 38-51.

[37] Licensing and compensation describe the tendency for individuals to "balance" prior behavior when subsequent moral decisions are made.

possible with available data and a lack of an appropriate control group. As an experimental study is not possible, researchers cannot test these hypotheses.

Marginal Financial Incentive

If individuals are motivated by marginal financial incentives, one would expect that they would reduce their consumption more as they extend their streaks because they receive an increasingly large financial reward. Conversely, one would expect individuals to reduce their consumption less if the streak is lost because their compensation reverts to the lower base rate. Prior work in electricity consumption has suggested that households do not always respond to the marginal price of electricity[38] and that the magnitude of marginal incentives seems to have a relatively modest effect on consumption during critical peak events.[39] However, it is possible that the design of the streak incentive could increase sensitivity to marginal price by increasing salience[40,41] or the perception of relative magnitude.[42]

If participants are motivated by marginal financial incentives, those who maintain and extend their streak would reduce their consumption more compared to those who lose it. That difference would be expected to increase as the length of the streak (and relative difference between marginal incentives) increases.

Medium Maximization

Work in marketing has shown that the "medium" of award (that is, the form of the award, such as points or money) can affect the amount of effort that individuals expend in a task even when the tangible reward is unchanged. For example, in one experiment, individuals were given points that could be exchanged only for ice cream, and different flavors cost different numbers of points. Researchers found that many participants worked longer to earn more points than they needed to purchase their preferred flavor, even though the points had no additional value.[43] It is possible that, while the streak itself has no material value, participants are motivated to build and protect their streaks independent of the financial awards. While their effect has not been extensively studied, many learning and habit-building

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[38] Ito, K. 2014. Do Consumers Respond to Marginal or Average Price? Evidence from Nonlinear Electricity Pricing." *American Economic Review,* 104(2), 537-63.

[39] Gillan, J. 2017. "Dynamic Pricing, Attention, and Automation: Evidence from a Field Experiment in Electricity Consumption." Working paper.

[40] Chetty, Raj, Adam Looney, and Kory Kroft. 2009. "Salience and Taxation: Theory and Evidence." *American Economic Review.* 99.4: 1145-77.

[41] Kahn, M. E., and F. A. Wolak. 2013. *Using Information to Improve the Effectiveness of Nonlinear Pricing: Evidence From a Field Experiment*. California Air Resources Board, Research Division.

[42] Hsee, C. K. and J. Zhang, 2010. "General Evaluability Theory." *Perspectives on Psychological Science*, *5*(4), 343-355.

[43] Hsee, C. K., F. Yu, J. Zhang, and Y. Zhang. 2003. "Medium Maximization." *Journal of Consumer Research*, *30*(1), 1-14.

apps employ streak designs with no financial component to motivate participants.[44] This suggests that streaks might motivate effort independent of the accompanying financial rewards. If participants are motivated to build streaks, one might expect to see greater overall conservation under this incentive scheme than under a system with identical financial rewards but no streak framing. However, given the structure of the data, researchers cannot estimate that overall effect.

While medium maximization might increase overall effort, it does not produce clear predictions about the relative effort individuals would expend when they were maintaining an existing streak versus starting a new one. If individuals exhibit loss aversion, one would expect that individuals work harder to retain their streak than to rebuild a new one. If this were true, researchers would not be able to disentangle the effect of marginal financial incentives from medium maximization using existing data.

Moral Licensing and Compensation

OhmConnect emphasizes the environmental benefits of conserving in addition to the financial incentives. If prosociality, or benefitting others, is the driving motivation for some participants, one might observe moral licensing and compensation. Licensing and compensation describe the tendency for individuals to "balance" prior behavior when subsequent moral decisions are made.[45,46] If moral licensing and compensation affect behavior, one might see laxity among individuals who have built a long streak or see increased effort after failing to meet their baseline. As a result, individuals who begin an event with a streak would reduce their consumption by less than those who lost their streak in the last event. Researchers did not detect this pattern in this analysis.

Learning

Individuals may make a greater effort in a subsequent event after failing to extend their streak because they learn about the amount of effort required to beat their baseline. If failing an event leads an individual to revise his or her estimation of how much effort is needed to maintain the streak, one would expect individuals that lose their streak to conserve a greater amount of energy than those who maintained their streak. This effect would be more pronounced when the participant is new to the program and has less knowledge of how actions translate into savings. However, researchers did not observe that effect even when restricting the analysis to early events.

5.2.2 Status Method

Like OhmConnect's streak-based incentive, the status incentive structure is novel, and the research team is not aware of any prior work that attempted to assess the effect of this type

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[44] Renfree, I., D. Harrison, P. Marshall, K. Stawarz, and A. Cox. 2016. "Don't Kick the Habit: The Role of Dependency in Habit Formation Apps." In *Proceedings of the 2016 CHI Conference Extended Abstracts on Human Factors in Computing Systems* (pp. 2932-2939). ACM.

[45] Zhong, C. B., K. Liljenquist, and D. M. Cain. 2009. *Moral Self-Regulation: Licensing and Compensation.*

[46] Merritt, A. C., D. A. Effron and B. Monin. 2010. "Moral Self - Licensing: When Being Good Frees Us to Be Bad." *Social and Personality Psychology Compass*, 4(5), 344-357.

of incentive structure on effort. While this incentive design clearly affects material incentives in predictable ways, the design could plausibly activate nonfinancial incentives. The research team used the same method as with streaks, regression discontinuity design, which is a statistical method to non-experimentally test differences between groups above and below a threshold. Researchers used a regression discontinuity approach to estimate the marginal effect of maintaining a status relative to losing it (and the associated bonus) on energy consumption reductions. The regression also controlled for the magnitude of the baseline, temperature, event number, and prior streak.

Researchers identified several potential mechanisms through which status-based incentives could affect participant willingness to conserve. These hypotheses included marginal financial incentive, category preferences, and symbolic reward, described in detail below. It is possible that multiple mechanisms were at work and that there could have been heterogeneity of response within the population. Unfortunately, researchers were unable to definitively disentangle which mechanism was at work, given that an experimental study is not possible at this time. Without an appropriate control group, it is not possible to assess the overall effect of the incentive regime on conservation. However, researchers can employ a regression discontinuity to estimate the effect of moving between statuses.

Marginal Financial Incentives

Individuals who move into a higher status receive an increase in the marginal incentive they receive for reducing consumption. As a result, one would expect that individuals would be willing to engage in more inconvenient or uncomfortable conservation behaviors. However, this effect could be muted if those who reach these high levels of conservation (40 percent consumption reduction in the case of the platinum level) have already undertaken all reasonable conservation actions and simply have no further discretionary electricity to cut. While research on increasing block tariffs has suggested that individuals do not always respond to the marginal price of electricity,[47] one would expect that the marginal incentive is made particularly salient by the status design.

Moving into a higher status could therefore result in individuals conserving more during #OhmHours since they face a higher marginal incentive. Researchers could underestimate the marginal effect of the status incentive if those who are close to achieving the next status work harder to move into the next tier. Working harder to move into a higher status is essentially an investment in future earnings. That dynamic would increase conservation within the group being used as a control and would lead to an underestimation of the effect using the regression discontinuity design.

Category Preferences

One consistent finding of the literature on the use of social comparisons for energy consumption is that individuals who consume more than average expend considerable effort to decrease their use. On the other hand, those who learn that they consume less than average

[47] Ito, K. 2014. "Do Consumers Respond to Marginal or Average Price? Evidence from Nonlinear Electricity Pricing." *American Economic Review*, *104*(2), 537-63.

often respond by increasing their use.[48,49,50,51] While the status award does not provide individuals with any information about peer behavior, they may exhibit a similar motivation to move into the relatively superior category or relax if they are already in that superior category. One would therefore expect to see individuals who are close to moving into the gold or platinum statuses to expend greater effort in pursuit of the higher status. Conversely, one might see those who are awarded gold or platinum status relax their efforts.

Symbolic Reward

While the study of symbolic rewards in economics is new,[52] research in other domains suggests that rewards can increase motivation to contribute to public goods even when those rewards generate no material or reputational benefit.[53] It has been hypothesized that this could occur by increasing an individual's perceived competence.[54] There is a large body of work in psychology that has documented the role of perceived competence in intrinsic motivation across domains.[55] If there is an effect of the reward, researchers would expect that those who narrowly move into a higher status will exhibit a marked increase in effort. Unfortunately, researchers are not able to disentangle the effect of symbolic reward from marginal incentive using the regression discontinuity design.

5.3 Streak Results

Researchers find no effect of extending the streak relative to losing it despite differences in marginal financial incentives. When researchers estimate the effect among an individual's first 20 events, they find that those who extend their streak reduce their energy consumption more than those who have lost their streak if their prior streak was five or longer. For detailed tables showing the results of all statistical regressions, see Appendix D.

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[48] Schultz, P. W., J. M. Nolan, R. B. Cialdini, N. J. Goldstein, and V Griskevicius. 2007. "The Constructive, Destructive, and Reconstructive Power of Social Norms." *Psychological Science*, *18*(5), 429-434.

[49] Allcott, H. 2011. "Social Norms and Energy Conservation." *Journal of Public Economics*, *95*(9-10), 1082-1095.

[50] Allcott, H., & T. Rogers. 2014. "The Short-Run and Long-Run Effects of Behavioral Interventions: Experimental Evidence from Energy Conservation." *American Economic Review*, *104*(10), 3003-37.

[51] Byrne, D. P., A. La Nauze, and L. A. Martin. 2017. "Tell Me Something I Don't Already Know: Informedness and the Impact of Information Programs." *Review of Economics and Statistics*, (0).

[52] Frey, B. S. and J. Gallus. 2017. "Towards an Economics of Awards." *Journal of Economic Surveys*, *31*(1), 190-200.

[53] Gallus, J. 2016. "Fostering Public Good Contributions with Symbolic Awards: A Large-Scale Natural Field Experiment at Wikipedia." *Management Science*, *63*(12), 3999-4015.

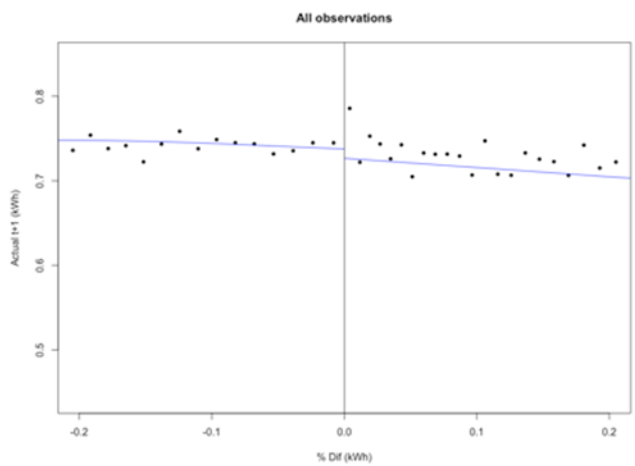
[54] Gallus, J., and B. S. Frey. 2016. "Awards: A Strategic Management Perspective." *Strategic Management Journal*, *37*(8), 1699-1714.

[55] Ryan, R. M., and E. L. Deci. 2000. "Self-Determination Theory and the Facilitation of Intrinsic Motivation, Social Development, and Well-Being. *American Psychologist*, *55*(1), 68.

The following graph shows the relationship between the running variable (the percentage difference between baseline and actual consumption) and consumption in the next event. The analysis includes a visualization of the relationship between the percentage difference of baseline and actual consumption and consumption in the next event. If maintaining a streak changes behavior, one would expect a noticeable shift in the amount of electricity used by those who barely maintain the streak compared to those who barely lose it. The plots include a line fitted to the data and points that represent the average of local observations. As a result, researchers expected to see a shift in the function at the point where percentage difference is equal to zero. Figure 22 includes the entire sample. Appendix D includes additional graphs visualizing the discontinuity by streak length and by restricting the sample to the first 20 events (since engagement is observed to decline around that time). Researchers failed to visually detect a marked change in conservation in the next event at the discontinuity. There is no clear discontinuity in any of the graphs, suggesting that any effect of receiving the higher marginal incentive is small. Observations where the difference is positive (to the right of zero) exceed the baseline and will receive no bonus in the next event.

There are several potential explanations for why increased conservation among those who maintain their streak is not seen. Participants may simply be insensitive to price level as observed in Gillan 2017 presumably due to inattention. Or there may be heterogeneous effects upon different sub-populations that researchers failed to control for.

Figure 22: Visualizing the Discontinuity of the Entire Sample

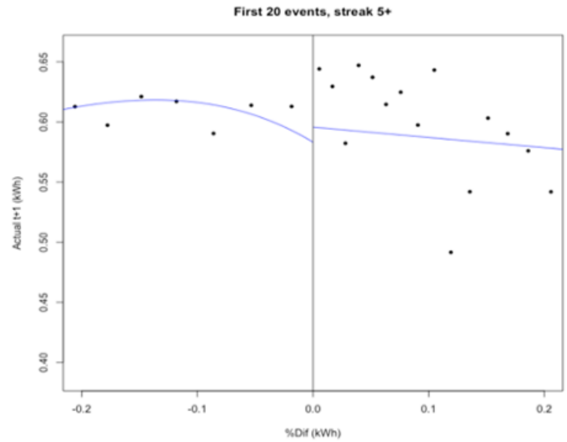


Source: UCLA Luskin Center for Innovation.

The results of the regression discontinuity analysis largely concur with the visualization of the relationship. Researchers did not detect a statistically significant relationship between a user extending his or her streak and consumption in the next event. Appendix D includes the regression tables that show all streak analysis results.

When restricting the sample to a user's first 20 events, there is still no detectable overall effect of extending the streak. However, among those with a streak of five or longer, extending the streak is associated with a 0.088 kWh average reduction in the user's consumption in the next event. Figure 23 shows the graph visualizing the regression discontinuity for this result.

Figure 23: Visualizing the Regression Discontinuity in the First 20 Events for Streaks Lengths Greater Than Five



Source: UCLA Luskin Center for Innovation.

To test whether different customer segments respond differently to the streak incentive, the research team repeated the analysis by demographic sub group. Researchers analyzed those in income-qualified rates (CARE and FERA), those not in income-qualified rates, those in each individual climate zones, and those with and without automation technologies. The analysis did not suggest that any of these subgroups exhibited a significant response to maintaining the streak and receiving the bonus incentive.

The goal of this analysis was to identify how changes in marginal incentives associated with OhmConnect's streak design affect consumption. Though one might expect individuals to respond to the streak bonus, these findings are generally consistent with the literature. Other studies have demonstrated that electricity consumers fail to respond to marginal price,[56] and other experiments using OhmConnect's platform have demonstrated a marked insensitivity to the level of incentive.[57]

The findings are generally consistent with either of the following two scenarios. First, participants are largely inattentive to marginal price, even under the streak design. However, the incentive difference becomes salient and inspires greater effort when the bonus is sufficiently large and when individuals are more engaged. Second, the structure and framing of the streak incentive either increase the salience of the marginal financial or provide additive motivation via medium maximization. However, the effect is obscured because other individuals conserve more after failing an event due to moral cleansing and or learning.

For a validity test of the regression discontinuity design methods, see Appendix E.

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[56] Ito, K. 2014. "Do Consumers Respond to Marginal or Average Price? Evidence from Nonlinear Electricity Pricing." *American Economic Review*, 104(2), 537-63.

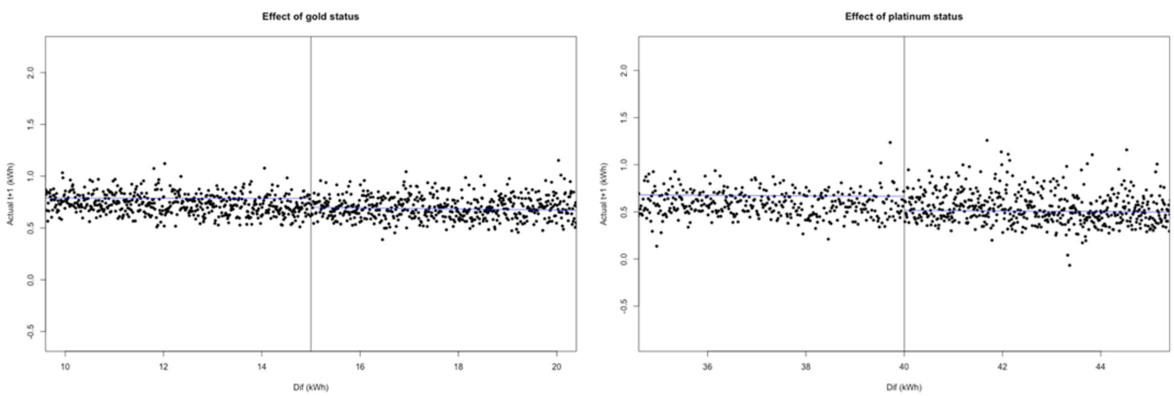
[57] Gillan, J. 2017. "Dynamic Pricing, Attention, and Automation: Evidence from a Field Experiment in Electricity Consumption." Working paper.

5.4 Status Results

Researchers do not find an effect of changing status on consumption when looking at the entire sample. However, when controlling for previous status, researchers find that moving from silver to gold status leads to more consumption reductions in the next event. Researchers also find that receiving gold status appears to lead to an increased likelihood in investment in devices like smart thermostats. Researchers do not observe a statistical relationship between status and subsequent consumption when moving between gold and platinum levels. For detailed tables showing the results of all statistical regressions, see Appendix D.

