# A Field Experiment to Assess the Impact of Information Provision on Household Electricity Consumption

ARB Contract 08-325

Matthew E. Kahn
Institute of the Environment
Department of Economics
University of California—Los Angeles
mkahn@ioe.ucla.edu

Frank A. Wolak
Director, Program on Energy and Sustainable Development
Department of Economics
Stanford University
wolak@zia.stanford.edu

January 25, 2013

Prepared for the California Air Resources Board and the California Environmental Protection Agency

The statements and conclusions in this Report are those of the contractor and not necessarily those of the California Air Resources Board. The mention of commercial products, their source, or their use in connection with material reported herein is not to be construed as actual or implied endorsement of such products.

*Acknowledgment* . We thank Adele Bihn of Data Marketing and Marian Brown and Eric Karlson.. This Report was submitted in fulfillment of 08-325 by UCLA and Stanford under the sponsorship of the California Air Resources Board. Work was completed as of January 10th 2013.

**Abstract**

We report on the results of two field experiments that we ran by partnering with two California electric utilities. In late 2011, 2,012 households participated in a customized on-line interactive educational program that taught them how their monthly electricity bill was determined from nonlinear retail pricing scheme they face. Each household was also shown their own location on this nonlinear pricing schedule. Participants were taught how changes in their major electricity-consuming activities would affect their monthly bill under the nonlinear pricing scheme. Using data from before and after this intervention for households that took the educational program (our treatment) and a randomly selected set of control households who did not take our treatment, we applied a standard average treatment effects estimation procedure to assess the impact of our information invention on a household's monthly electricity consumption. For both utilities, we find that households that learn they face a high marginal price for consuming electricity reduce their electricity consumption relative to the control group. We also find that households that learn they face a low marginal price increase their electricity consumption relative to the control group. These results emphasize that the need to provide timely and actionable information to households in order to maximize the effectiveness of nonlinear retail pricing schemes.

## Executive Summary

Background. California's AB32 requires that the state sharply reduce its production of greenhouse gas emissions. Reductions in aggregate electricity demand would help to achieve this goal. The residential sector is a major electricity consumer. Household consumers face a complex non-linear pricing tariff and many households are unaware of how actions such as setting the thermostat at 72 degrees affects their electricity consumption. These facts suggest that an intervention that targets educating households with customized information can help them become more sophisticated consumers and in aggregate help California to achieve its AB32 goals.

Methods. In a partnership with two major California electric utilities, 2012 households who live in single family homes were enrolled in a 30 minute customized education program that took place on the Internet. This group of "treated households" was enrolled through a field experiment research design. Starting with a population sample of households who live in a single family home, a subset of households was drawn at random. This subset was then randomly assigned to the control group and to the "invite for treatment group". Each member of the "invite for treatment group" was then randomly assigned a dollar amount of an Amazon Gift card to reward them for participating in this field experiment. Each household in the "invite for treatment group" was sent an invitation letter (or email) that briefly explained why the household was receiving the letter, the likely benefits from participating in the educational program and that listed the Amazon Gift card amount that the household would receive once it had completed the educational experience.

For those households who were invited to participate and chose to do so, they logged in to an Internet website and over the course of a 30 minute interactive session were educated about their electric utility's non-linear pricing system for electricity. Using household specific data on past electricity consumption, the household learned exactly where its recent consumption placed it on the pricing schedule and how changes in its consumption behavior would affect its monthly bill. During the interaction session, each participant provided information about his/her home's physical attributes and appliances. This information was used to provide the household with customized advice for how it could reduce its monthly electricity bill.

In a unique data partnership, the two electric utilities provided us with months of household specific electric utility consumption data both before and after the treatment date to allow us to conduct a "before/after" comparison of changes in electricity consumption for both the treatment group, the invite to treatment group and the control group. To maintain customer privacy, at no time did we have access to the names or addresses of any subject in any of these three groups. The two electric utilities and a third party data vendor created an experiment specific identification number that allowed us to track subjects without knowing their actual identity.

The longitudinal household data from both utilities was used to estimate econometric models that allow us to test a number of hypotheses related to how new information about the marginal price of electricity affects household electricity consumption.

Conclusions. When households learn that the marginal price of electricity is high, they choose to reduce their consumption. The estimated effects are large. Conversely, when households learn that the marginal price of electricity is low, they choose to increase their consumption. These estimates are insensitive to the size of the Amazon Gift card that households were offered. These results suggest that a potentially cost-effective strategy for the ARB to achieve its AB32 goals would be to target educational treatments such as the one piloted in this study to households who are high baseline consumers.