Researchers first plotted the percentage saved below the baseline in the past 10 events and consumption in the next period, shown in Figure 24. For each user, the average percentage saved over the past 10 events (x-axis) is plotted against the consumption in the event just after the user just misses or just maintains his or her status. Because the cutoff point for gold is 15 percent, anyone over this threshold receives the additional 1.5 times bonus in the next event. If that incentive induces a greater effort to conserve, one would expect to see an increase in consumption reductions at the discontinuity. Similarly, as individuals cross the platinum cutoff of 40 percent reductions, one would expect to see a marked reduction in consumption in the next event. However, the graphs do not reveal an obvious jump.

Figure 24: Consumption in Next Event Compared to Past Consumption



Source: UCLA Luskin Center for Innovation.

It is possible that the experience of gaining status (moving from silver to gold) is psychologically distinct from losing status, which would result in different responses to the change in the marginal incentive. To isolate these effects, researchers again plotted the percentage savings in the past 10 events against consumption in the next event but grouped by users who had the same status in the previous event. These additional graphs are shown in Appendix D. It is still difficult to visually detect a clear effect.

As in the streak analysis, researchers next estimated the treatment effect. The detailed results are included in Appendix D. Researchers failed to observe an effect of status on consumption.

As with the streak analysis, researchers also examined effects among demographic subgroups, including those in and out of income-qualified rates (CARE and FERA), those in different climate zones, and those with and without automation. Researchers found no clear evidence of associations between status and consumption for any of these subgroups. The regression tables showing these results in detail are included in Appendix D.

Then researchers examined the effect of status on consumption two events after a user misses or maintains that status. Researchers found that the additional consumption reduction persists into the subsequent event, indicating that the effect is not so short-lived that it disappears after the first event. Moving to gold status leads to a 0.036 kWh reduction in consumption two events after the user gained that status.

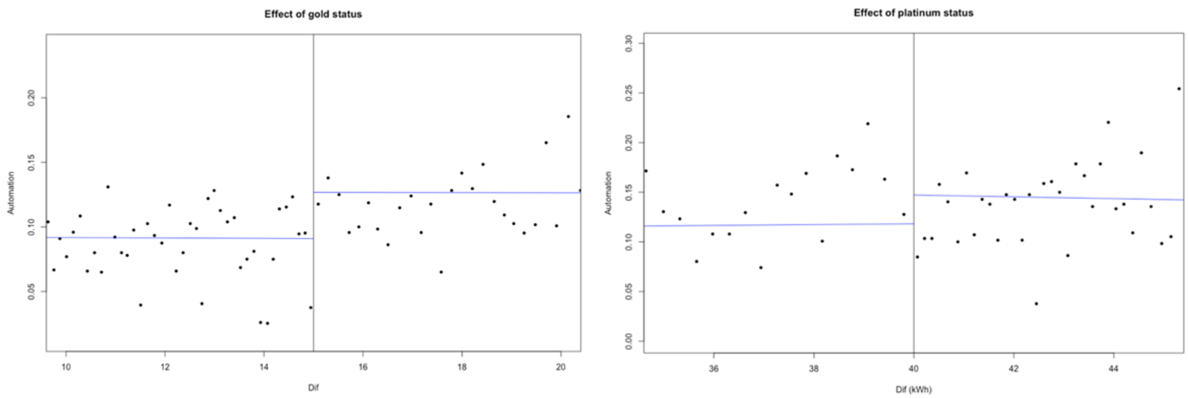
Researchers examine why gold status has a different effect for those who were previously in silver versus those who were already in gold. One potential reason is that the effect of gold status might diminish over time. This reason would suggest that status affects consumption via salience (increasing either the salience of marginal incentives or the salience of the symbolic reward). That salience would be at the highest point when participants move from silver to gold but would diminish over time barring another change in status. The effect persists into the next event (t+2) but may still diminish over time. Another explanation is that gold status induces a durable change in behavior that could be driven by the material incentive or symbolic award, but that losing that status leads to an even greater increase in effort. Losing gold status could increase effort because individuals who have lost their status are more aware (relative to those who have been in silver but are equally close) that they are close to the status cutoff and are willing to expend more effort to secure a higher financial incentive in future events. Or status losers may be dismayed at dropping into a lower category and are more motivated to move back to the higher status category.

This analysis has many limitations. If different mechanisms are at work, researchers might underestimate effects. This underestimation could be the case if marginal incentives increase effort, but preferences to move up to the higher status also increase effort among those who are close to the threshold.

5.4.1 Effect of Gaining Status on Automation

In addition to actual consumption in the next event, researchers assessed whether changes in incentives increase the likelihood that individuals invest in automation technology. Researchers found a statistically significant effect of gold status on subsequent investment in automation technology within 50 days of receiving the new status. This finding means there is a difference in subsequent investment in automation between those who barely earned gold status versus those who barely did not. If the effect was just due to time, researchers would not see a difference between the two groups. Those who achieve gold status are 2.3 percent more likely to invest in automation. Researchers did not find that those who achieve platinum status are more likely to invest in automation. This may be due to the fact that most individuals who were considering automation already made the investment when they moved into gold status prior to platinum status. Figure 25 illustrates the proportion of users who invested in automation within 50 days after just gaining gold or platinum status.

Figure 25: Proportion of Users Who Invest in Automation After Gaining Status



Source: UCLA Luskin Center for Innovation.

For a validity test of the regression discontinuity design methods, see Appendix E.

CHAPTER 6: Incentives, Economic Benefits, and Moral Messaging (Chai Energy Study) Project Results

As noted, this study aimed to understand what influences customer behavior regarding energy consumption during critical periods when the marginal price of electricity is high. Accordingly, this analysis examines how different types of financial incentives and messaging affects consumers' willingness to change energy consumption during peak periods. As a secondary analysis, researchers analyzed how weather and household characteristics affect individuals' participation in demand response events and responsiveness to different types of messaging.

Currently, demand response events are used almost exclusively on hot days. However, as solar continues to grow as a part of California's energy generation, the weather conditions under which demand shifts are necessary will change. As a result, understanding whether demand events have the same effectiveness on different temperature days is essential to maximizing the cost-effectiveness of demand events in the future. Further, relatively little is known about how the effectiveness of demand response events varies across households with different economic, demographic, and energy use characteristics. Better understanding these relationships allows policy makers and utilities to deploy demand response events in the most cost-effective way possible.

6.1 Experimental Design

To conduct this analysis, researchers partnered with Chai Energy to launch a randomized experiment to nearly 3,000 of its users. Chai Energy is a demand response provider that notifies users of critical periods through their free smartphone application and associated push notifications. More information on Chai Energy, its user recruitment, and its smartphone application can be found in section 1.1.1.

In this analysis, Chai Energy users randomly assigned to the treatment group received 10 demand events between September and November 2017 on 10 randomly chosen weekdays, with each event lasting two hours. Each user received two messages alerting them of each upcoming demand response event: one the night before the event and one an hour before the event was set to start. The users also received a notification after the event ended encouraging them to check the Chai Energy smartphone application to examine their progress.

All customers receiving demand response event messages were informed that it was necessary to reduce energy during the event period to help the grid, along with an additional message depending on the treatment group they were randomized into: economic benefits message, moral tax message, or moral subsidy message. These are described in more detail in the Treatment 2 section.

Customers receiving demand response events were also assigned to receive different financial incentives for reducing electricity relative to some baseline value. Baseline values were set using California ISO's 10-in-10 method: the average energy use during the same two-hour period of the demand event in the 10 non-event weekdays preceding the event. Customers received rewards in the form of Chai points, which could be cashed out using PayPal at the exchange rate $0.01 per point. To answer the questions described above, users in the treatment group were randomly assigned to treatment subgroups by level of financial incentive, type of message, time of the event, and event frequency.

6.1.1 Treatment 1: Financial Incentives

This treatment examined a question essential to improving the design of any demand event strategy: how willing are consumers to reduce consumption during certain periods in response to financial incentives? By understanding the average demand curve for reduction, it is possible to set the demand response event incentive closer to the optimal economic level. In this treatment, researchers randomly varied the level of incentives available to users during a demand response event to study the price elasticity of consumers' willingness to reduce consumption.

To assess these changes, the research team randomized roughly half of the treatment sample into this experimental condition. Customers in this treatment were randomly assigned into one of seven financial incentive levels:

- Information only ($0)
- $0.05 per kWh saved during peak period
- $0.50 per kWh saved during peak period
- $1 per kWh saved during peak period
- $2 per kWh saved during peak period
- A randomly selected price (1 of $0.50, $1, $2 with equal probability) per kWh saved during peak periods
- $5 per kWh saved during peak period

Customers were informed of their incentive level for a given event in the messaging they received before the event. The incentive level was also prominently described within the smartphone application on their personalized demand event page.

Researchers also examined the extent to which this elasticity changes under different climatic conditions, by time of day, by access to instantaneous electricity consumption data, and among consumers of different demographic and socioeconomic status groups. These results are important because if significant heterogeneity in responsiveness exists (and researchers show that it does), it suggests that targeted demand response programs (in other words, focusing on the types of days or people that are much more responsive to incentives) may be much more cost-effective than a utility wide approach.

6.1.2 Treatment 2: Economic Benefits and Moral Messaging

In this treatment, researchers investigated how different messages about the purposes and consequences of participating in the demand response events affect consumers' willingness to conserve electricity during peak times. Previous work has shown that moral messaging (with a particular emphasis on health effects) around electricity conservation can have large effects on willingness to reduce consumption.[58] This analysis builds on this by including two moral messages, one that emphasizes the positive consequences of participating in the experiment and the other that emphasizes the negative consequences of not participating. Understanding these differences is crucial to designing effective messaging-based interventions in the future.

All participants in the treatment sample received one of three messages:

- Economic benefits message that emphasized the cost-savings that occur with lower energy use
- Moral subsidy message that emphasized the positive moral and social consequences of conserving electricity during peak times
- Moral tax message that emphasized the negative moral and social consequences of not saving during peak times

Researchers then examined whether the introduction of financial incentives with messaging induced larger or smaller levels of conservation. Users in this treatment sample were further randomly assigned to different incentive levels. Users receiving the economic benefits message were randomly assigned to any of the seven incentive levels described in Treatment 1. Customers receiving either the moral subsidy or moral tax messages were randomized into one of three financial incentive levels:

- Information only ($0)
- $0.05 per kWh saved during peak periods
- $2 per kWh saved during peak period

Table 7 shows the number of individuals randomized into each treatment. Individuals received the relevant framings in the messages that introduced them to the demand response event program, in the messaging alerting them to an upcoming event, and in the messaging congratulating them after finishing an event. Table 6 compares the messages customers received depending on their treatment group. Figure 26 and Figure 27 provide examples of the messages individuals saw in each treatment group.

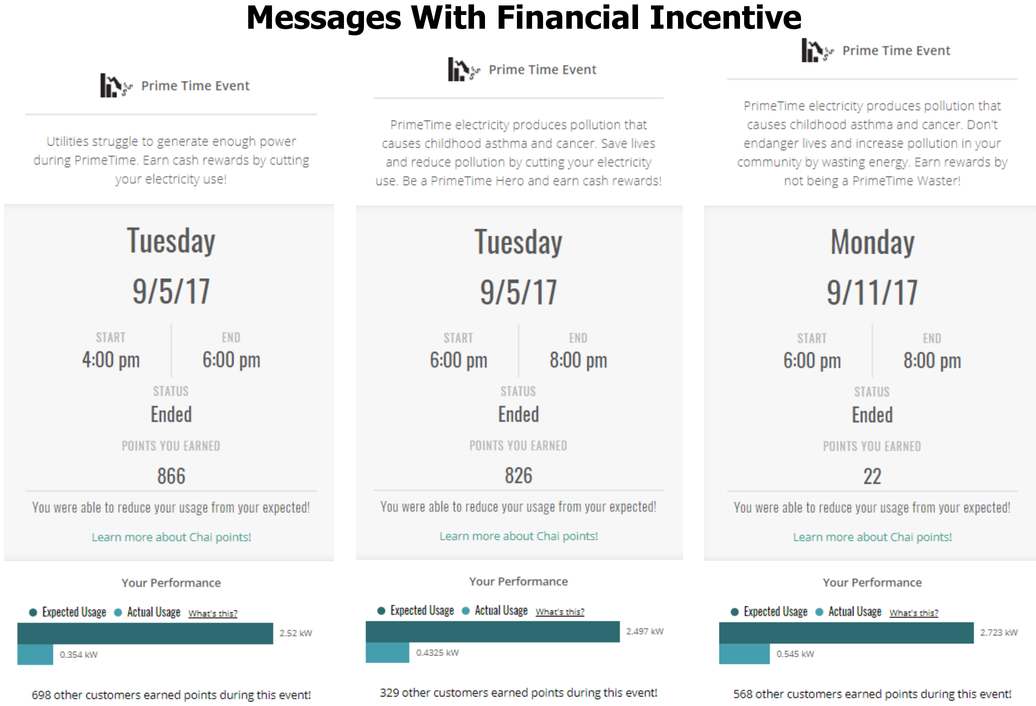
[58] Asensio, Omar I. and Magali A. Delmas. 2015. "Nonprice Incentives and Energy Conservation." *Proceedings of the National Academy of Sciences* 112.6: E510-E515.

Table 6: Demand Response Event Messages Received by Each Treatment Group

Messaging Treatment Group	With Any Financial Incentive	Without Financial Incentive
Economic Benefits	Utilities struggle to generate enough power during PrimeTime. Earn cash rewards by cutting your electricity use!	Utilities struggle to generate enough power during PrimeTime. Lower your utility bill by cutting your electricity use!
Moral Subsidy	PrimeTime electricity produces pollution that causes childhood asthma and cancer. Save lives and reduce pollution by cutting your electricity use. Be a PrimeTime Hero and earn cash rewards!	PrimeTime electricity produces pollution that causes childhood asthma and cancer. Save lives and reduce pollution by cutting your electricity use. Be a PrimeTime Hero!
Moral Tax	PrimeTime electricity produces pollution that causes childhood asthma and cancer. Don’t endanger lives and increase pollution in your community by wasting energy. Earn rewards by not being a PrimeTime Waster!	PrimeTime electricity produces pollution that causes childhood asthma and cancer. Don’t endanger lives and increase pollution in your community by wasting energy. Don’t be a PrimeTime Waster!

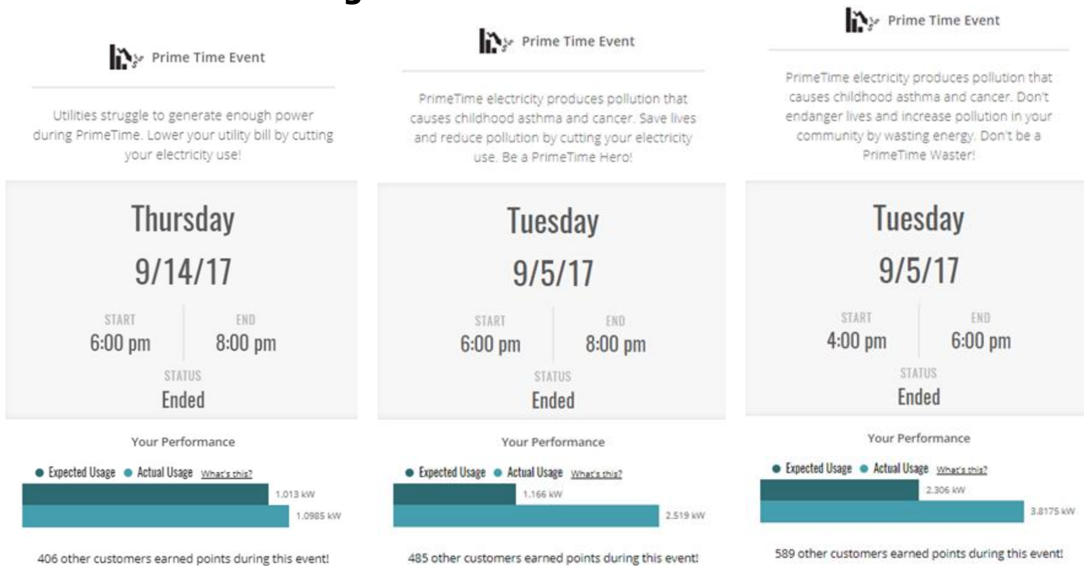
Source: UCLA Luskin Center for Innovation.

Figure 26: Economic Benefits (left), Moral Subsidy (center), and Moral Tax (right) Messages With Financial Incentive



Source: Chai Energy smartphone application

Figure 27: Economic Benefits (left), Moral Subsidy (center), and Moral Tax (right) Messages Without Financial Incentive



Source: Chai Energy smartphone application

6.1.3 Method

Table 7 shows the number of individuals assigned into each group.

Table 7: Number of Individuals Assigned to Each Treatment Group

Message	Financial Incentive per	Sample Size
Control	Control	640
Economic Benefits	$0	179
	$0.05	169
	$0.50	151
	$1	163
	$2	190
	Random incentive	276
	$5	70
Moral Subsidy	$0	196
	$0.05	190
	$2	204
Moral Tax	$0	170
	$0.05	207
	$2	184
	Total	*2,989*

Source: UCLA Luskin Center for Innovation.

Half of all treatment individuals were also randomly assigned to different event times and frequencies. These individuals were randomly assigned to either the high- or low-frequency event group, and in each event individuals were randomized into the 4:00 p.m. or 6:00 p.m. event start.