# 1. Introduction

Virtually all residential electricity customers in the United States face an increasing block tariff (IBT) pricing structure where the price paid for an additional unit of consumption, what is typically called the marginal price, varies with the amount of electricity consumed within the month. An IBT pricing structure sets increasing constant marginal prices per kilowatt-hour (KWh) for increasing ranges of monthly consumption. The IBT pricing schedule resembles a staircase with the height of each step equal to the constant marginal price and the length equal to the range of monthly consumption that the marginal price applies to.

An IBT pricing structure allow consumers to purchase their "necessary" monthly electricity consumption at a low marginal price and then charges consumers progressively higher marginal prices for more discretionary electricity uses. Under an IBT, electricity consumers that use more KWh during the month face a higher marginal price, and therefore should have stronger incentive to reduce their monthly consumption relative to consumers that use less KWh during the month and therefore face a lower marginal price.

There are a number of necessary conditions for IBT pricing to provide these incentives. First, consumers must understand how their monthly electricity bills are determined from an IBT. Second, consumers must understand where they are likely to end the month on the IBT schedule in order to determine the appropriate marginal price to use for their electricity consumption decisions during the month. Third, consumers need to understand how their electricity-using actions translate into KWhs of electricity consumption.

Residential electricity demand is derived from a consumer's demand for such household activities as lighting, television watching, computer use, and electricity-consuming appliance services in general. Although most households are able to predict the dollar amount of their

typical summer and winter monthly electricity bills, there is considerable debate among industry observers whether households understand how their electricity bills are determined from an IBT, what their marginal price for the month is likely to be, and how their appliance-using actions translate into KWhs of consumption and dollars on their monthly electricity bill. Suppose that households do not know how much electricity they are likely to consume in the month. Even if these households understood how their monthly bill was computed under IBT pricing, they would not know the marginal price of electricity for that month and would therefore be forced to use less efficient approaches to managing their monthly electricity bill.

Shin (1985) argues that lack of information about the monthly marginal price (the marginal price for the last KWh consumed in the month), may lead households to adopt rules of thumb for determining their monthly electricity consumption. Shin postulates that consumers respond to the monthly average price—the household's monthly electricity bill divided by their monthly electricity consumption—and he presents empirical evidence consistent with this hypothesis. Borenstein (2009) argues that lack of information about the monthly marginal price, because the households cannot accurately forecast their monthly electricity consumption, leads them not to respond to the monthly marginal price. Ito (2012) proposes an empirical test of whether households respond to the monthly marginal price versus the monthly average price and finds evidence consistent with the hypothesis that households respond to average prices.

One explanation for the empirical results of Shin (1985) and Ito (2012) is that households are unaware of their monthly marginal price, or they do not understand how their monthly electricity bill is determined from an IBT or how their electricity-consuming actions translate into dollars on their monthly electricity bill. By providing households with this information, one

would expect them to make more efficient electricity consumption choices, rather than resort to ad hoc decisions rules for determining their monthly electricity consumption.

This study employs a randomized field experiment to study whether households that are provided with the information necessary to respond to the monthly marginal price actually alter their behavior in response to this information. We provide customers in our treatment group with: (1) information about how their electricity bill is determined from an IBT pricing function, (2) the value of their typical monthly marginal price, and (3) information about how their appliance-using actions translate into dollars on their monthly electricity bill. Our hypothesis is that households can respond to IBT pricing structures and other more complex retail pricing structures such as hourly retail prices that vary with hourly wholesale prices, but they lack the necessary information that would allow them to do so. Our on-line educational treatment provides the basic information necessary for households to respond to a IBT pricing structure.

Starting in the year 2011, we partnered with two major California electric utilities and implemented a field experiment with households from each utility that resulted in roughly 2,012 households taking an our Internet educational course that provided with them with the minimum information necessary to respond to an IBT pricing structure. At each of the two electric utilities, we were provided with a random sample of single-family households. We randomly assigned the households to the intent-to-treat (ITT) group and the remaining households to the control group. All households in the ITT group received an encouragement letter or e-mail inviting them to complete our treatment, a 30-minute Internet educational course that provided the household with: (1) information about how its electricity bill is determined from its IBT pricing function, (2) the value of its typical monthly marginal price, and (3) information about

how the household's appliance-using actions translate into dollars on their monthly electricity bill.

After completing the Internet course, we tracked the changes in electricity consumption for the ITT group, which is composed of households that were offered the opportunity to take our educational course but refused (the offered-but-refused-treatment group) and households that were offered the opportunity to take the course and actually took it, and the control group. We were able to tract household electricity consumption over time because we partnered with the electric utilities and they granted us access to their administrative data base. As we discuss below, household privacy was guaranteed at all times because we never observed any household's name or street address. We were able to track households over time because a unique experimental identification number was assigned to each household.