Table 7 shows that the number of individuals in each treatment are quite small. This small number was not part of the original research design; it occurred because a technical error led to a substantial overestimation of the number of individuals available for randomization that was not discovered until the experiments had already been launched. Unfortunately, this means that this analysis lacks sufficient statistical power to examine many of the original research questions. Accordingly, to gain statistical power while still maintaining the ability to answer the key identified questions, researchers aggregated the subtreatments into the following groups:

Incentive Levels: All messages are combined and use the following three groups:

- Group 1: No incentive ($0)
- Group 2: Small incentives ($0.05 to $1)
- Group 3: Large incentives (greater than $1)

Message: Only $0, $0.05, and $2 incentive levels were used as these are the only incentive amounts common across all framing groups. Researchers then categorized the remaining observations into the following three groups:

- Group 1: Economic benefits message
- Group 2: Moral subsidy message
- Group 3: Moral tax message

Message x Incentive Level: To examine whether the effect of message framings varies with incentive levels, researchers created the following six groups:

- Group 1: Economic benefits message, no incentive
- Group 2: Moral subsidy message, no incentive
- Group 3: Moral tax message, no incentive
- Group 4: Economic benefits message, any incentive
- Group 5: Moral subsidy message, any incentive
- Group 6: Moral tax message, any incentive

For a more detailed explanation of the method, sample, and equations used in this analysis, see Appendix F.

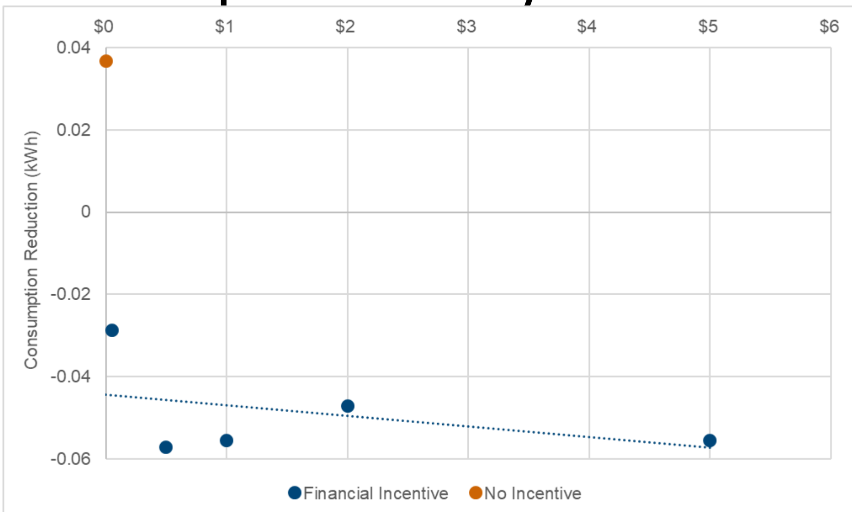
6.2 Results

For detailed tables showing the results of all statistical regressions, see Appendix G.

6.2.1 Financial Incentives

Figure 28 shows the effect of financial incentives on customer's willingness to conserve during peak periods. Across all events, providing some financial reward led to between 0.03 and 0.06 kWh, or 1.7 percent and 3.4 percent, less electricity being used per hour during demand response events, but there did not appear to be large differences between higher or lower financial incentives. Across all events, the absence of financial reward did not lead to any observable reduction in electricity consumption.

Figure 28: Consumption Reductions by Financial Incentive Level



Source: UCLA Luskin Center for Innovation.

However, a different pattern emerged when examining the effects of the treatments on hot days (greater than 90 degrees Fahrenheit[59]) and nonhot days. On hot days, the effect of demand response events was much larger and demonstrated a clearer gradient across financial incentive levels. Relative to the control group, the highest incentive treatments (greater than $2 per kWh saved) lead to a 0.11 kWh reduction in energy use, the low incentive treatments lead to a 0.08 kWh reduction, and the information-only treatment lead to a 0.03 kWh reduction.

Next, researchers examined the effect of the financial incentive subtreatments on energy use on hot and nonhot days relative to the control. Again, the trend was clear; on nonhot days demand response events did not work to reduce electricity usage even under relatively high financial incentives. In contrast, on hot days, even information-only demand events were effective, and response to demand events was relatively elastic to the level of incentives used, especially as these incentives increase. This result could be because consumers had an easy reduction strategy during hot days: they could turn down the AC. On cooler days, it can be more difficult to reduce, which may explain the lack of effect. For detailed results on this analysis, see Appendix G.

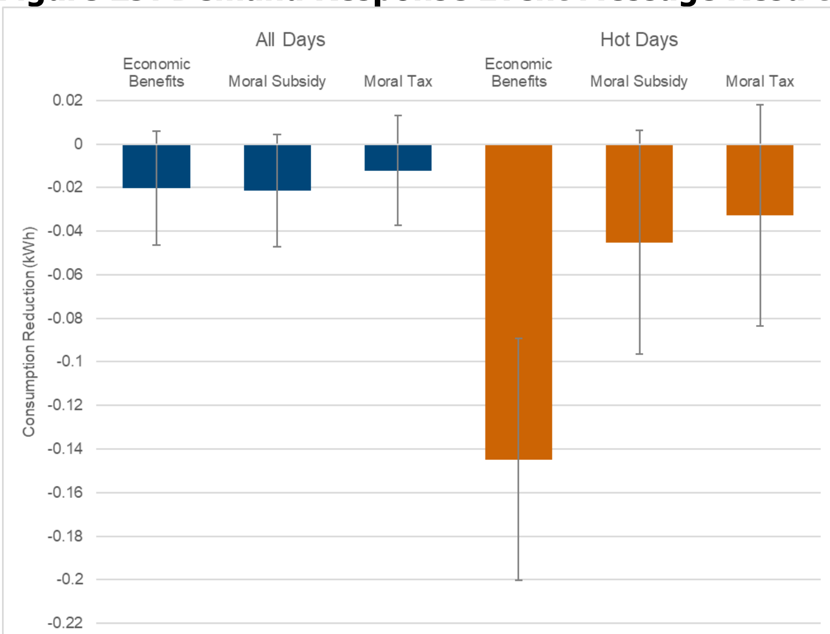
6.2.2 Message Contents

The next analysis examined the effect of different types of messages on customers' energy consumption during demand response events. The economic benefits message, which emphasized the cost savings from reducing electricity or the potential to receive incentives, was more successful at reducing electricity consumption than the moral message, although it was only statistically significant on high-temperature days. On these days, the economic

[59] Using weather station readings throughout California, researchers interpolated temperature estimates by taking the inverse distance weighted average of all stations within 25 miles of a zip code centroid.

benefits message reduced usage by 0.14 kWh, or about 6 percent. The moral subsidy and moral tax messages resulted in a 0.05 kWh and 0.03 kWh reduction, or 2 percent and 1 percent, respectively, although these results are not statistically significant. On days below 90 degrees Fahrenheit, no measureable reduction was detected. Figure 29 shows the main results.

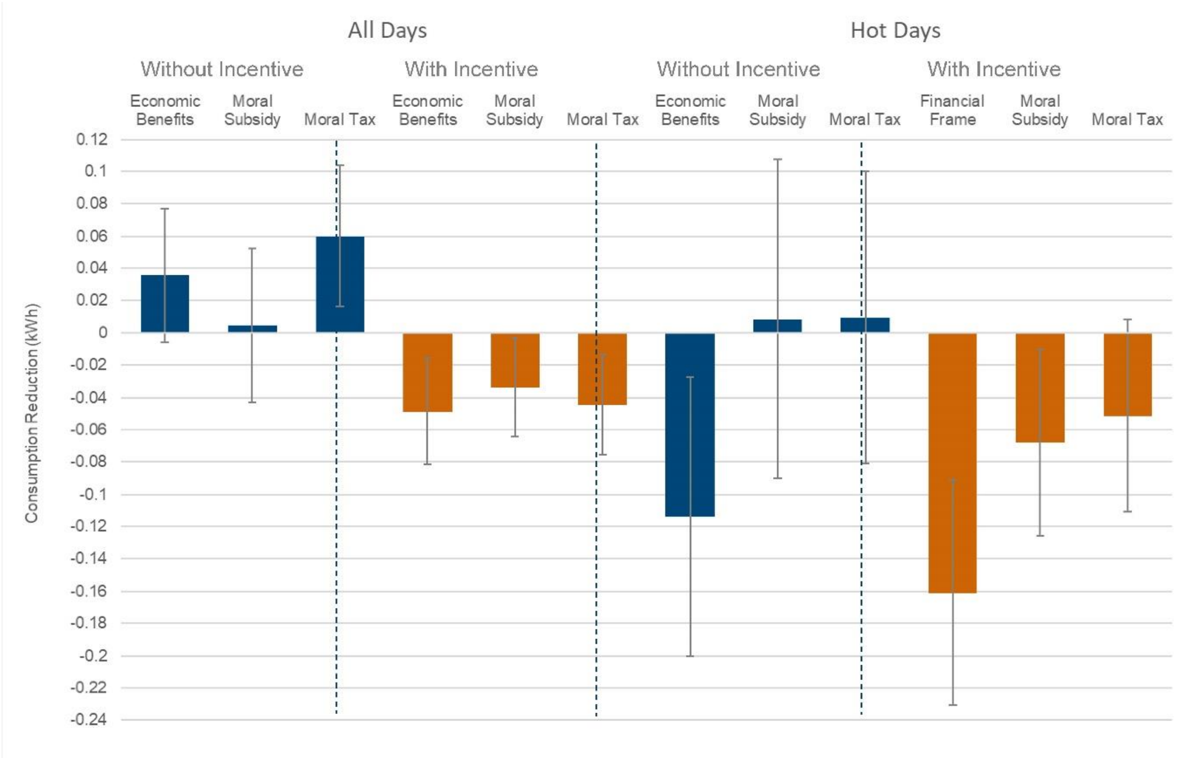
Figure 29: Demand Response Event Message Results



Source: UCLA Luskin Center for Innovation.

These results differ from those found by Asensio and Delmas (2017). They found that exposure to information about the health and environmental effects of energy consumption (similar to the moral messages used in this study) led to greater energy reduction than information about cost savings. The difference in results could be driven by several factors. First, their research took place in the context of an informational intervention that targeted overall energy use rather than during demand events. Second, while the messaging in this study also discussed health and environmental effects of energy use, it was not identical to the Asensio and Delmas (2017) messaging. Finally, the financial and moral messaging also included financial incentives, which may change the effectiveness of both messages. Figure 30 examines this possibility explicitly, comparing the effects of demand response events between the different messages without financial incentives (blue bars) and with financial incentives (orange bars). Because of the small sample size, it is hard to draw any firm conclusions from this table. However, on high-temperature days, the financial (cost-saving) message is more effective, especially when offered with a financial incentive. On cooler days and without financial incentives, none of the messages are particularly effective.

Figure 30: Effects of Messages With and Without Financial Incentives



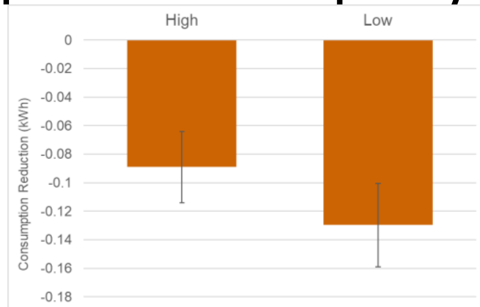
Source: UCLA Luskin Center for Innovation.

6.2.3 Timing and Frequency

This section presents whether energy consumption reductions are different depending on the demand response event frequency and time. Individuals in the high-frequency treatment received three events per week for the first two weeks and then one event every two weeks for the remaining eight weeks. Those in the low-frequency treatment received one event per week for all 10 weeks. The table shows results separately for hot and nonhot days. Demand response events started at 4:00 p.m. or 6:00 p.m. and lasted two hours.

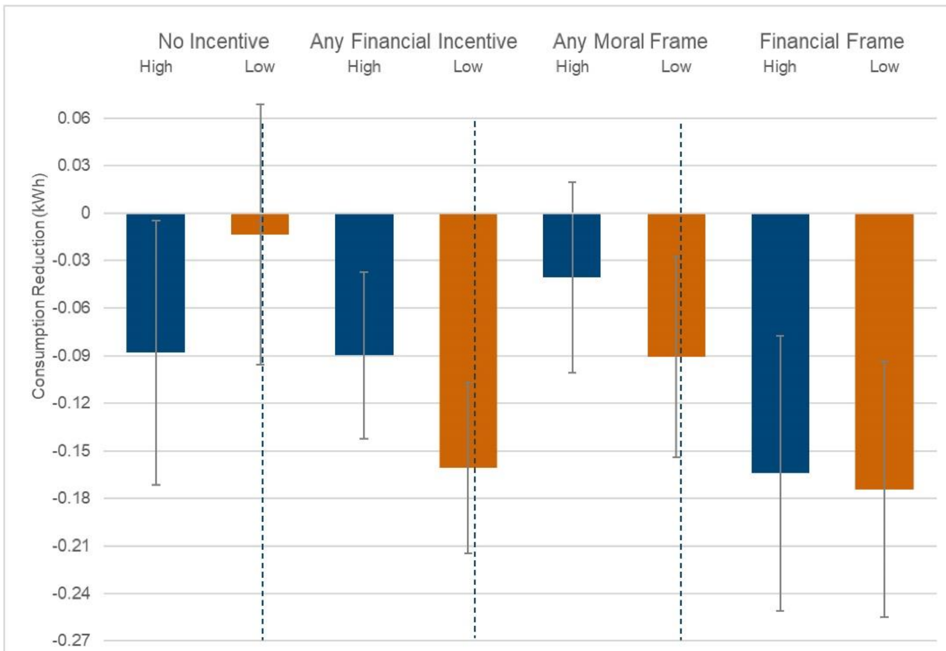
The results for the high- and low-frequency treatments are shown in Figure 31 and Figure 32. These figures only show effects on days with a high temperature above 90 degrees Fahrenheit, as no treatment type reduced usage on nonhot days, consistent with other results in this section. Generally, the low-frequency treatment was slightly more effective with either the economic benefits message or the moral messages. Consistent with the results in the previous section, the consumption reductions with the economic benefits message were larger for the high- and low-frequency groups compared to the moral messages. Financial incentives appear more effective in the low-frequency treatment. However, high-frequency events were more effective with no financial incentive. Conversely, the high-frequency treatment responded more to the no-financial incentive condition (although the difference is not statistically significant), possibly because the message was reinforced more frequently.

Figure 31: Demand Response Event Consumption by High and Low Frequency



Source: UCLA Luskin Center for Innovation.

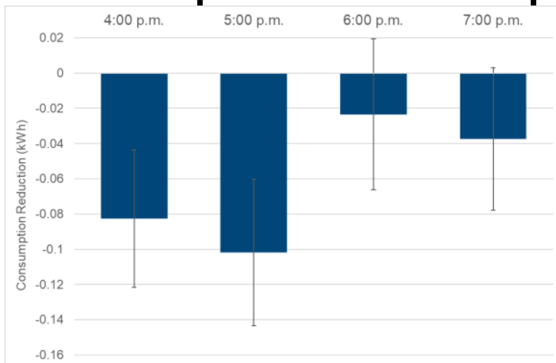
Figure 32: Demand Response Event Frequency Consumption by Message and Incentive



Source: UCLA Luskin Center for Innovation.

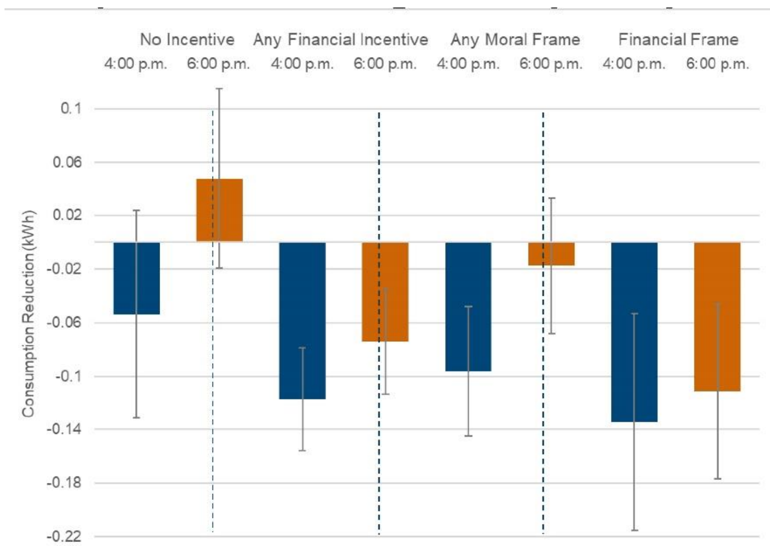
Next, researchers examined how different event timing affects use. There is evidence for time-of-day effects, illustrated in Figure 33 and Figure 34. Consumption reductions were greatest at 4:00 p.m. and 5:00 p.m. compared to at 6:00 p.m. and 7:00 p.m. When examining how timing varied by message and incentive, researchers found that demand response events beginning at 4:00 p.m. resulted in slightly greater consumption reductions than those beginning at 6:00 p.m. Events at 4:00 p.m. resulted in 0.04 kWh more energy saved in the financial incentive condition and 0.1 kWh more energy saved in the no-financial incentive condition. Events at 4:00 p.m. reduced energy consumption by 0.02 kWh with an economic benefits message and 0.08 more with a moral message. Figure 33 and 34 show these effects only for hot days as these effects are much larger, although demand response events at 4:00 p.m. were generally more effective across all days as well. With this analysis and with the OhmConnect analysis (Chapter 3), researchers found that 5:00 p.m. was the most effective time for demand response events. However, the effectiveness of demand response events at other times varied by demand response provider, message, and financial incentive. This finding suggests that demand response event timing may be context-specific and relies on several varying factors. More qualitative work is needed to better understand what might be driving these results.

Figure 33: Demand Response Event Consumption by Time



Source: UCLA Luskin Center for Innovation.

Figure 34: Demand Response Event Timing Consumption by Message and Incentive



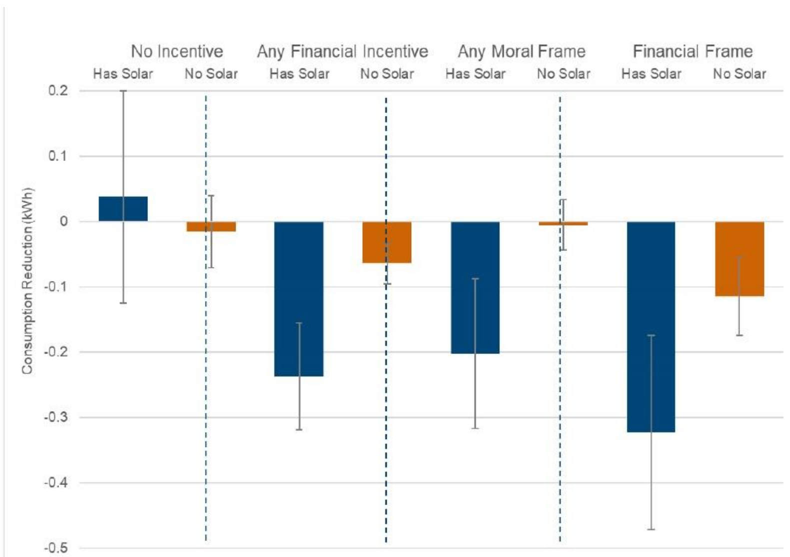
Source: UCLA Luskin Center for Innovation.

6.2.4 Demographic Analysis

Next, researchers examined whether energy consumption reductions differ based on whether or not a household has solar PV and the household's income level (proxied by zip code median income). There are differences in effects between households with and without solar PV and differences between those with above- and those with below-median income, seen primarily on hot days. Solar PV customers are much more responsive to demand events than customers without solar PV. Figure 35 shows these results on hot days. Across all events, especially on hot days, customers with solar PV outperformed those without when they received an economic benefits message or a financial incentive. On hot days, customers with solar PV in the financial incentive group reduced usage by 0.24 kWh, or 10 percent, and those receiving the economic benefits message reduced usage by 0.32 kWh, or 14 percent. Customers without solar PV also responded to demand response events with a financial incentive and economic benefits message, but at much lower levels; customers without solar PV with financial incentives reduced usage by around 0.06 kWh, or 2 percent, while those receiving the economic benefits message reduced by 0.12 kWh, or 4 percent. While moral messages were effective on hot days for those with solar PV, economic benefits messages were 6 percentage points more effective. Without a financial incentive, neither those with or without solar PV reduced their energy consumption during demand response events.

Solar PV owners may be more likely to reduce than other customers for several reasons. First, solar PV owners may be more likely to engage in other types of automation that lowers the effort required to participate in demand response events. Second, solar PV owners may be more knowledgeable about energy use more generally, making participation easier. Finally, solar PV owners may be more concerned about the environment and, therefore, more receptive to messaging about energy conservation. More follow-up research is necessary to better understand why this group of users is more willing to reduce consumption during demand events. This finding suggests that solar PV owners could be targeted for a more focused demand response program.

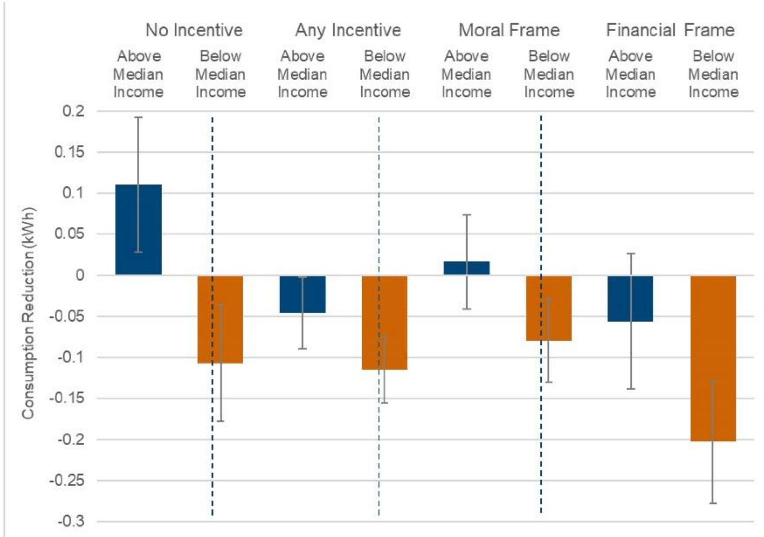
Figure 35: Results for Customers With and Without Solar PV



Source: UCLA Luskin Center for Innovation.

Figure 36 shows the differential responses to demand events based upon whether individuals live in zip codes that have median incomes above or below California's median. Users living in zip codes below the median income reduced their consumption by more than those above the median income for all treatment groups. Similar to all previous analyses, on hot days, statistically significant effects were seen only for financial incentives and economic benefits messaging groups for below median income users. Large differences between income groups were not seen when looking at events on all days. These findings differ slightly from the demographic analysis completed with the OhmConnect customer sample (Chapter 3). Researchers believe this difference occurred because of the different compositions in customer bases between the two demand response providers. Notably, the median income is higher with the Chai Energy sample than with the OhmConnect sample, possibly affecting these results. More qualitative research is necessary to better understand this phenomenon.

Figure 36: Results for Customers by Median Income



Source: UCLA Luskin Center for Innovation.

CHAPTER 7: Policy and Program Design Recommendations

One of the primary purposes of these analyses is to inform effective demand response program design. These findings can be useful to demand response providers, and other relevant stakeholders in California and across the country, to maximize demand response program participation and effectiveness. This study focused on residential customers and evaluated different elements of demand response programs, including baselines, incentives, messaging, timing, and frequency. Moreover, researchers analyzed how these results varied by demographics and temperature conditions. Based on the results described in previous chapters, researchers conclude with the following key policy recommendations.

7.1 Targeting Demand Response by User Demographics

Demand response events are effective at reducing consumption, but reductions vary by program design and user characteristics. There were only minor differences in responsiveness among most demographic subgroups.

"Energy-engaged users" (those with PEV, solar PV, or automation) had the greatest consumption reductions during demand response events. Policy support for programs that increase the uptake of these technologies could contribute to wider responsiveness during demand response events. Whether such a policy would be cost-effective depends on the expected value of the energy reductions on the grid, given the high cost of these technologies. Another important consideration is the differences between demographic groups in capacity to reduce consumption during events. Similar to how users' have a greater capacity to reduce on hot days when they can turn of their AC, users with PEVs and users with above-median consumption have larger reductions to demand response events, likely because of their ability to reduce more.

Customers with automation devices in particular are highly correlated with greater responsiveness to events across all demographic groups. Automation is key for residential demand response programs, as users with this technology exhibit high levels of responsiveness because the effort of reducing consumption is reduced. As researchers found some evidence that income differences were driven by differential adoption rates of these technologies, equipping low-income customers with automation devices could be one way to increase responsiveness and maintain engagement with demand response events. Because low-income users are more price-sensitive, but high-income users are more likely to have the resources necessary to easily respond to demand events, differences in event responsiveness for subgroups located between those two extremes could be masked by these two countervailing factors.

Similarly, automation devices could be important for perpetuating the effectiveness of demand response events as more customers switch to a TOU rate. When looking at non-energy-engaged customers, TOU users reduce less than users on other tariffs. This finding likely reflects the fact that customers who have voluntarily enrolled in TOU have already taken action to reduce their electricity consumption during peak times every day, resulting in more limited ability to reduce consumption further during demand response events. However, these results are inverted when looking at energy-engaged customers. In this specific context, TOU customers reduced their electricity consumption by 37 percent, while non-TOU customers reduced their consumption by 27 percent. Favoring energy technologies such as automation seems essential to maintain high demand response efficiency, even as California transitions more customers to TOU pricing.

7.2 Most Effective Financial Incentives and Messaging for Demand Response Events

Users responded best to the economic benefits of demand response events. Financial incentives and messages emphasizing cost savings were two of the most effective program designs at reducing consumption. Offering an incentive is important to inducing consumption reduction, users do not respond linearly to greater financial incentives. These results suggest that, in general, using low incentives is likely most cost-effective for achieving energy reductions. Larger incentives should be used only when demand response providers need to increase electricity consumption reductions as much as possible, regardless of cost-effectiveness.

Furthermore, researchers found that the additional nonlinear financial incentives offered by maintaining successful streaks or statuses of energy consumption reductions with OhmConnect did not induce greater or more consistent reductions on their own. Downplaying the financial incentives in such programs, such as offering a flat incentive structure, might result in greater conservation per program dollar spent. Alternatively, these programs could emphasize the nonfinancial aspects of consistent performance, as it is possible that consumption reductions could be achieved by employing a streak or status framing without additional financial bonuses. It is also possible that the streak and status program designs have other positive effects that were impossible to notice due to the lack of control group, or that have non-energy consumption related effects, such as cheaper customer acquisition, greater organic growth, or higher customer retention.

Demand response providers should emphasize the cost savings that customers can achieve from reducing energy consumption. Messaging that emphasized the cost-saving benefit of demand response was more successful than messaging that emphasized either the benefits or consequences on health and the environment. Emphasizing cost savings resulting from electricity consumption reductions outperformed health and environmental messages even without the provision of financial incentives. This finding gives pause to the idea that moral messaging can be used as a substitute for financial incentives or even messaging about cost savings.

7.3 Most Effective Times for Demand Response Events

Demand response events were most effective in the spring and summer, especially on days hotter than 90 degrees Fahrenheit. This result is likely because on these days, users have a greater capacity to reduce consumption by turning off their AC. In the randomized control trial analysis, demand response events were relatively ineffective on days cooler than 90 degrees. Similarly, when non-experimentally analyzing the OhmConnect data, researchers also found less effectiveness on cooler days. This finding suggests that residential demand events may not be an effective way of accomplishing these types of demand shifts on cooler days. As renewables become a larger part of California's energy portfolio, it may become more necessary to manage demand not only on hot days, but on cooler days and when weather or lack of daylight cause sharp changes in renewable generation. More research is needed to understand how to better induce consumption reductions on cooler days when users have less capacity to reduce consumption. Moreover, with increasing renewables, the electrical grid may be faced more frequently with excess solar and the associated negative prices in the wholesale electricity market. Further research could examine how to induce users to increase consumption or shift demand to these times.

Without automation devices, residential demand response relies on behavioral changes to energy consumption, which may constrain some users in their ability to participate in events at some times during the day. With OhmConnect and Chai Energy, demand response events at 5:00 p.m. resulted in the greatest consumption reductions. At other times, the effectiveness varied by context and other factors, such as accompanying message, financial incentive, or demographics of users. More qualitative research is necessary to better understand what is driving this phenomenon.

7.4 Maintaining Customer Engagement

User engagement and user fatigue are important considerations for residential demand response programs. User engagement tends to fall over time. Researchers found that users reduced consumption by 30 percent more during their first 20 demand response events relative to later events. Moreover, researchers found when examining streak and status programs, which reward users for conserving over an extended period or repeatedly conserving beneath a goal, respectively, that a user's streak length and status level decreased over time, suggesting users were less engaged over time. A central challenge of all demand response providers is how to not only attract customers, but ensure that they remain active participants in the long term. OhmConnect's strategy of emphasizing automation may be an effective way to accomplish this goal. Customer automation adoption should be encouraged, particularly during a user's first 20 events before a decrease in a customers' willingness to undertake behavioral consumption reductions.

Furthermore, a balance needs to be found between maintaining user engagement and demand response event frequency. While users who received a lower frequency of demand response events generally performed better per event, there is a risk of customers leaving the platform if they do not continually receive demand response events. With Chai Energy, researchers observed high levels of customer attrition after only a few months without demand response events. OhmConnect offers a potential solution to this as it conducts a few demand response events during the winter or when temperatures are not high to maintain customer engagement. Winter events may come with associated costs that can provide a barrier to demand response providers and new market entrants.

OhmConnect's innovative gamification of demand response events through its streak and status programs is possibly one of the reasons for their success in California. Given data limitations, the analysis in this study examined only the effectiveness of the marginal incentives offered by the streak and status programs and not the programs themselves. The streak and status programs may induce greater overall effort or lower attrition, even if customers’ electricity consumption behavior does not exhibit sensitivity to their increasing marginal incentives. In fact, researchers found that when users gain gold status, which is when they reduce their consumption by at least 15 percent below their baseline for the last ten demand response events, they are more likely to invest in automation. Further research is needed to evaluate how the existence of streaks and statuses affect improved customer relationship with the platform compared to other demand response programs that do not offer gamified programs. Further research should also examine other tools to maintain user interest to ensure the long-term success of demand response.

CHAPTER 8: Benefits to Californians

According to the U.S. Department of Energy, "the most important benefit of demand response is improved resource efficiency of electricity production due to closer alignment between customers' electricity prices and the value they place on electricity."[60] This results in a variety of economic, health, environmental, and operational benefits for California, its residents, and its ratepayers, as described in this chapter.

8.1 Benefits to California

8.1.1 Greater Energy Reliability and Increased Safety

As the share of renewable energy increases in California, the need for demand flexibility increases to ensure reliable, safe, and stable grid operations. Demand response providers have the ability to aggregate customers and reduce their electricity load at the most important times, adding flexibility to the load when most needed and avoiding risk of outages and electricity interruption.[61] Moreover, the participation of electricity customers in maintaining grid operation helps defer further infrastructure investments.[62] Finally, demand response provides wholesale market improvement as it helps reduce price volatility and diminish the market power of some energy providers at times of high stress on the grid and highly volatile prices.[63] One study showed that a 5 percent reduction in demand during the California energy crisis could have reduced costs by 50 percent.[64]

8.1.2 Health and Environmental Benefits

Demand response programs avoid the consumption of electricity when demand is abnormally high and requires a lot of expensive power supply, including peak power plants and other old fossil fuel generators. By reducing electricity consumption at those times, California helps reduce the emission of greenhouse gas and criteria air pollutants into the atmosphere.

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[60] U.S. Department of Energy. 2006. *Benefits of Demand Response in Electricity Markets and Recommendations for Achieving Them.*

[61] Albadi, M., and E. El-Saadany. 2007. "A Summary of Demand Response in Electricity Markets." *Electric Power Systems Research,* 78 (11) November 2008.

[62] Goel, L., W. Qiuwei, and W. Peng, 2006. *Reliability Enhancement of a Deregulated Power System Considering Demand Response.*

[63] Barbose, G., C. Goldman, and C. Neenan, 2004. *A Survey of Utility Experience with Real-Time Pricing*. Lawrence Berkeley National Laboratory.

[64] Caves, D., K. Eakin, and A. Faruqui, 2000. *Mitigating Price Spikes in Wholesale Markets Through Market-Based Pricing in Retail Markets.* The Electricity Journal 13(3):13-23.

In this specific solicitation, the CEC assumes that each kWh of electricity saved results in 0.73 pounds of avoided carbon dioxide emissions.[65] The demand response events conducted with OhmConnect and Chai Energy over this study period resulted in about 200 megawatt-hours (MWh) of cumulative electricity consumption reduction during peak times. This reduction resulted in an estimated 66 metric tons of carbon dioxide ($MTCO_2e$) in avoided emissions.

The burning of fossil fuels for electricity generation also results in criteria pollutant emissions. Exposure to criteria pollutants is associated with adverse health impacts, including respiratory and cardiovascular issues. Disadvantaged communities have the most significant exposure to these emissions, including communities in nonattainment air basins for ozone, particulate matter (PM) 10 and PM 2.5; those with high poverty, minority populations, unemployment rates, or a combination thereof; and those with a high percentage of age-sensitive populations. The energy consumption reductions that occurred during this study period reduced the need for electricity generation at times when it was most needed, thereby avoiding the emission of these criteria pollutants. A reduction in these pollutant emissions can improve public health of the most vulnerable Californians.

8.2 Benefits to Electricity Ratepayers in California

8.2.1 Study Participant Benefits

First, electricity customers who participate in demand response events reduce their electricity usage, resulting inevitably in bill savings compared to what it would have been if they consumed more electricity. These financial savings are even higher for customers consuming electricity in higher consumption tiers and customers enrolled in TOU rates. In total, participants saved 200 MWh during the study. Based on the monthly average price of electricity calculated by the California Public Utilities Commission,[66] this collective reduction in consumption would result in $34,700 in direct bill savings for participants.

Then, participants who successfully reduce their consumption compared to their baseline could earn money if the demand response provider offers a financial incentive for successful participation. In the study conducted with Chai Energy, $1,700 incentives were distributed to a portion of the study participants and paid for with CEC funds. In the study conducted with OhmConnect, participating customers earned about $1 million over two years without any financial contribution from the CEC.

8.2.2 Nonparticipant Benefits

The benefits of this study and demand response in general are considerable for nonparticipants as well. Demand response results in better use of existing generation resources (including renewable energy and fossil fuel) and transmission and distribution assets. A more efficient use of the infrastructure defers investments that California ratepayers will not have to pay. A reduced load at critical times, when prices are high, not only results in

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[65] California Energy Commission 2015. "Grant Funding Opportunity: Advancing Solutions that Allow Customers to Manage Their Energy Demand."