Because all treated households were told their typical monthly marginal price and the theory of household utility-maximizing choice subject to an IBT implies that the level of this marginal price should impact a household's electricity consumption choices, we estimate a statistical model of electricity consumption dynamics that allows the effect of our information treatment on electricity consumption to differ by the level of the household's typical monthly marginal price.

We then estimate pricing-tier-specific treatment effects regressions for our educational program on the treatment versus control sample and the offered-but-refused-treatment and the treatment sample for each utility. Consistent with the view that households armed with information about their typical monthly marginal price will use this information to use electricity more efficiently, we find that households that learn that they face a high marginal price for electricity *reduce* their consumption while households that learn that they face a low marginal

price for electricity *increase* their consumption. This result is consistent with the view that the households that do not complete our treatment (those in the control group or offered-but-refused group) are using rules-of-thumb based on their average price of electricity to determine their monthly electricity consumption. Those that complete our on-line educational course and are provided with information that their marginal price is less than this average price decide to consume more and those that find their marginal price is above this average price decide to consume less. If our educational treatment did not provide the treatment households with new information about how their electricity-using actions impact their monthly electricity bill, then we would expect to see no change in behavior in our treatment versus control and treatment versus offered-but-refused comparisons.

A unique feature of our study is that we ran the same experiment at two independent electric utilities and obtained qualitatively the same results at both locations. This raises our confidence in the results that we report. There are also crucial differences across the two utilities in terms of their IBT pricing structures, climate conditions and the type of data we can access so that we learn more from combining insights from two experiments than if we had run our experiment at only one site.

This study adds to an emerging literature on educating households about non-linear incentives such as the tax code and evaluating the impact of providing this information on household behavior. Chetty and Saez (2013) assess the impact of tax preparers giving simple, personalized information to a random sample of their clients about the Earned Income Tax Credit (EITC) on the subsequent earnings of these clients.

This literature and our field experiments assess the impact of lowering the cost of information acquisition of economic behavior. In our case, the on-line educational course lowers

the cost to the household of learning the information necessary to respond to IBT for electricity and in the case of Chetty and Saez (2013), their treatment lowers the cost to the taxpayer of learning about the incentives to work created by the EITC. In both cases the information is randomly assigned to individuals and then a statistical model is used to test for a behavioral change in response to the provision of this information. Because both experiments assume that the only reason for the differences in the behavior of the treatment and control groups is due to the information provided, any change in behavior between the treatment and control groups is therefore caused by the information provided. In our case, making households aware of their monthly marginal price, how their monthly electricity bill is determined under an IBT and how their monthly bill varies with changes in their electricity-consuming activities appears to cause changes in their monthly electricity consumption in a manner consistent with these households making beneficial use of this information.

Our findings emphasize that the timely provision of actionable information to final electricity consumers is a crucial complement to smart grid technology delivering economic benefits to electricity consumers. The "smart grid" has been touted as mechanism for reducing electricity bills, increasing energy efficiency, and reducing greenhouse gas (GHG) emissions from the electricity sector. Residential electricity consumption accounts for roughly 33% of total electricity consumption in the United States (US) and the electricity sector produces approximately 40% of US GHG emissions. Consequently, if smart grid technologies can produce modest reductions in household-level electricity consumption, particularly during periods of peak electricity demand when GHG-emissions-intensive generation units must be relied on to produce electricity, this can yield intangible reductions in US GHG emissions.

That consumers are responsive to marginal prices when informed through our treatment supports the claim that by accompanying the universal deployment of interval metering at California's three large investor-owned utilities with dynamic retail pricing and the timely provision of actionable information to households on these pricing plans will induce significant behavioral changes that reduce both annual and peak-period electricity consumption, which would also reduce California's annual GHG emissions. Households with interval meters that are also provided with information on the hourly retail price of electricity and their real-time electricity consumption and understand how electricity-using actions translate into dollars on their monthly electricity bill can make more cost-effective appliance utilization decisions.

Although our results are directly relevant to the impact of information provision on the behavior of households subject to IBT pricing structures, it does not seem to be a stretch to extend them to cases of marginal prices that differ over time. Specifically, our results suggest that notifying households that they face an hourly price that is higher than their annual average retail price will cause them to reduce their consumption and notifying households that they face an hourly price that is lower than their annual average retail price will cause them to increase their consumption. This logic is also consistent with the results of Wolak (2010), which uses an experiment to study how residential consumers respond to retail electricity prices that vary with hourly wholesale prices. Wolak (2010) presents evidence of substantial demand reductions in response to high hourly retail prices and documents that even low-income households are adept at responding to the higher hourly prices. These results highlight how appropriate price signals combined with timely information provision can play a key role in helping California achieve its ambitions AB32 goals.

**Materials and Methods**

## 2. Impact of Marginal Price Information

To understand how notifying households of their typical monthly marginal price is likely to impact their electricity consumption, consider the following two models of utility-maximizing behavior subject to linear and nonlinear or IBT pricing. Economists model households as having a complete and transitive preference ordering over all possible bundles of goods that it could consume. Under certain regularity conditions, discussed in Varian (1992, Chapter 7), this preference ordering can be represented by a utility function over bundles of goods. Specifically, the household prefers bundle A to bundle B if the value of the household's utility function for bundle A is greater than the value of its utility function for bundle B.

Suppose that the household faces an IBT for electricity with two pricing tiers. For consumption between zero and $E_1$ the household faces a marginal price of $p_1$. For consumption greater than $E_1$ the household faces a marginal price of $p_2$ that is strictly greater than $p_1$. Suppose that household is only told its monthly electricity bill is B dollars and its consumption is E KWhs. Suppose that based on this information, the household concludes that it faces a price of $p_A \equiv B/E$ for electricity. Assume the household has a budget constraint of M dollars and that the only other good available to the household is a composite good X, that has a price of $p_X$. The household's preferences are assumed to be described by the utility function, U(E,X), which is increasing in each argument.

Consider the following simple model of household electricity consumption subject to a linear price of electricity set equal to the average price faced by the household, $p_A$. In this case, that household's utility maximization problem is:

$$\text{Max}_{\{E,X\}}\ U(E,X) \text{ subject to } p_X X + p_A E = M$$

If E* and X* are the solutions to this problem then they satisfy the following first-order condition: $U_X(E^*,X^*)/p_X = U_E(E^*,X^*)/p_A$, where $U_S(E^*,X^*)$ is the partial derivative of U(E,X) of with respect to S for S=E,X evaluated at (E*,X*).

Suppose that $E^* > E_1$, which implies that $p_1 < p_A < p_2$. Now suppose that the household receives our information treatment and is notified that its monthly marginal price is $p_2$ and that it in fact faces an IBT pricing structure. In this case, the household utility-maximization problem is:

$$\text{Max}_{\{E,X\}}\ U(E,X) \text{ subject to } p_X X + p_2 \max((E - E_1),0) + p_1 \min(E_1,E) = M.$$

If E+ and X+ are the solutions to this problem then they satisfy the following first-order condition: $U_X(E+,X+)/p_X = U_E(E+,X+)/p_2$ because the household has been told that $p_2$ is its monthly marginal price. Note that because $p_2 > p_A$, $U_E(E^*,X^*)/p_A > U_E(E^*,X^*)/p_2$, which implies that $E+ < E^*$, if we make the usual assumption that $U_E(E,X)$ is decreasing in E and increasing in X and $U_X(E,X)$ is decreasing in X and increasing in E. In other words, telling a household that formerly thought it was maximizing utility subject to a linear price equal to the average price of electricity, that it is facing a IBT and it has a marginal price of $p_2 > p_A$, will result in that household reducing its electricity consumption. By similar logic telling the household it faces an IBT and a marginal price of $p_1 < p_A$, will result in that household increasing its electricity consumption. We test these hypotheses about the impact of providing this information using the field experiment that we describe in the next section.

# 3. Field Experiment Implementation Steps

To conduct this field experiment, we partnered with two major California electric utilities. Throughout this research, we never accessed data that identified a household's name or street address. By partnering with these electric utilities, we are able to access household-level data on electricity consumption before and after our intervention took place. One of the electric utilities is located in Northern California and throughout this report we will refer to it as the "Northern Utility". The other utility is located in Southern California and we will refer to it as the "Southern Utility".

We now provide an overview of how we implemented this field experiment and recruited a subject pool and provide a summary of the educational course's content. Our two field

experiments were accomplished in several steps. First, we chose a random subset of two electric utility's residential customers. Second, we randomly assigned these households to the intent-to-treat group and the control group. Third, we randomized a participation payment amount offer to each member of the intent-to-treat group. Fourth, we invited each member of the intent-to-treat group to take our on-line education course with the promise of the randomly assigned payment amount in an Amazon.com gift code if they completed the course. Fifth, a subset of households in the intent-to-treat group chose to complete our on-line course to become members of our treatment group. At both experimental sites the enrolled subjects took the same educational treatment tailored to the specific IBT the household faced. Sixth, we tracked the post-treatment electricity consumption for the intent-to-treat group (the treatment group and the offered-but-refused group) and the control group. These panel data allow us to estimate the econometric models we present below. We now provide details about each of these steps.