[66] California Public Utilities Commission. 2018. *California Customer Choice: An Evaluation of Regulatory Framework Options for an Evolving Electricity Market.*

cheaper wholesale rates for all customers, but reduces the need for short-term capacity, resulting in fewer investments in generation capacity. In some regions of the grid that are congestion-constrained, one could also imagine that demand response can reduce the cost of congestion as well as defer distribution and transmission infrastructure investment. All these avoided costs are reflected in the price of electricity for participants and nonparticipants. For example, OhmConnect claims that each demand response it has in summer displaces four power plants.[67] Finally, to the extent that demand response avoids greenhouse gas emissions in the electricity sector, it may also reduce the amount of allowances that electricity distribution utilities have to purchase in the cap-and-trade auction market. This reduction also reduces the overall cost for electricity customers in California.

[67] OhmConnect. 2019. Home page.

GLOSSARY AND LIST OF ACRONYMS

Term	Definition
AC	Air conditioner
Baseline	An estimate for how much electricity a user would have consumed without a demand response event. Users are often rewarded for their consumption reductions relative to their baseline. The current method for calculating the baseline is California ISO's method, which is the user's average consumption in the same hour of the demand response event during the previous 10 non-event, nonholiday weekdays.
CARE	California Alternative Rates for Energy. This rate schedule offers a percentage discount for low-income customers on their electricity bill.
Chai Energy	A demand response provider.
CPUC	California Public Utilities Commission
Demand response event	An hour or a few hours during critical electricity demand periods when demand response providers alert participants to shift or reduce their energy consumption.
Demand response provider	An entity that aggregates customer energy consumption changes at necessary times.
CEC	California Energy Commission
EPIC	Electric Program Investment Charge, is research funding administered by the California Energy Commission, Pacific Gas and Electric, San Diego Gas & Electric, and Southern California Edison.
FERA	Family Electric Rate Assistance. This rate schedule offers a percentage discount for low-income customers on their electricity bill.
Information targeting	A theory that users use informational cues as guidance for behavior, such as using a baseline as a cue for the magnitude to which a user needs to adjust their energy consumption behavior.
IOU	Investor-owned utility
kWh	Kilowatt-hour. A unit of electricity, one kilowatt-hour is equivalent to the amount of electricity generated by one kilowatt for one hour.
Loss aversion	An economic theory that suggests that people are generally more motivated to prevent losses than accumulate similarly sized gains.
Metric ton	A unit of measurement. 1 metric ton is equivalent to 1.10231 United States tons.
$MTCO_2e$	Metric tons of carbon dioxide equivalent

Term	Definition
MWh	Megawatt-hour, a unit of electricity equivalent to 1,000 kilowatt-hours.
OhmConnect	A demand response provider.
#OhmHour	OhmConnect's name for a demand response event.
PM	Particulate matter, a type of air pollution, is composed of small solid and liquid particles.
PEV	Plug-in electric vehicle
PG&E	Pacific Gas and Electric, an investor-owned utility that provides gas and electricity in Northern California.
PrimeTime	Chai Energy's name for a demand response event.
SCE	Southern California Edison, an investor-owned utility that provides electricity in Southern California.
SDG&E	San Diego Gas & Electric, an investor-owned utility that provides gas and electricity in San Diego County and part of Orange County.
Solar PV	Solar photovoltaic. A type of solar panel used to generate electricity.
TOU	Time of use. Refers to a rate in which users are charged different electricity rates per kWh depending on what time of day the electricity is consumed.
True counterfactual consumption	The actual amount of electricity a user would have consumed in the absence of a demand response event.
UCLA	University of California, Los Angeles

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APPENDIX A: Data Collection and Data Transfer to UCLA

The University of California, Los Angeles Luskin Center for Innovation (UCLA), received household electricity consumption and other relevant data from Chai Energy and OhmConnect. These demand response providers collected data from users through Green Button Data, which allows residential customers to access their 15-minute interval energy consumption data. Customers within the three main California IOU territories have access to their Green Button Data. This data access allows users to participate fully in demand response events, as demand response providers are able to quantify their energy consumption reductions during events and subsequently reward them.

There are steps a user must take to provide a demand response provider with their data. For Chai Energy, users must first download the smartphone application. For OhmConnect, users must first sign up by email, Facebook, or Google on the OhmConnect website landing page. To become active users, users then must register their account with their utility provider to grant demand response providers permission to obtain access to the users' utility data.

Users sign up via a streamlined process that allows them to connect their electric meter information through software protocols. The Open Authorization (OAuth)[68] click-through authorization process provides customers with a streamlined and simplified means to share their data with third parties. The process provides customers, third parties, utilities, and policy makers with a safe and secure method to authorize data sharing. OhmConnect's click-through process uses OAuth 2.0 technology and is similar to what many website service providers use to allow customers to create an account on a website using credentials from another service, such as Google or Facebook. OhmConnect noted that the new OAuth 2.0 click-through process improved customer conversion rates from signups to active users, primarily due to customer familiarity with OAuth and the automatic approval of the data-sharing agreement once the customer completes authorization. OhmConnect implemented the click-through process for each of the three main California IOUs, shown in Figure A-1. This process also reduced the barrier to customer recruitment that posed a significant challenge for Chai Energy.

[68] The Open Authorization (OAuth) click-through authorization process was approved by the California Public Utilities Commission in Resolution E-4868.

Figure A-1: Click-Through Example

Source: OhmConnect, Inc.

Chai Energy also has access to higher-resolution consumption data for Chai Pro customers. Chai Energy Pro customers have gateway devices, which interface directly with a user's smart meter to collect real-time energy consumption data. Chai Pro gateway devices request usage data from the smart meter every 7-10 seconds.

Chai Energy and OhmConnect then transferred this collected data to UCLA for analysis. Chai Energy developed a researcher portal to allow researchers to manage data from the study participants. The web portal provided (1) a connection of Chai Energy's backend systems and data to a web interface; (2) organized access to key participant information, energy consumption data, data analytics, and demand response event performance; and (3) the ability to create, manage, and administer demand response events. Chai Energy provided UCLA with data on hourly energy consumption for each customer, zip code, annual energy usage in the year prior to the start of the experiment, and whether the customer had a Chai Pro gateway device. OhmConnect provided UCLA with data on hourly energy consumption for each customer, zip code, and energy consumption in the previous year through an encrypted data transfer for a random sample of 20,000 OhmConnect users.

APPENDIX B: General Demand Response Regression Tables

Table B-1 shows results for consumption during a demand response event under increasingly strict controls. Columns (3) and (6) show researchers' preferred specification. Columns (4) through (6) estimate whether event behavior changed if a user also had an event the day before, which reflects a situation more closely related to a TOU setting. Table B-2 shows the same analysis but restricts the sample to a user's first 20 demand response events.

Table B-1: Demand Response Event Consumption

VARIABLES	(1) kWh	(2) kWh	(3) kWh	(4) kWh	(5) kWh	(6) kWh
Event	-0.139***	-0.142***	-0.145***	-0.136***	-0.140***	-0.142***
	(0.0126)	(0.0127)	(0.0135)	(0.0123)	(0.0126)	(0.0133)
Event Prev Day				-0.0250*	-0.0231*	-0.0263**
				(0.0131)	(0.0137)	(0.0122)
Observations	62,652,773	62,559,677	61,973,403	62,652,773	62,559,677	61,973,403
R-squared	0.565	0.588	0.633	0.565	0.588	0.633
User x Temp FE	Y	Y	Y	Y	Y	Y
User x Hour FE	Y	Y	Y	Y	Y	Y
Day x Hour FE	Y	Y	Y	Y	Y	Y
User x Temp x Hour FE	N	Y	N	N	Y	N
Day x Zip Code FE	N	N	Y	N	N	Y
Dep. Var. Mean	0.796	0.796	0.796	0.796	0.796	0.796

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Source: UCLA Luskin Center for Innovation

Table B-2: Demand Response Event Consumption During First 20 Events

VARIABLES	(1) kWh	(2) kWh	(3) kWh	(4) kWh
Event	-0.176***	-0.171***	-0.135***	-0.132***
	(0.0175)	(0.0166)	(0.0130)	(0.0129)
Event_before		-0.0638***		-0.0278**
		(0.0217)		(0.0133)
Observations	61,187,519	61,187,519	61,742,146	61,742,146
R-squared	0.634	0.634	0.634	0.634
Sample	1st 20 Events	1st 20 Events	After 20 Events	After 20 Events
User x Temp FE	Y	Y	Y	Y
User x Hour FE	Y	Y	Y	Y
Day x Hour FE	Y	Y	Y	Y
User x Temp x Hour FE	N	N	N	N
Day x Zip Code FE	Y	Y	Y	Y
Dep. Var. Mean	0.786	0.786	0.788	0.788

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Source: UCLA Luskin Center for Innovation.

Table B-3 and Figure B-1 show the spillover effects of demand response event consumption reductions into the two hours before and two hours after an event. Table B-4 and Figure B-2 show the spillover effects of demand response event consumption into the two days before and two days after an event.

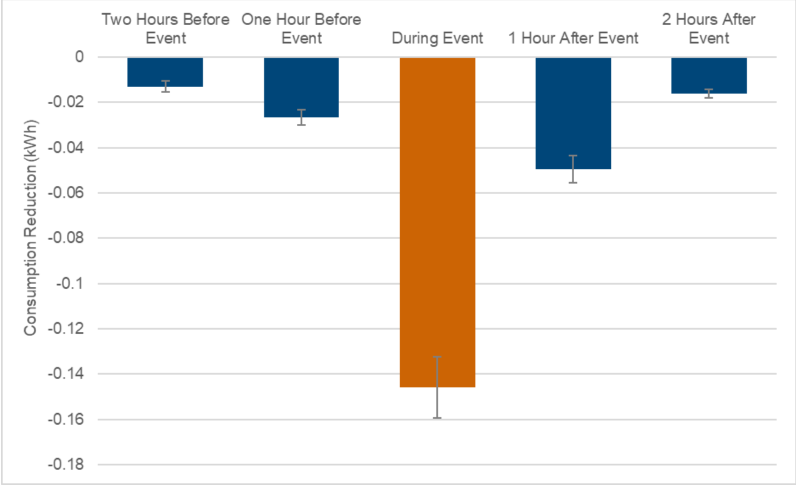
Table B-3: Demand Response Event Spillover Effects Into Hours Surrounding Event

VARIABLES	(1) kWh	(2) kWh	(3) kWh	(4) kWh	(5) kWh
Event	-0.0130***	-0.0266***	-0.146***	-0.0496***	-0.0162***
	(0.00244)	(0.00344)	(0.0136)	(0.00611)	(0.00193)
Observations	55,987,133	55,995,402	55,995,484	55,986,922	55,742,886
R-squared	0.639	0.639	0.637	0.638	0.639
Hour Relative to Event	-2	-1	0	1	2
User x Temp FE	Y	Y	Y	Y	Y
User x Hour FE	Y	Y	Y	Y	Y
Day x Hour FE	Y	Y	Y	Y	Y
User x Temp x Hour FE	N	N	N	N	N
Day x Zip Code FE	Y	Y	Y	Y	Y
Dep. Var. Mean	0.803	0.803	0.803	0.803	0.803

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Source: UCLA Luskin Center for Innovation

Figure B-1: Demand Response Spillover Effects Into Hours Surrounding Event



Source: UCLA Luskin Center for Innovation

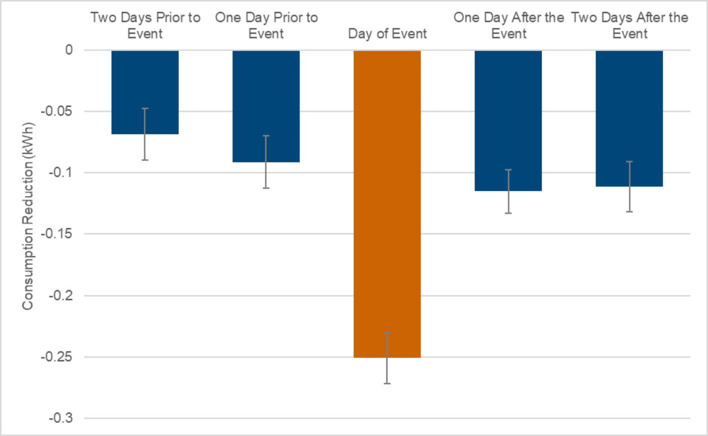
Table B-4: Demand Response Event Spillover Effects Into Days Surrounding Event

VARIABLES	(1) kWh	(2) kWh	(3) kWh	(4) kWh	(5) kWh
Event	-0.0684***	-0.0913***	-0.251***	-0.115***	-0.111***
	(0.0210)	(0.0214)	(0.0206)	(0.0177)	(0.0205)
Observations	3,949,939	4,036,496	4,075,622	4,042,521	3,943,299
R-squared	0.761	0.759	0.759	0.759	0.762
Days Since Event	-2	-1	0	1	2
Dep. Var. Mean	6.938	6.936	6.926	6.927	6.923

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Source: UCLA Luskin Center for Innovation.

Figure B-2: Demand Response Spillover Effects Into Days Surrounding Event



Source: UCLA Luskin Center for Innovation.

Table B-5 shows how demand response event consumption varies by temperature and season. Table B-6 shows how demand response event consumption varies by the hour the event takes place. Table B-7 shows how demand response event consumption varies by demographic subgroup, and Table B-8 shows how demand response event consumption varies by a user's energy profile.

Table B-5: Demand Response Event Consumption by Temperature and Season

VARIABLES	(1) kWh	(2) kWh	(3) kWh	(4) kWh	(5) kWh	(6) kWh
Event	-0.368***	-0.0953***	-0.0693***	-0.122***	-0.239***	-0.0678***
	(0.0196)	(0.00550)	(0.00530)	(0.0144)	(0.0149)	(0.00453)
Observations	7,585,998	54,360,877	17,384,249	17,354,670	17,261,311	9,698,063
R-squared	0.643	0.558	0.556	0.675	0.691	0.604
Sample	Temp >90	Temp <90	Q1	Q2	Q3	Q4
User x Temp FE	Y	Y	Y	Y	Y	Y
User x Hour FE	Y	Y	Y	Y	Y	Y
Day x Hour FE	Y	Y	Y	Y	Y	Y
User x Temp x Hour FE	N	N	N	N	N	N
Day x Zip Code FE	Y	Y	Y	Y	Y	Y
Dep. Var. Mean	1.761	0.650	0.632	0.699	1.093	0.684

Clustered standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Source: UCLA Luskin Center for Innovation.

Table B-6: Demand Response Event Consumption by Hour

VARIABLES	(1) kWh	(2) kWh	(3) kWh	(4) kWh	(5) kWh	(6) kWh
Event	-0.118***	-0.111***	-0.181***	-0.176***	-0.152***	-0.114***
	(0.0258)	(0.0181)	(0.0262)	(0.0207)	(0.0163)	(0.00840)
Observations	6,116,876	6,169,212	6,202,876	6,362,656	6,365,880	6,339,167
R-squared	0.644	0.628	0.618	0.611	0.602	0.592
Sample	3PM	4PM	5PM	6PM	7PM	8PM
User x Temp FE	Y	Y	Y	Y	Y	Y
User x Hour FE	Y	Y	Y	Y	Y	Y
Day x Hour FE	Y	Y	Y	Y	Y	Y
User x Temp x Hour FE	N	N	N	N	N	N
Day x Zip Code FE	Y	Y	Y	Y	Y	Y
Dep. Var. Mean	0.621	0.729	0.862	0.955	0.973	0.977

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Source: UCLA Luskin Center for Innovation.

Table B-7: Demand Response Event Consumption by Demographic Subgroup

VARIABLES	(1) kWh	(2) kWh	(3) kWh	(4) kWh	(5) kWh	(6) kWh	(7) kWh	(8) kWh	(9) kWh	(10) kWh
Event	-0.159***	-0.130***	-0.175***	-0.115***	-0.147***	-0.142***	-0.113***	-0.149***	-0.185***	-0.106***
	(0.0146)	(0.0125)	(0.0169)	(0.0102)	(0.0129)	(0.0142)	(0.0143)	(0.0134)	(0.0197)	(0.00776)
Observations	30,967,014	31,006,389	30,863,054	31,110,349	31,087,420	30,872,574	7,510,659	54,035,303	30,723,921	31,249,482
R-squared	0.629	0.637	0.635	0.625	0.614	0.646	0.672	0.634	0.643	0.581
Sample	> Median White	<Median White	> Median Homeown	<Median Homeown	>Median Income	<Median Income	CARE	Non-CARE	>Median Single Family Home	< Median Single Family Home
User x Temp FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
User x Hour FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Day x Hour FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
User x Temp x Hour FE	N	N	N	N	N	N	N	N	N	N
Day x Zip Code FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Dep. Var. Mean	0.787	0.790	0.873	0.704	0.709	0.868	0.916	0.770	0.971	0.622

Clustered standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Source: UCLA Luskin Center for Innovation.

Table B-8: Demand Response Event Consumption by Energy Profile

VARIABLES	(1) kWh	(2) kWh	(3) kWh	(4) kWh	(5) kWh	(6) kWh	(7) kWh	(8) kWh	(9) kWh	(10) kWh
Event	-0.311***	-0.129***	-0.302***	-0.114***	-0.349***	-0.108***	-0.164***	-0.142***	-0.203***	-0.0845***
	(0.0344)	(0.0118)	(0.0341)	(0.00978)	(0.0330)	(0.00986)	(0.0162)	(0.0132)	(0.0201)	(0.00660)
Observations	4,597,299	56,337,092	9,691,857	50,814,945	5,657,430	54,211,335	4,334,172	56,398,358	30,436,125	30,541,412
R-squared	0.777	0.620	0.682	0.626	0.725	0.635	0.743	0.635	0.597	0.590
Sample	Solar	Non-Solar	PEV	No PEV	Ever Automation	No Automation	ToU	Non-ToU	>Median Consumption	< Median Consumption
User x Temp FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
User x Hour FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Day x Hour FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
User x Temp x Hour FE	N	N	N	N	N	N	N	N	N	N
Day x Zip Code FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Dep. Var. Mean	0.568	0.568	1.202	0.698	0.746	0.803	0.808	0.787	1.195	0.382

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Source: UCLA Luskin Center for Innovation.