**The Southern Utility's Experiment Specifics**

The Southern Utility provided a third party, Data Marketing, Inc. (DMI), with the confidential data for residents in 1,407,500 single family homes in its service area.[1] DMI had to be provided with the name and street address of each of these residents because it sent out the invitation letters that we describe below. These households were all residents in single-family homes who faced the most common residential rate structures used by the Southern Utility.

DMI was employed to guarantee data confidentiality. DMI created a unique household identifier and provided data to us only using this identifier. This procedure guaranteed the privacy of all households in our treatment group and control group. As shown in Table 1, from the population of the Southern Utility's single family residential customers, 12,273 households

[1] The sample that the Southern Utility provided included single family residences that were continuously on a domestic rate for at least one year.

were randomly assigned to the ITT category and 10,964 households were randomly assigned to the control group. The control group received no correspondence from us.

Each member of the intent-to-treat (ITT) group was randomly assigned an Amazon Gift Card Amount. Data Marketing incorporated this information in the invitation letter that was sent out to each member of ITT group. We used this household specific randomized payment amount to test several hypotheses related to participating in our experiment and for testing for heterogeneous treatment effects associated with our information intervention.

DMI mailed out 7,500 invitation letters on July 29th 2011, an additional 3,000 letters on August 17th 2011 and a final batch of 2,500 letters on September 23rd 2011. Below, we will present our statistics on who chose to participate and how this propensity varies with the size of the Amazon Gift Card offered.

The subset of households that took our treatment logged into an Internet website and used a household-specific ID (rather than their name) and password to login. Their household ID and password were provided in their invitation letter. Once participating individuals logged in, they received customized information about the electricity consumption that we describe below and they answered a set of survey questions. Upon finishing the Internet Education Program, they were e-mailed the promised Amazon gift card and a set of tips for reducing their electricity bills customized based on their answers to a number of survey questions.[2] At this point, those in the treatment group did not interact with us again.

DMI worked with the Southern Utility to compile household-level electricity data, covering the time period before and after the experimental start date. DMI merged in the

[2] DMI handled the processing of the Amazon Gift Cards so at no point did we have access to treated households' e-mail addresses. DMI also e-mailed the customized electricity conservation tips.

experimental ID and stripped away household identifiers and then provided us with anonymous household-level electricity consumption data for households in the intent-to-treat and control groups.

**The Northern Utility Specifics**

The general content and intent of the Internet Education Program was identical at both electric utilities but there are some important differences in how we implemented the experiment at the Northern Utility site. In choosing the treatment group and control group, we selected a random sample of single-family homeowners that had an electronic account with the Northern Utility. Such households receive their communications from the electric utility via e-mail rather than through the United States Postal Service. According to the Northern Utility, roughly 20% of residential customers have electronic accounts. This population tends to be younger and more ethnically diverse than the utility's overall service population.

Our Northern Utility experiment population is composed of all electronic account customers who had an interval meter installed as of Autumn of 2011. At that time roughly 50% of the utility's meters had been installed. The interval meters were installed by geographic territories within the utility's service area and the roll out of these meters was completed by April 2012. We recognize that these selection rules mean that we do not have a random sample of single-family homeowners in the service area. Instead, our sample can be thought of as a random sample of households that have electronic accounts and whose geographic area had had smart meters installed as of Autumn 2011. We were also provided with household-specific demographic data for all of the households. The major advantage of working with a sample of households that have interval meters is that we have access to hourly consumption data, which allows us to measure our treatment effects with greater temporal granularity.

We followed the same steps at the Northern Utility that we did at the Southern Utility to randomly assign households to be in our sample and then randomly assigned this group to the intent-to-treat group and the control group. For those assigned to the treatment group, we randomly assigned Amazon Gift Card payments of $0, $5, 20, $25, $30, $35 and $50 to all treatment group customers for completing the course. We randomly varied this payment amount in order to have an observable variable that impacts the probability a household completes the course. We also randomly assigned a subset of the intent-to-treat group a zero dollar payment, which meant that we sent a solicitation e-mail asking them to take the course without any promise of a financial payment.

On October 18th 2011, we launched the Northern Utility experiment by sending out the solicitation e-mails with randomly assigned Amazon amounts, including a solicitation letter with no promise of payment. An example of this email is presented in Appendix 1. On October 26th 2011 another 4,500 emails were sent out to those who did not open the first email. After a household completed our on-line education program, DMI emailed the household their Amazon Gift card and the customized electricity consumption tips. DMI worked with the Northern Utility to provide us with anonymous household-level electricity consumption data with an experiment identifier assigned to each household in the intent-to-treat group and control group.

Table 1 gives the details of the experiment design for the Southern Utility and Northern Utility experiments. The breakdown for the intent-to-treat, treatment, and control groups reflects that fact that data errors after receiving the final data from Southern Utility and Northern Utility required deleting a number of households from each of the three groups. At the Southern Utility, 12,273 households were invited to participate and 1,227 households accepted this invitation. Using random assignment, 10,964 households were assigned to the control group. At

the Northern Utility, 5715 households were invited to participate and 785 households accepted this invitation. 1,000 households were randomly assigned to the control group.

Tables 2 and 3 give a breakdown of the treatment acceptance rates for each Amazon Gift card amount for each experiment. For both experiments, the null hypothesis of an acceptance probability that is monotone increasing in the Amazon Gift card amount offered cannot be rejected. At the Southern Utility, the average participation rate was 9.1%. Those households who were randomly assigned a lower Amazon Gift card were less likely to participate. For those assigned a $10 Gift card, the average participation rate was 4.9% while for those assigned a $50 Gift card the participation rate was 11%. As shown in Table 3, participation rates were higher at the Northern Utility with 6% of invited households who were offered $0 participating while those households who were offered $50 to participate had an average participation rate of 16.6%. As shown in Table 3, the probability of participating increases up to $30 but then is flat between an offer of $30 and $50.

## 4. Internet Educational Treatment Specifics

The basic structure of the Internet education course was to convey the three pieces of information described earlier: (1) the household's typical monthly marginal price, (2) how the household's bill was determined from its IBT, and (3) how the household's monthly electricity bill changes in response to changes in how the household uses its electricity-consuming appliances.

The survey was organized in three sections. Section 1 demonstrates how the IBT works and where the customer is typically located on the schedule during the three months before each survey was administered. This section also shows how the marginal price of electricity changes

depending on how much electricity the household uses in the month. Section 2 surveyed the household about the characteristics of its home and the appliances in it. Section 3 used the answers provided in Section 2 to determine how changes in the utilization of these appliances would impact the household's monthly electricity bill.

**Differences in IBT Pricing Between the Two Utilities**

Figure 1 displays the IBT for the Southern Utility for the coastal portion of its service area. This is the dominant rate structure for single family home owners in the Southern Utility service territory, the lowest marginal price is 12 cents per kWh and the highest is 31 cents/KWh. The only difference between the IBT for the coastal and inland areas for the Southern Utility is the length of each price step. Because of the more extreme temperatures in the inland the region of the Southern Utility service territory, the length of each pricing step in the IBT is longer for the inland versus coastal region.

Households in the intent-to-treat group that took the course were presented with their IBT schedule and shown the locational of their typical month's usage in KWh and the dollar cost of this typical monthly consumption. The graphic in the on-line education program would demonstrate that the monthly bill was the area under the IBT up to the household's typical monthly consumption. The program also gave participants access to a slider that allowed them to conduct their own thought experiments to see how their monthly bill would change if they increased or decreased their monthly consumption.

Figure 2 demonstrates that the two electricity retailers in our study differ sharply with respect to the steepness of their pricing tiers. The Southern Utility has 5 pricing tiers with marginal prices that differ by almost a factor of three from the lowest to highest-priced tier. The other retailer, the Northern Utility, only has two pricing tiers, and the top tier is slightly more

than 50 percent higher than the price on the first tier. These differences in the IBT between the two utilities allows us to implement a more robust test of whether information on a household's typical monthly marginal prices yields the anticipated behavioral response described in Section 2.

## Data

For the Southern Utility, our unit of analysis is a household/month. We have billing cycle level-data that we converted to monthly electricity consumption data for the intent-to-treat group and the control group starting in July 2010 and running through June 2012. For those assigned to the treatment group, we create a dummy variable that equals one if the month takes place after treatment and is the fraction of the month after treatment for the month in which the treatment took place. At the Northern Utility, our unit of analysis is the household/hour. Table 1 reports the time period that we study at the two utilities. At the Southern Utility, our data cover the time period December 2010 until June 2012 and at the Northern utility, our data cover the time period April 2011 to the end of March 2012. These time intervals include a "pre-treatment" and "post-treatment" interval as the experiment started in August 2011 at the Southern Utility and in October 2011 at the Northern Utility (see Table 1).

## Results

### Characteristics of the Treatment Group and the Control Group

To document the effectiveness of the randomization of households into the treatment group and the control group, we compared the distribution of average daily electricity consumption for the intent-to-treat group to the distribution of the average daily electricity

consumption for the control group during the pre-intervention period before our first solicitation letter was sent out for the Southern Utility sample. These distributions were found to lie on top of each other and various statistical tests of the null hypothesis of the equality of these distributions were not rejectedindicating that our randomization process for selecting households into the intent-to-treat and control groups was valid.