Table B-9: Demand Response Event Consumption by Rate Schedule and Energy Profile

VARIABLES	(1) kWh_	(2) kWh	(3) kWh_	(4) kWh_
Event	-0.341***	-0.286***	-0.0540***	-0.0859***
	(0.0422)	(0.0310)	(0.00557)	(0.00712)
Constant	0.978***	1.080***	0.666***	0.712***
	(0.000833)	(0.000691)	(7.43e-05)	(0.000104)
Observations	1,304,471	10,378,146	2,133,324	44,891,958
R-squared	0.769	0.699	0.738	0.620
Sample	ToU + Act. Egy	NonToU + Act. Egy	ToU + Non-Act Egy	NonToU + Non-Act Egy
User x Temp FE	Y	Y	Y	Y
User x Hour FE	Y	Y	Y	Y
Day x Hour FE	Y	Y	Y	Y
User x Temp x Hour FE	N	N	N	N
Day x Zip Code FE	Y	Y	Y	Y
Dep. Var. Mean	0.928	1.075	0.722	0.714

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Source: UCLA Luskin Center for Innovation.

Table B-10 shows how demand response event consumption varies by CARE status and energy profile.

Table B-10: Demand Response Event Consumption by CARE Status and Energy Profile

VARIABLES	(1) kWh	(2) kWh	(3) kWh	(4) KWh
Event	-0.245***	-0.287***	-0.0807***	-0.0856***
	(0.0392)	(0.0308)	(0.0100)	(0.00643)
Observations	773,095	11,606,535	6,343,274	41,331,250
R-squared	0.733	0.695	0.680	0.616
Sample	CARE + Act. Egy	NonCARE + Act. Egy	CARE + Non-Act Egy	NonCARE + Non-Act Egy
User x Temp FE	Y	Y	Y	Y
User x Hour FE	Y	Y	Y	Y
Day x Hour FE	Y	Y	Y	Y
User x Temp x Hour FE	N	N	N	N
Day x Zip Code FE	Y	Y	Y	Y
Dep. Var. Mean	1.242	1.033	0.862	0.690

Clustered standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Source: UCLA Luskin Center for Innovation.

APPENDIX C:
Baseline Analysis Regression Tables

The results from the baseline analysis are shown in Table C-1. The coefficients all refer to the estimated effect of the baseline on outcomes using the procedure outlined in the above section. Columns (1) and (2) show that baseline levels affect actual consumption. The odd columns show the results for using baseline calculation Days 9 and 10 as the instrument, while the even columns show the results for using just Day 10.[69] The effect is similar regardless of the instrument used, although only statistically significant when researchers use the 9- and 10-day instrument. Columns (3) and (4) are a placebo test, demonstrating the effect of an increase in baseline on usage during the next non-event weekday following an event. Because baselines should affect only event-day performance, if there was an effect, the instrument could be correlated with other factors that affect contemporaneous consumption and results could be spurious. However, the coefficients are consistently small, statistically insignificant, and in the opposite direction of the main result, increasing confidence that there is a causal effect. Columns (5) and (6) provide an additional test of the assumption that the instrument is uncorrelated with other factors that might affect event-day consumption. Researchers found that an increase in baseline is not economically or statistically associated with higher event-day temperatures; taken literally, a 0.1 kWh increase in baseline leads to a statistically insignificant 0.07 degree Celsius increase in event-day maximum temperature, far too small to explain the size of the results. This result provides more evidence that there is a causal effect between baselines and consumption during a demand response event.

Table C-1: Results From Baseline Analysis

VARIABLES	(1) Actual Use	(2) Actual Use	(3) Placebo Use	(4) Placebo Use	(5) Max Tmp	(6) Max Tmp
Baseline (using IV)	0.173**	0.148	-0.00682	-0.0371	0.716	0.900
	(0.0718)	(0.0989)	(0.122)	(0.167)	(1.010)	(1.699)
Observations	866,342	866,342	869,377	869,377	866,341	866,341
R-squared	0.189	0.186	0.241	0.238	0.464	0.458
Instrument	Days 9-10	Days 10	Days 9-10	Days 10	Days 9-10	Day 10
Dep. Var. Mean	.921	.921	.953	.953	25.78	25.78

Clustered standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Source: UCLA Luskin Center for Innovation.

Reassuringly, neither automated nor nonautomated users' energy consumption on the next non-event weekday responds to the baseline providing evidence that the results here are causal. The results of this analysis are in Table C-2.

[69] In all cases, the F-stat on the first stage are far above 10, suggesting that these instruments are highly correlated with baseline, and the instruments are relevant.

Table C-2: Results From Baseline Analysis on Automated and Nonautomated Users

VARIABLES	(1) Actual Use	(2) Actual Use	(3) Placebo Use	(4) Placebo Use	(5) Max Tmp	(6) Max Tmp
Baseline (using IV)	-0.0313	0.203**	-0.133	0.0214	0.543	0.734
	(0.0546)	(0.0770)	(0.141)	(0.123)	(0.811)	(1.049)
Sample	Autom	Non-Autom	Autom	Non-Autom	Autom	Non-Autom
Observations	125,602	740,657	125,603	743,691	125,602	740,656
R-squared	0.093	0.209	0.241	0.240	0.470	0.464
Instrument	Days 9-10	Days 9-10	Days 9-10	Days 9-10	Days 9-10	Days 9-10
Dep. Var. Mean	0.704	0.956	0.924	0.958	25.45	25.84

Clustered standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Source: UCLA Luskin Center for Innovation.

Table C-3 shows the results comparing those above and below median income.

Table C-3: Results of Baseline Analysis by User Income

VARIABLES	(1) Actual Use	(2) Actual Use	(3) Placebo Use	(4) Placebo Use	(5) Max Tmp	(6) Max Tmp
Baseline (using IV)	0.0759	0.215**	-0.0543	0.0285	0.213	1.124
	(0.0763)	(0.0909)	(0.132)	(0.123)	(0.753)	(1.258)
Sample	>Med. Inc	<Med. Inc	>Med. Inc	<Med. Inc	>Med. Inc	<Med. Inc
Observations	434,860	431,044	436,238	432,698	434,860	431,043
R-squared	0.149	0.208	0.222	0.248	0.432	0.475
Instrument	Days 9-10	Days 9-10	Days 9-10	Days 9-10	Days 9-10	Days 9-10
Dep. Var. Mean	0.818	1.024	0.834	1.073	24.85	26.72

Clustered standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Source: UCLA Luskin Center for Innovation.

Table C-4 shows the effect of a changing baseline on actual event consumption for high savers and nonhigh savers.

Table C-4: Results of Baseline Analysis on High Savers and NonhighSavers

VARIABLES	(1) Actual Use	(2) Actual Use	(3) Placebo Use	(4) Placebo Use	(5) Max Temp	(6) Max Temp
Baseline (using IV)	0.164***	0.275***	-0.0523	0.00492	0.706	0.606
	(0.0572)	(0.0928)	(0.115)	(0.132)	(0.802)	(1.140)
Sample	High Savers	Non-HS	High-Savers	Non-HS	High-Savers	Non-HS
Observations	181,882	684,439	181,223	688,132	181,882	684,438
R-squared	0.087	0.262	0.193	0.259	0.433	0.471
Instrument	Days 9-10	Days 9-10	Days 9-10	Days 9-10	Days 9-10	Days 9-10
Dep. Var. Mean	0.760	0.965	1.081	1.081	26.978	25.422

Clustered standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Source: UCLA Luskin Center for Innovation.

APPENDIX D:
Streaks and Status Analysis Additional Information

To analyze user events over time, researchers performed a regression analysis controlling for temperature, invariant user effects, and average zip code performance on an event. In Table D-1, Columns (1) through (3) show the effect of each coefficient relative to a user's performance during events 0 through 10. Columns (3) through (5) show the effect relative to when the user had completed between 10 and 30 events. This is because a streak longer than 10, or any status of gold or platinum is not possible during a user's first 10 events.

Table D-1: User Consumption per Event Controlling for Different Factors

VARIABLES	(1) Usage	(2) Streak=0	(3) Streak>10	(4) Gold or Plat.	(5) Platinum
10-30 events	0.0200***	0.0177***			
	(0.00551)	(0.00333)			
30-50 events	0.0401***	0.0262***	0.000878	-0.0462***	-0.00956***
	(0.00765)	(0.00429)	(0.00256)	(0.00475)	(0.00312)
>50 events	0.0475***	0.0294***	-0.00104	-0.0670***	-0.0141***
	(0.0105)	(0.00519)	(0.00369)	(0.00664)	(0.00463)
Observations	813,214	810,170	722,262	722,210	722,210
R-squared	0.755	0.417	0.705	0.724	0.800

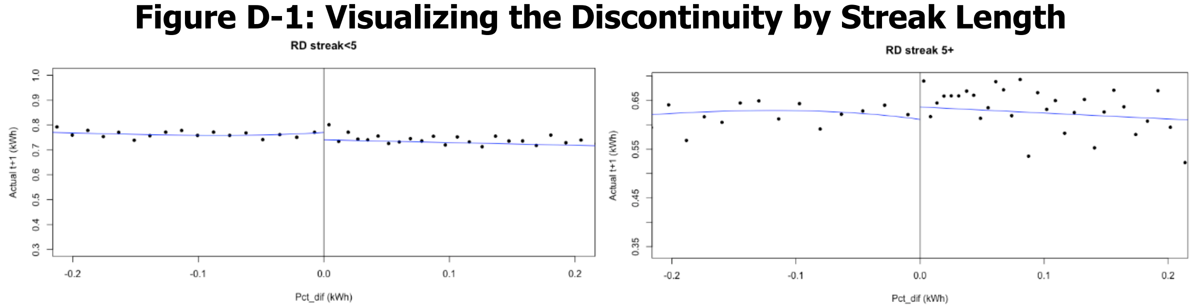
Clustered standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Source: UCLA Luskin Center for Innovation.

Streak Analysis Visualizing the Discontinuity Additional Graphs

Figure D-1 illustrates those with short streaks (shorter than 5, left) and those with long streaks (longer than 5, right).

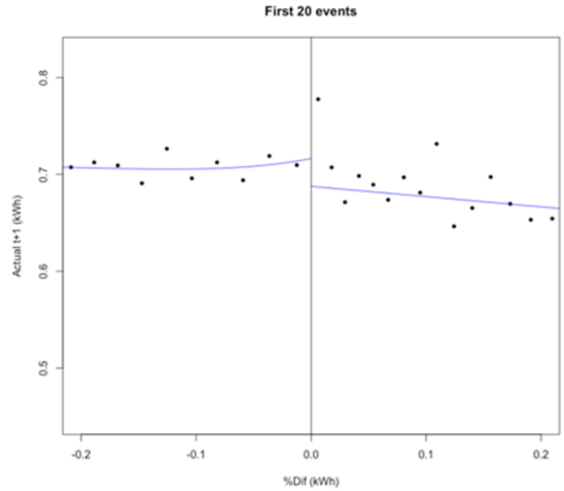
Figure D-1: Visualizing the Discontinuity by Streak Length



Source: UCLA Luskin Center for Innovation.

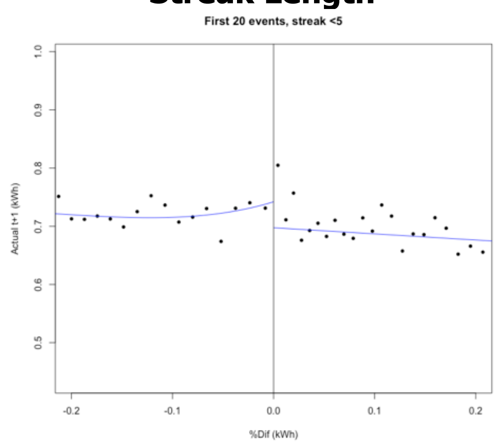
Figure D-2 shows the streak analysis but restricts the sample to users' first 20 events, and Figure D-3 looks at streaks longer than five during the first 20 events.

Figure D-2: Visualizing the Discontinuity in the First 20 Events for Entire Sample



Source: UCLA Luskin Center for Innovation.

Figure D-3: Visualizing the Regression Discontinuity in the First 20 Events by Streak Length



Source: UCLA Luskin Center for Innovation.

Streak Analysis Regression Tables

Table D-2 and Table D-3 show the statistical regression results for the streak regression discontinuity analysis with the whole sample and restricted to the first 20 events, respectively. Table D-4 shows these results by demographic subgroup.

Table D-2: Regression Discontinuity Analysis With Full Dataset

Dataset	N_left	N_right	MSE_optimal_bandwidth	Coef_ext_streak	Robust_P_value	Robust_CI_Lower	Robust_CI_Upper	Covariates
Full	220253	105351	0.141	0.002	0.924	-0.020	0.018	baseline_kwh:tempbin:status
Streak<5	169431	92451	0.173	0.011	0.350	-0.008	0.030	baseline_kwh:tempbin:status
Streak5+	50806	12893	0.178	-0.035	0.194	-0.085	0.009	baseline_kwh:tempbin:status

Source: UCLA Luskin Center for Innovation.

Table D-3: Effect of Maintaining Streak on Consumption During First 20 Events

Dataset	N_left	N_right	MSE_optimal_bandwidth	Coef_ext_streak	Robust_P_value	Robust_CI_Lower	Robust_CI_Upper	Covariates
Full	55217	25035	0.166	-0.024	0.206	-0.065	0.009	baseline_kwh:tempbin:status
Streak<5	42059	21670	0.196	-0.007	0.668	-0.048	0.028	baseline_kwh:tempbin:status
Streak5+	13147	3363	0.175	-0.088	0.037	-0.187	-0.019	baseline_kwh:tempbin:status

Source: UCLA Luskin Center for Innovation.

Table D-4: Effect of Maintaining Streak on Consumption by Demographic Subgroup

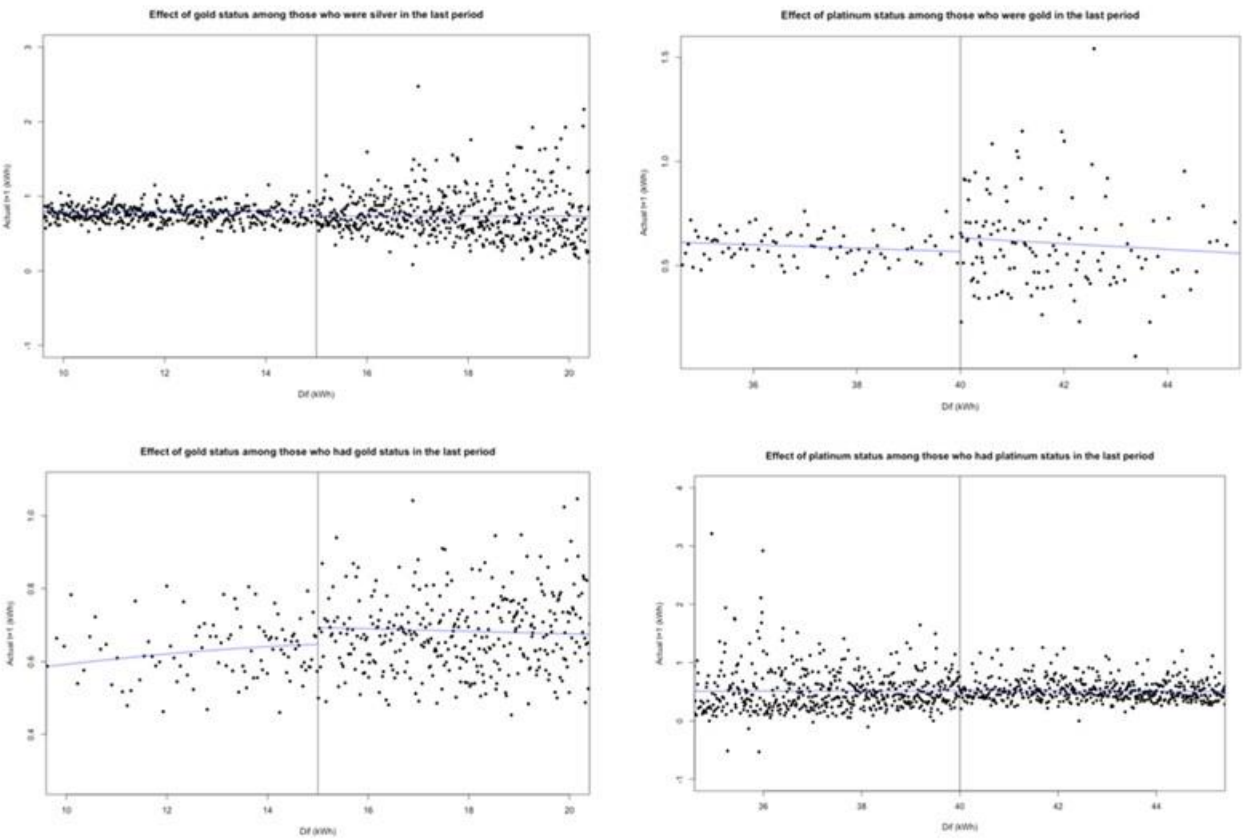
Dataset	N_left	N_right	MSE_optimal_bandwidth	Coefficient	Robust_P_value	Robust_CI_Lower	Robust_CI_Upper	
Income Qualified	26025	14312	0.225	-0.017	0.304	-0.039	0.010	baseline_kwh:tempbin:event_number:status
Not Income Qualified	194228	91039	0.223	-0.008	0.202	-0.017	0.003	baseline_kwh:dow:tempbin:event_number:status
Climate Zone 1	1603	660	0.249	0.048	0.484	-0.078	0.187	baseline_kwh:dow:tempbin:event_number:status
Climate Zone 2	6112	2536	0.266	-0.024	0.426	-0.078	0.028	baseline_kwh:dow:tempbin:event_number:status
Climate Zone 3	37921	21084	0.225	-0.009	0.290	-0.023	0.006	baseline_kwh:dow:tempbin:event_number:status
Climate Zone 4	17848	8284	0.220	0.016	0.257	-0.011	0.052	baseline_kwh:dow:tempbin:event_number:status
Climate Zone 5	2752	1592	0.205	-0.046	0.069	-0.099	-0.003	baseline_kwh:dow:tempbin:event_number:status
Climate Zone 6	16819	9780	0.214	-0.019	0.160	-0.043	0.004	baseline_kwh:dow:tempbin:event_number:status
Climate Zone 7	16967	10266	0.201	-0.001	0.875	-0.023	0.028	baseline_kwh:dow:tempbin:event_number:status
Climate Zone 8	17392	9611	0.241	-0.017	0.350	-0.042	0.012	baseline_kwh:dow:tempbin:event_number:status
Climate Zone 9	11533	5603	0.224	0.006	0.619	-0.031	0.055	baseline_kwh:dow:tempbin:event_number:status
Climate Zone 10	21598	9451	0.239	0.011	0.435	-0.021	0.054	baseline_kwh:dow:tempbin:event_number:status
Climate Zone 11	6479	2160	0.371	0.032	0.626	-0.063	0.114	baseline_kwh:dow:tempbin:event_number:status
Climate Zone 12	21756	8032	0.246	-0.038	0.080	-0.091	0.000	baseline_kwh:dow:tempbin:event_number:status
Climate Zone 13	26452	9613	0.284	-0.024	0.257	-0.067	0.013	baseline_kwh:dow:tempbin:event_number:status
Climate Zone 14	6967	3425	0.259	-0.010	0.915	-0.060	0.052	baseline_kwh:dow:tempbin:event_number:status
Climate Zone 15	962	396	0.277	0.053	0.441	-0.105	0.276	baseline_kwh:dow:tempbin:event_number:status
Climate Zone 16	2761	1176	0.189	0.038	0.289	-0.032	0.136	baseline_kwh:dow:tempbin:event_number:status
Automation	11472	3489	0.272	-0.035	0.252	-0.083	0.016	baseline_kwh:dow:tempbin:event_number:status
No Automation	17897	5453	0.257	-0.013	0.616	-0.049	0.027	baseline_kwh:dow:tempbin:event_number:status

Source: UCLA Luskin Center for Innovation.

Status Analysis Visualizing the Discontinuity Additional Graphs

Figure D-4 on the left shows users who were silver in the previous event, who just miss or just make becoming gold in the next event. The graph on the right shows those who were gold and just missed or made platinum. Figure D-4 on the left, bottom row shows the effect of those who had gold in previous event who just missed and maintained gold in the next event. The right graphs show those who were platinum in the previous event and just missed or maintained platnimum.

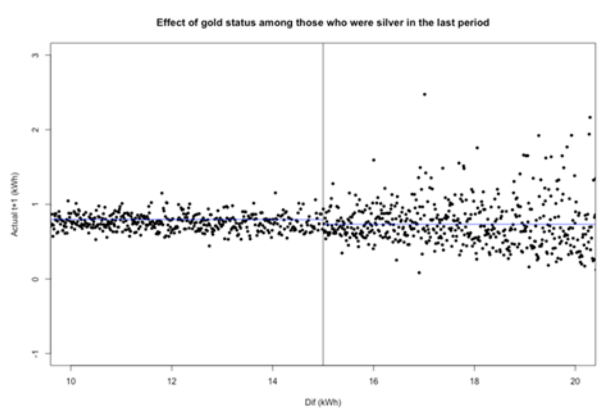
Figure D-4: Average Consumption in Next Period for Users With Same Previous Status



Source: UCLA Luskin Center for Innovation.

Figure D-5 looks at consumption for those who just missed or who just met the threshold to achieve gold status, restricting the sample to those who were silver in the last period.

Figure D-5: Average Consumption in Next Period for Users With Different Previous Status



Source: UCLA Luskin Center for Innovation.

Status Analysis Regression Tables

Table D-5 shows the statistical regression results for the status analysis, which looked at consumption in the event following a user just missing or meeting the threshold for a status level.

Table D-5: Effect of Status on Consumption in the Next Event

Prior Status	Cutoff	N_left	N_right	MSE_optimal_bandwidth	Coefficient	Robust_P_value	Robust_CI_Lower	Robust_CI_Upper	Covariates
All	Gold	208751	125780	20.308	-0.008	0.082	-0.024	0.001	baseline:tempbin:enumber:streak
Silver	Gold	196558	7700	13.898	-0.037	0.017	-0.062	-0.007	baseline:tempbin:enumber:streak
Gold	Gold	7492	72694	4.761	0.020	0.242	-0.011	0.058	baseline:tempbin:enumber:streak
All	Platinum	292205	42326	25.948	-0.007	0.276	-0.028	0.007	baseline:tempbin:enumber:streak
Gold	Platinum	77872	2314	5.413	0.007	0.689	-0.050	0.080	baseline:tempbin:enumber:streak
Platinum	Platinum	2768	38369	14.777	-0.026	0.203	-0.067	0.013	baseline:tempbin:enumber:streak

Source: UCLA Luskin Center for Innovation.

Table D-6 presents the effect of status on consumption two events after a user misses or maintains that status.

Table D-6: Effect of Status on Consumption Two Events After Gaining Status

Prior Status	Cutoff	N_left	N_right	MSE_optimal_bandwidth	Coefficient	Robust_P_value	Robust_CI_Lower	Robust_CI_Upper	Covariates
All	Gold	203283	122316	19.999	0.007	0.643	-0.012	0.020	baseline:tempbin:enumber:streak
Silver	Gold	191292	7504	15.949	-0.036	0.046	-0.068	-0.002	baseline:tempbin:enumber:streak
Gold	Gold	7358	70957	5.861	0.008	0.662	-0.030	0.051	baseline:tempbin:enumber:streak

Source: UCLA Luskin Center for Innovation.

Tables D-7 and D-8 present the effect of gold and platinum status, respectively, on consumption by demographic subgroup.

Table D-7: Effect of Gold Status on Consumption in the Next Event by Demographic Subgroup

Dataset	N_left	N_right	MSE_optimal_bandwidth	Coefficient	Robust_P_value	Robust_CI_Lower	Robust_CI_Upper	
Gold Income Qualified	30284	11064	22.966	0.022	0.231	-0.010	0.060	baseline_kwh:tempbin:event_number:streak
Gold Not Income Qualified	178467	114716	20.364	-0.012	0.030	-0.028	-0.002	baseline_kwh:dow:tempbin:event_number:streak
Gold Climate Zone 1	1413	926	32.530	0.031	0.742	-0.092	0.138	baseline_kwh:dow:tempbin:event_number:streak
Gold Climate Zone 2	4990	3969	17.715	-0.074	0.043	-0.163	-0.013	baseline_kwh:dow:tempbin:event_number:streak
Gold Climate Zone 3	36598	24101	29.259	-0.005	0.399	-0.026	0.009	baseline_kwh:dow:tempbin:event_number:streak
Gold Climate Zone 4	15103	11782	23.056	-0.068	0.000	-0.112	-0.038	baseline_kwh:dow:tempbin:event_number:streak
Gold Climate Zone 5	2900	1565	20.407	0.055	0.106	-0.003	0.121	baseline_kwh:dow:tempbin:event_number:streak
Gold Climate Zone 6	19220	8012	22.372	-0.030	0.069	-0.066	-0.003	baseline_kwh:dow:tempbin:event_number:streak
Gold Climate Zone 7	18135	9858	33.701	-0.001	0.955	-0.025	0.027	baseline_kwh:dow:tempbin:event_number:streak
Gold Climate Zone 8	19747	7906	21.085	-0.027	0.229	-0.068	0.011	baseline_kwh:dow:tempbin:event_number:streak
Gold Climate Zone 9	11758	5806	21.906	0.095	0.002	0.046	0.163	baseline_kwh:dow:tempbin:event_number:streak
Gold Climate Zone 10	20808	11077	35.467	0.005	0.882	-0.041	0.035	baseline_kwh:dow:tempbin:event_number:streak
Gold Climate Zone 11	4999	3897	41.519	-0.022	0.514	-0.109	0.049	baseline_kwh:dow:tempbin:event_number:streak
Gold Climate Zone 12	17832	12892	30.793	-0.010	0.581	-0.058	0.030	baseline_kwh:dow:tempbin:event_number:streak
Gold Climate Zone 13	21188	15789	29.576	-0.002	0.976	-0.043	0.041	baseline_kwh:dow:tempbin:event_number:streak
Gold Climate Zone 14	7153	3506	22.491	0.021	0.620	-0.048	0.088	baseline_kwh:dow:tempbin:event_number:streak
Gold Climate Zone 15	886	506	17.399	0.232	0.263	-0.110	0.605	baseline_kwh:dow:tempbin:event_number:streak
Gold Climate Zone 16	2611	1428	19.308	0.108	0.118	-0.015	0.279	baseline_kwh:dow:tempbin:event_number:streak
Gold Automation	6022	9493	32.796	-0.021	0.274	-0.080	0.020	baseline_kwh:dow:tempbin:event_number:streak
Gold No Automation	9479	14303	38.885	0.033	0.229	-0.012	0.065	baseline_kwh:dow:tempbin:event_number:streak

Source: UCLA Luskin Center for Innovation.

Table D-8: Effect of Platinum Status on Consumption in the Next Event by Demographic Subgroup

Dataset	N_left	N_right	MSE_optimal_bandwidth	Coefficient	Robust_P_value	Robust_CI_Lower	Robust_CI_Upper	
Platinum Income Qualified	38284	3064	21.328	0.026	0.493	−0.042	0.102	baseline_kwh:tempbin:event_number:streak
Platinum Not Income Qualified	253921	39262	25.085	−0.009	0.218	−0.031	0.006	baseline_kwh:dow:tempbin:event_number:streak
Platinum Climate Zone 1	2018	321	20.151	0.021	0.900	−0.197	0.229	baseline_kwh:dow:tempbin:event_number:streak
Platinum Climate Zone 2	7686	1273	22.962	−0.047	0.406	−0.131	0.043	baseline_kwh:dow:tempbin:event_number:streak
Platinum Climate Zone 3	53404	7295	33.907	0.003	0.754	−0.022	0.031	baseline_kwh:dow:tempbin:event_number:streak
Platinum Climate Zone 4	22668	4217	31.842	−0.021	0.460	−0.065	0.025	baseline_kwh:dow:tempbin:event_number:streak
Platinum Climate Zone 5	4043	422	18.675	0.003	0.760	−0.116	0.167	baseline_kwh:dow:tempbin:event_number:streak
Platinum Climate Zone 6	25222	2010	22.652	−0.019	0.446	−0.090	0.034	baseline_kwh:dow:tempbin:event_number:streak
Platinum Climate Zone 7	25231	2762	32.596	−0.014	0.607	−0.056	0.030	baseline_kwh:dow:tempbin:event_number:streak
Platinum Climate Zone 8	25199	2454	18.241	0.023	0.577	−0.048	0.096	baseline_kwh:dow:tempbin:event_number:streak
Platinum Climate Zone 9	15701	1863	25.483	−0.038	0.434	−0.123	0.045	baseline_kwh:dow:tempbin:event_number:streak
Platinum Climate Zone 10	28035	3850	39.064	−0.030	0.394	−0.090	0.030	baseline_kwh:dow:tempbin:event_number:streak
Platinum Climate Zone 11	7127	1769	44.715	−0.088	0.131	−0.190	0.007	baseline_kwh:dow:tempbin:event_number:streak
Platinum Climate Zone 12	25800	4924	30.117	−0.042	0.284	−0.096	0.021	baseline_kwh:dow:tempbin:event_number:streak
Platinum Climate Zone 13	30814	6163	36.471	0.013	0.707	−0.041	0.066	baseline_kwh:dow:tempbin:event_number:streak
Platinum Climate Zone 14	9401	1258	35.666	0.040	0.387	−0.049	0.148	baseline_kwh:dow:tempbin:event_number:streak
Platinum Climate Zone 15	1215	177	20.039	−0.269	0.466	−0.728	0.280	baseline_kwh:dow:tempbin:event_number:streak
Platinum Climate Zone 16	3568	471	13.783	−0.194	0.076	−0.500	−0.007	baseline_kwh:dow:tempbin:event_number:streak
Platinum Automation	11223	4292	35.482	−0.006	0.717	−0.062	0.041	baseline_kwh:dow:tempbin:event_number:streak
Platinum No Automation	16434	7348	31.830	−0.029	0.139	−0.085	0.008	baseline_kwh:dow:tempbin:event_number:streak

Source: UCLA Luskin Center for Innovation.

Table D-9 looks at the effect of status on a user's likelihood to adopt automation technology.

Table D-9: Effect of Status on Automation

Prior Status	Cutoff	N_left	N_right	MSE_optimal_bandwidth	Coefficient	Robust_P_value	Robust_CI_Lower	Robust_CI_Upper	Covariates
All	Gold	15502	23801	30.362	0.023	0.012	0.005	0.034	baseline:tempbin:enumber
All	Platinum	27660	11643	44.325	0.010	0.452	-0.009	0.023	baseline:tempbin:enumber

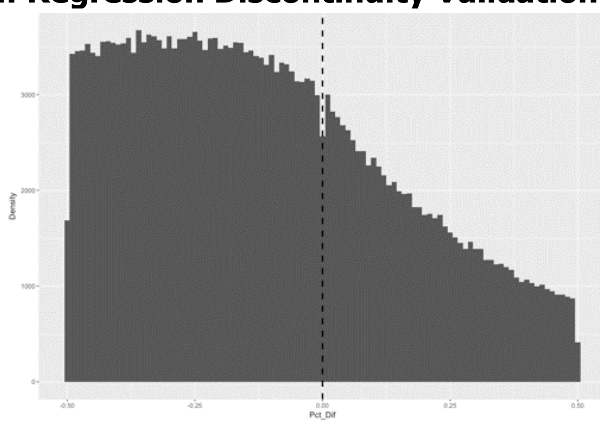
Source: UCLA Luskin Center for Innovation.

APPENDIX E:
Validity Tests for Streak and Status Analyses

Validity for Streak Regression Discontinuity Design

One key assumption of a regression discontinuity design for causal identification is that individuals cannot control whether they receive the "treatment." In this case, researchers assume that individuals do not have precise control over their electricity consumption, making it random whether one falls immediately above or below their baseline. If individuals were sorting over the discontinuity, there would be an increased number of observations immediately on one side of the discontinuity (AKA bunching). To evaluate this, researchers include a histogram of the observations showing that bunching is not observed at the discontinuity (Figure E-1).

Figure E-1: Regression Discontinuity Validation Histogram



Source: UCLA Luskin Center for Innovation.

Researchers also repeat the regression discontinuity effect estimation using a "placebo outcome" that could not reasonably be affected by the "treatment" to ensure that researchers are not detecting a spurious correlation. Researchers use the same running variable (percentage difference between actual and baseline consumption) and measure the "effect" of the treatment of crossing the discontinuity on consumption in the previous event. Researchers do not observe a treatment effect in this scenario, which increases confidence that the effect of the analysis is not caused by endogenous differences between those on either side of the discontinuity (Table E-1).

Table E-1: Placebo Outcome Results

Dataset	N_left	N_right	MSE_optimal_bandwidth	Coefficient	Robust_P_value	Robust_CI_Lower	Robust_CI_Upper	Covariates
Full	280406	130863	0.149	0.004	0.724	−0.016	0.024	baseline_kwh:tempbin:event_number
Streak<5	169431	92451	0.183	0.004	0.753	−0.018	0.027	baseline_kwh:tempbin:event_number
Streak5+	57154	14722	0.159	−0.008	0.635	−0.037	0.021	baseline_kwh:tempbin:event_number

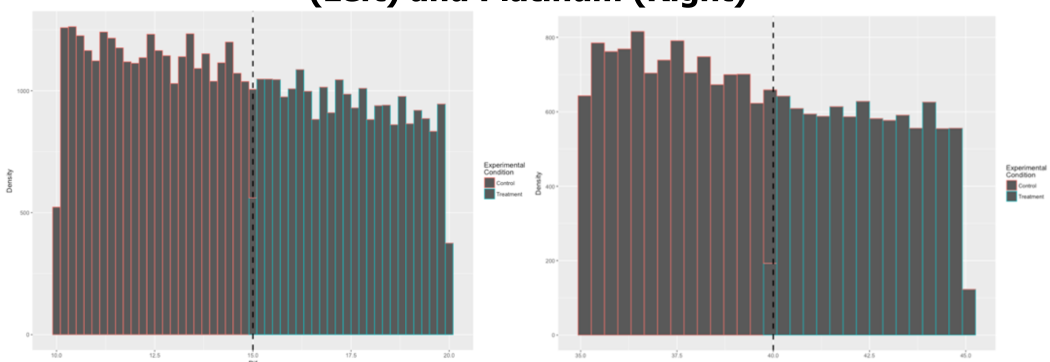
Source: UCLA Luskin Center for Innovation.