For the case of the Northern Utility sample, we compared the distribution of hourly consumption within the day for the intent-to-treat and control group for each day of the sample period. Once again, the distributions were found to lie on top of one another and we could not reject the null hypothesis of equality of these daily distributions for any day of the pre-intervention period, indicating that our randomization process for selecting the intent-to-treat and control groups was valid.

**Conditional on Being in The Intent-to-Treat Group, Who Took the Treatment?**

For the most part we found that the Amazon gift card amount was a major observable characteristic predicting whether a household in the intent-to-treat group decided to take the treatment. We experimented with a number of statistical models to predict whether a household took the treatment as function of observable demographic variables associated with the household and its dwelling characteristics and for the most part these factors were not statistically significant predictors of whether a household in the intent-to-treat group decided to take the treatment.

For the case of Southern Utility this result could be explained by the fact that we did not have household-specific demographic data and were only able to match households to Census Block group demographic characteristics. However, for the case of the Northern Utility we had access to some household-level demographic data, but with the exception of a few dwelling

characteristics these variables did not significantly improve our model's ability to predict whether a household decided to take our treatment.

## 5. Econometric Modeling Framework and Empirical Results

This section presents the tier-specific treatment effects differences-in-differences econometric modeling framework that we use estimate the impact of our informational intervention on the household's electricity consumption. We then present results of our model estimation for both the Southern Utility and the Northern Utility for the treatment versus control sample. To assess the impact of potential self-selection from the intent-to-treat group into the treatment group on our estimated treatment effect, we also report the estimates of our model for the offered-but-refused versus treatment sample and find nearly identically results to the treatment effects estimated for the treatment versus control sample for both the Southern Utility and the Northern Utility.

First consider the case of the Southern Utility. Let $y_{it}$ equal the logarithm of average hourly electricity consumption in month t for household i. This variable is constructed from the customer-level billing cycle-level data by computing an average hourly consumption for each billing cycle and then taking a weightedaverage of the average hourly consumption of each billing cycle in month i, where the weight is the share of days of month i associated with each billing cycle. For example, if a month has 30 days and 20 of them are in one billing cycle and the remaining 10 are in another, then the weights are 2/3 and 1/3. Let Tier(j,i) equal 1 if customer i's typical monthly marginal price is the one associated with tier j (for j=1,2,…,J) on the IBT schedule and zero otherwise. As shown in Figure 2, there are 5 pricing tiers so that J = 5. Let Treat(i,t) equal 1 if customer i completed the treatment by the start of month t and zero for

any month that customer had not completed the treatment by the end of month t. For the month in which the customer completed the treatment let Treat(i,t) equal the fraction of days in the month that were after the household completed the treatment. Model estimates setting Treat(i,t) for the month in which the household completed the treatment, did appreciably changes the parameter estimates.

In terms of this notation our tier-specific treatment effects model is:

$$y_{it} = \alpha_i + \lambda_t + \sum_{j=1}^{5} \beta_j * Tier(j,i) * Treat(i,t) + \varepsilon_{it}$$

where $\alpha_i$ is a household-level fixed-effect, $\lambda_t$ is a month-of-sample fixed-effect and the $\beta_j$ for j=1,2,…,5 are tier-specific treatment effects, and $\varepsilon_{it}$ are mean zero disturbance terms that are uncorrelated with household-level and day-of-sample fixed effects and the Treat(j,i)*Treat(i,t) variables. Note that for both the invited-but-refused and control samples Treat(i,t) equals zero for all i and t, so that Tier(j,i)*Treat(i,t) equals zero for all i and t in these samples. We estimate this model by ordinary least squares, but allow for arbitrary autocorrelation in the $\varepsilon_{it}$ across observations for each household and apply the Arellano (1987) heteroskedasticity and autocorrelation-consistent covariance matrix to compute standard error estimates for our tier-specific treatment effects estimates.[3]

For the case of the Northern Utility, our econometric model follows the same basic structure, but now the t subscript denotes the hour of the sample period and there are only two

[3] Bertrand, Duflo and Bertrand (2004) perform a Monte Carlo study based on actual datasets used in empirical research to estimate differences-in-differences models and find that these standard error estimate yields accurate size tests in small samples yet still yields tests with modest small-sample power properties, whereas procedures that ignore potential autocorrelation and heteroscedasticity significantly over-reject true null hypotheses. For this reason, Bertrand, Duflo, and Mullainathan (2004) recommend using the Arrellano (1987) covariance matrix for drawing inferences from in differences-in-differences estimates.