Validity for Status Regression Discontinuity Design

Researchers test for bunching at the discontinuity to confirm that the assumptions of the regression discontinuity design are met. This test confirms that the "treatment" is not associated with changes in variables that it could not reasonably cause.

First, researchers looked at density. A key assumption of the regression discontinuity design is that individuals cannot control whether they fall in to the "treatment" or "control" group. If individuals strategically sort into the treatment, there will be bunching around the discontinuity. If there is bunching, researchers therefore cannot assign that the treatment is essentially randomly assigned and cannot use the regression discontinuity design for identification of the treatment effect. The following two histograms demonstrate that observations were distributed evenly across the cutoffs and exhibited no bunching (Figure E-2 and Table E-2).

Figure E-2: Regression Discontinuity Design Test for Bunching for Gold Status (Left) and Platinum (Right)



Source: UCLA Luskin Center for Innovation.

Next, researchers used a placebo outcome to assess whether the effect of status changes subsequent behavior, rather than differences between those who fall above or below the cutoff. The placebo outcome used here is consumption in the previous event because it cannot be directly affected by the change in incentive. While researchers did not find a statistically significant correlation between treatment and prior consumption, the correlation among those that were silver in the last event was nearly significant. This near significance raised some suspicions that the effect observed earlier could be driven in part by preexisting differences between those who do and do not attain gold status rather than the status itself.

Table E-2: Effect of Status on Consumption in the Preceding Event

Prior Status	Cutoff	N_left	N_right	MSE_optimal_bandwidth	Coefficient	Robust_P_value	Robust_CI_Lower	Robust_CI_Upper	Covariates
All	Gold	208751	125780	18.691	0.002	0.463	-0.008	0.017	baseline:tempbin:enumber:streak
Silver	Gold	196558	7700	13.418	-0.029	0.065	-0.054	0.001	baseline:tempbin:enumber:streak
Gold	Gold	7492	72694	7.117	0.016	0.306	-0.011	0.043	baseline:tempbin:enumber:streak
All	Platinum	292205	42326	16.970	-0.008	0.217	-0.034	0.007	baseline:tempbin:enumber:streak
Gold	Platinum	77872	2314	6.084	-0.047	0.180	-0.103	0.013	baseline:tempbin:enumber:streak
Platinum	Platinum	2768	38369	16.193	-0.011	0.337	-0.048	0.016	baseline:tempbin:enumber:streak

Source: UCLA Luskin Center for Innovation.

APPENDIX F:
Financial Incentives and Messaging Analyses Method – Additional Information

Demand Response Messaging Test

Demand response messages were pretested by users on Amazon's Mechanical Turk. Four rounds of demand response events on several hundred test accounts were checked by UCLA researchers in July and August 2017 for technical issues and accurate messaging. Demand response treatments for the full sample of study participants began August 28, 2017.

Baseline Characteristics of Treatment Groups Compared to Sample

Tables F-1 and F-2 show how the treatment groups vary across various characteristics. All coefficients are relative to the control group. These tables show that there are only small and insignificant differences across the different treatment groups across most baseline characteristics. Unfortunately, there do appear to be meaningful differences in solar PV adoption across the moral subsidy and no-incentive groups. Researchers controlled for this imbalance by including controls for household fixed effects and solar PV adoption x temperature fixed effects in all the regressions. This means that the estimates come from comparing households with solar in different treatment groups on similar temperature days against one another, ensuring that different prevalences of solar are not driving the results. Moreover, the imbalance affects only one treatment arm in both sets of analyses, making it unlikely that the results observed from the other sets of treatments are driven by confounders.

Table F-1: Baseline Characteristics of Framing Treatment Groups Relative to Control Group

VARIABLES	(1) No Solar	(2) Chai Pro	(3) Annual Usage	(4) Ln Annual Usage	(5) Missing Zip Code
Financial	0.0202	-0.0192	11.18	-0.0318	-0.00312
	(0.0227)	(0.0185)	(316.3)	(0.0482)	(0.0159)
Moral Subsidy	0.0500**	-0.0268	-309.9	-0.0418	0.00550
	(0.0213)	(0.0178)	(285.5)	(0.0456)	(0.0159)
Moral Tax	0.00695	-0.0104	-310.6	-0.0344	-0.00449
	(0.0229)	(0.0187)	(295.2)	(0.0448)	(0.0157)
Observations	2,239	2,239	2,239	2,238	2,239
R-squared	0.003	0.001	0.001	0.000	0.000
Dep. Var. Mean	0.802	0.104	7469	8.720	0.0790

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Source: UCLA Luskin Center for Innovation.

Table F-2: Baseline Characteristics of Incentive Treatment Group Relative to Control Group

VARIABLES	(1) No Solar	(2) Chai Pro	(3) Annual Usage	(4) Ln Annual Usage	(5) Missing Zip Code
No Incentive	0.0538**	-0.0293	-136.7	-0.0177	-0.0137
	(0.0243)	(0.0202)	(360.8)	(0.0504)	(0.0173)
Small Incentive	0.0131	-0.0229	20.58	-0.0129	0.00702
	(0.0204)	(0.0165)	(271.6)	(0.0417)	(0.0145)
Large Incentive	0.0190	-0.0102	-323.9	-0.0479	-0.000844
	(0.0195)	(0.0161)	(253.0)	(0.0397)	(0.0136)
Observations	2,871	2,871	2,871	2,870	2,871
R-squared	0.002	0.001	0.001	0.001	0.001
Dep. Var. Mean	0.802	0.104	7469	8.720	0.0790

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Source: UCLA Luskin Center for Innovation.

Analysis Equation

For each analysis type, researchers estimate the following equation: a

$$Y_{it} = \alpha_i + \tau_t + \beta Treat_i * Event_{it} + Z_{it} + \epsilon_{it}$$

Where Y_{it} is amount of watt-hours used by household *i* in time *t*, α_i is a vector of indicators for each household, which controls for all time-invariant household characteristics, τ_t is a day x hour fixed-effect controlling for all unit-invariant time characteristics, $Treat_i$ is a vector of treatment indicators corresponding to the groups described above. The omitted group is always the control group unless otherwise noted. $Event_{it}$ is an indicator for whether an event is occurring in a given hour for a given household. The coefficient on the interaction between the treatment and event indicator is the coefficient of interest, β, it tells us the effect of being in a given treatment group in an event hour relative to being the control. Z_{it} is a vector of household specific covariates that vary with time. In the primary specification, researchers include daily high temperature interacted with an indicator for whether or not a household has solar PV as both temperature alone and temperature interacted with solar are important predictors of daily energy use and so increase the power to detect any effects caused by the experimental treatments. The inclusion of this variable also helps control for any imbalance in randomization that occurred. Finally, ϵ_{it} is a mean zero-error term. Researchers estimate the above equation using all pre-event and post-event data between the hours of 4:00 p.m. and 8:00 p.m. Researchers do not include non-event hours for event participants during event days because there is a concern that event usage will spill over into these non-event hours. Because this study is an experiment, if randomization were performed correctly, researchers could simply compare the means across the different treatment groups to obtain unbiased estimates of the treatment effect. Researchers choose to use this more complex estimation method for two reasons. First, as mentioned above, the sample is significantly smaller than planned for, so including energy use in the non-event periods greatly increases the power by controlling for extraneous variation in energy use. Second, as Tables X and X show, despite the random assignment, there is some imbalance across treatments in the level of solar use. Including non-event hours and additional covariates allows researchers to better control for this imbalance to ensure that it is not driving the results.

APPENDIX G: Financial Incentives and Messaging Analyses Regression Tables

Table G-1 shows consumption reductions by financial incentive level. It also shows how this varies across days hotter than 90 degrees Fahrenheit, days cooler than 90 degrees Fahrenheit, and all days.

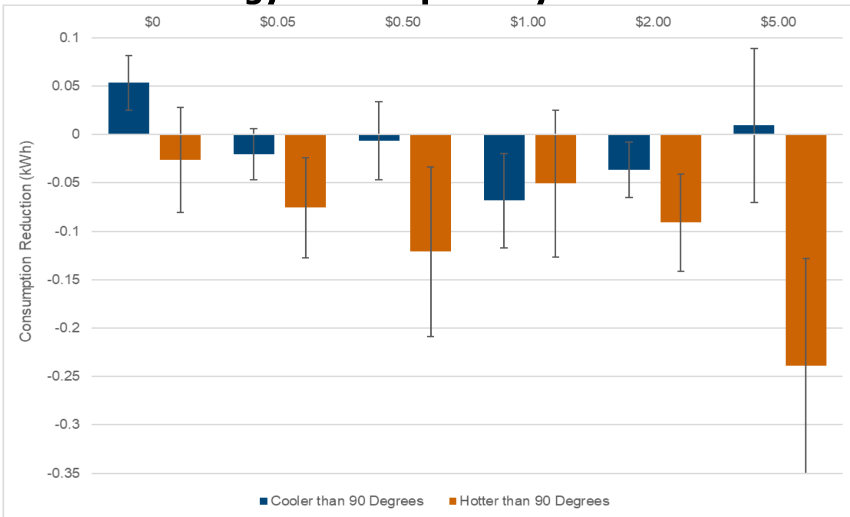
Table G-1: Financial Incentives Results

VARIABLES	(1) Watt-hour	(2) Watt-hour	(3) Watt-hour	(4) Watt-hour	(5) Watt-hour
Info-only	36.65	-26.23	53.39*		
	(25.49)	(54.33)	(28.03)		
5 Pts	-28.68	-75.60	-20.27		
	(23.76)	(51.78)	(26.13)		
50 Pts	-57.14	-121.0	-6.359		
	(41.63)	(87.42)	(40.48)		
100 Pts	-55.40	-50.54	-68.33		
	(43.66)	(76.02)	(48.82)		
200 Pts	-47.17*	-91.06*	-36.48		
	(27.55)	(50.34)	(28.54)		
500 Pts	-55.47	-239.1**	9.472		
	(67.82)	(111.1)	(79.77)		
Info-only				-26.33	53.35*
				(54.33)	(28.02)
5-100 Pts				-78.24*	-26.62
				(40.86)	(20.48)
200-500 Pts				-107.9**	-31.46
				(46.97)	(26.80)
Observations	364,481	85,714	278,767	85,714	278,767
R-squared	0.529	0.565	0.499	0.565	0.499
Sample	All	>90 Deg	<90 Deg	>90 Deg	<90 Deg
Dep. Var. Mean	1702	2572	1426	2572	1426

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Source: UCLA Luskin Center for Innovation.

Figure G-1: Reduction in Energy Consumption by Incentive Level and Temperature



Source: UCLA Luskin Center for Innovation.

Table G-2 shows the effect on consumption of different messages on all days, days hotter than 90 degrees Fahrenheit, and days cooler than 90 degrees Fahrenheit. Table G-2 also examines how the effect of messages differs when offered with or without financial incentives.

Table G-2: Demand Response Event Message Framings Results

VARIABLES	(1) Watt-hour	(2) Watt-hour	(3) Watt-hour	(4) Watt-hour
Fin Frame x Finan Incent			-48.63	-160.9**
			(32.84)	(70.02)
Fin Frame x Info Only			35.55	-113.8
			(41.55)	(86.63)
Moral Sub x Finan Incent			-33.88	-68.16
			(30.58)	(57.73)
Moral Sub x Info Only			4.828	8.722
			(47.52)	(98.84)
Moral Tax x Finan Incent			-44.38	-51.22
			(30.96)	(59.54)
Moral Tax x Info Only			60.07	9.484
			(43.59)	(90.47)
Economic benefits message	-20.21	-144.8***		
	(26.23)	(55.62)		
Moral Subsidy	-21.47	-45.11		
	(25.68)	(51.36)		
Moral Tax	-12.19	-32.84		
	(25.09)	(50.84)		
Observations	314,873	74,079	314,873	74,079
R-squared	0.530	0.563	0.530	0.563
Sample	All	>90 Deg Day	All	>90 Deg Day
Dep. Var. Mean	1702	2572	1702	2572

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Source: UCLA Luskin Center for Innovation.

Table G-3 looks at the treatment effects for high- and low-frequency demand response events. This table shows the differences in effects for high- and low-frequency events by incentive, message, and high-temperature days.

Table G-3: Event Frequency Results

VARIABLES	(1) Watt-hour	(2) Watt-hour	(3) Watt-hour	(4) Watt-hour	(5) Watt-hour	(6) Watt-hour	(7) Watt-hour	(8) Watt-hour
Info Only	49.97	-88.00	20.23	-13.73				
	(39.14)	(83.56)	(45.09)	(82.25)				
Any Incent.	-42.77	-89.41*	-25.85	-160.7***				
	(26.40)	(52.61)	(30.78)	(53.57)				
Fin Frame					-41.97	-164.2*	5.180	-174.3**
					(39.12)	(86.92)	(43.99)	(80.67)
Moral Frame					13.78	-40.60	-39.68	-90.90
					(30.41)	(60.30)	(35.53)	(63.36)
Observations	244,008	56,741	250,384	59,889	202,392	47,257	205,732	49,296
R-squared	0.522	0.555	0.530	0.570	0.526	0.556	0.531	0.568
Frequency	High	High	Low	Low	High	High	Low	Low
Sample	All	>90 Deg Day	All	>90 Deg Day	All	>90 Deg Day	All	>90 Deg Day
Dep. Var. Mean	1712	2590	1695	2567	1712	2590	1695	2567

Clustered standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Source: UCLA Luskin Center for Innovation.

Table G-4 shows the treatment effects for events starting at 4:00 p.m. and 6:00 p.m. This table shows how consumption reductions vary depending on if the user received an incentive and which message they received. It also examines the differences between events on all days and only events that occurred on days hotter than 90 degrees Fahrenheit.

Table G-4: Demand Response Event Timing Results

VARIABLES	(1) Watt-hour	(2) Watt-hour	(3) Watt-hour	(4) Watt-hour	(5) Watt-hour	(6) Watt-hour	(7) Watt-hour	(8) Watt-hour
Info Only	63.94**	47.66	12.78	-53.84				
	(29.91)	(67.26)	(31.14)	(77.58)				
Any Incent	-20.44	-74.26*	-39.09**	-117.3***				
	(16.48)	(39.58)	(17.10)	(38.26)				
Fin Frame					-14.92	-111.4*	-28.19	-134.2*
					(29.55)	(65.50)	(33.38)	(80.98)
Moral Frame					6.131	-17.49	-39.95*	-96.35**
					(20.87)	(50.36)	(21.06)	(48.31)
Observations	200,573	47,132	200,568	47,024	157,445	37,108	157,428	36,971
R-squared	0.575	0.616	0.577	0.611	0.578	0.616	0.581	0.610
Event Start	6PM	6PM	4PM	4PM	6PM	6PM	4PM	4PM
Sample	All	>90 Deg Day	All	>90 Deg Day	All	>90 Deg Day	All	>90 Deg Day
Dep. Var. Mean	1876	2736	1527	2408	1876	2736	1527	2408

Clustered standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Source: UCLA Luskin Center for Innovation.

Table G-5 shows the differences in treatment effect between customers with and without solar PV.

Table G-5: Results for Customers With and Without Solar PV

VARIABLES	(1) Watt-hour	(2) Watt-hour	(3) Watt-hour	(4) Watt-hour	(5) Watt-hour	(6) Watt-hour	(7) Watt-hour	(8) Watt-hour
Info Only	117.0*	37.54	34.94	-15.73				
	(69.26)	(162.1)	(26.44)	(55.22)				
Any Incent	-61.05*	-237.7***	-26.06*	-64.77**				
	(36.52)	(82.31)	(14.95)	(31.08)				
Fin Frame					-69.55	-323.1**	-11.26	-115.1*
					(65.52)	(148.9)	(27.93)	(59.20)
Moral Frame					-8.440	-202.6*	-14.65	-5.651
					(46.49)	(114.5)	(18.68)	(38.52)
Observations	69,009	15,496	332,132	78,654	53,710	11,848	261,163	62,225
R-squared	0.503	0.526	0.570	0.601	0.497	0.520	0.574	0.600
Solar	Yes	Yes	No	No	Yes	Yes	No	No
Sample	All	>90 Deg Day	All	>90 Deg Day	All	>90 Deg Day	All	>90 Deg Day
Dep. Var. Mean	1400	2393	1764	2608	1400	2393	1764	2608

Clustered standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Source: UCLA Luskin Center for Innovation.

Table G-6 shows the differences in treatment effect between customers above- and below-median income.

Table G-6: Results for Customers by Median Income

VARIABLES	(1) Watt-hour	(2) Watt-hour	(3) Watt-hour	(4) Watt-hour	(5) Watt-hour	(6) Watt-hour	(7) Watt-hour	(8) Watt-hour
Info Only	38.44	110.5	31.81	-107.0				
	(40.40)	(82.02)	(33.21)	(71.07)				
Any Incent	-22.61	-46.00	-37.72**	-115.4***				
	(23.92)	(43.77)	(17.72)	(40.58)				
Fin Frame					-28.44	-56.27	-21.25	-202.8***
					(44.44)	(82.17)	(32.86)	(74.41)
Moral Frame					-5.582	16.54	-25.94	-79.20
					(29.89)	(57.22)	(22.37)	(50.56)
Observations	149,140	42,020	251,841	52,112	117,896	33,434	196,817	40,621
R-squared	0.550	0.575	0.515	0.557	0.554	0.576	0.518	0.555
Income	>Med	>Med	<Med	<Med	>Med	>Med	<Med	<Med
Sample	All	>90 Deg Day	All	>90 Deg Day	All	>90 Deg Day	All	>90 Deg Day
Dep. Var. Mean	1717	2586	1682	2560	1717	2586	1682	2560

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Source: UCLA Luskin Center for Innovation.