pricing tiers in the IBT so that J =2. In this case, $y_{it}$ is the logarithm of the electricity consumption of household i during hour-of-sample t. Tier(j,i) is defined the same way as it is for the Southern Utility, but j can only take on the value 1 or 2. Treat(i,t) equals one for household i for all hours of the sample period after the household takes the treatment. The $\alpha_i$ are still household-level fixed-effects, $\lambda_t$ is an hour-of-sample fixed-effect and the $\beta_j$ for j=1,2 are tier-specific treatment effects, and $\varepsilon_{it}$ are mean zero disturbance terms that are uncorrelated with household-level and hour-of-sample fixed effects and the Treat(j,i)*Treat(i,t) variables. Subject to these notational differences, the model for the Northern Utility takes the form:

$$y_{it} = \alpha_i + \lambda_t + \sum_{j=1}^{2} \beta_j * Tier(j,i) * Treat(i,t) + \varepsilon_{it}$$

For this case, we also use the Arrellano (1987) heteroSouthern Utilitydasticity and autocorrelation consistent covariance matrix to compute standard error estimates.

**Estimation Results**

Figure 3 plots the tier-specific treatment effects for the Southern Utility for the treatment versus control estimation sample. The thin bars on the graph denote the 95% percent confidence intervals for these tier-specific treatment effects using the Arrellano (1987) covariance matrix. Consistent with our hypothesis outlined in Section 2, we find that households that were told their typical marginal prices was the lowest priced-tiers increased their consumption in response to our information treatment by over 5%. Households that were told their typical marginal price was the high-priced priced tier reduced their consumption by roughly 3%. As shown in Figure 3, these estimates for the 1st and 5th tiers are statistically significant. Households that were informed that their marginal price was in the middle of the IBT did not alter their consumption in response to our information treatment.

Although the percentage reduction of customers on the two higher marginal price tiers was smaller than the percentage increase of customers on the two lower marginal price tiers, the fact that there were more customers on the higher priced tiers and their average level of consumption was higher implies that the overall impact of our information treatment was small reduction in total electricity consumption for households in our treatment group in response to our information treatment.

Figure 4 plots the tier specific treatment effects for the Northern Utility sample for the treatment versus control sample. Again consumers that were informed that their typical marginal price was on the low price tier increased their consumption in response to our information treatment. The estimated effect is large (10%) and is statistically significant. Those households that were informed their typical marginal prices was on the high price tier reduced their consumption by roughly 5%. Again, the percentage increase was larger for households on the low-price tier, but because there were more households on high priced tier and their consumption was higher, the overall impact of our information treatment was a reduction in total consumption of the treatment group.

In evaluating the effectiveness of our educational intervention it is important to recognize that our post-treatment period is relatively short. We recognize that a single information intervention may not yield persistent effects. It is quite possible that further reinforcement is required. Future research should consider studying this.

**Investigating the Impact of Self-Selection on Treatment Effect Estimates**

As we discussed above, households were randomly assigned to the intent to treat group and the control group. The households that were randomly assigned to the intent to treat group

were also randomly assigned an Amazon Gift Card amount as their reward for participating. Individual households in the intent to treat group chose whether to take the treatment or not and this raises the possibility that the group who took the treatment is a select subset of the population. For example, it is possible that the most motivated to be "smarter electricity consumers" might be more likely to enroll. In this case, it would not be valid to extrapolate from the results recovered by our field experiment to how the behavior of a random household in the general population would be affected by participating in the Internet educational course. Conversely, if households have no basis for anticipating what they might learn from participating in our course then there might be no systematic enrollment by unobserved type. In this case, our field experiment's estimates would be valuable information for extrapolating about how the greater population would be affected by taking our treatment.

To investigate the impact of self-selection into the treatment group on our parameter estimates, we re-estimated each model purely on the intent–to-treat sample, which was composed of households that were invited-to-take the treatment and refused and those that took the treatment. Figures 5 and 6 present these treatment effects estimates and their 95% confidence intervals for this sample of households. The key finding here is that the estimated treatment effects based on comparing the treatment group to the intent to treat sample who refused are almost identical to the results that compare the treatment group to the control sample. This suggests that there is little reason to be concerned about selection bias in this setting. Our explanation for this finding is that households have many different priorities over how they allocate their scarce time and when we invited households to participate they had little information about the actual content of our educational experience. If households are generally

ignorant about issues related to electricity consumption they may not know what they would gain, before they participate, from participating in a high quality content experience.

## Discussion

### Targeting and Program Design to Achieve Electricity Conservation Goals

This section explores the possible role that Internet Education courses such as the one we have designed can have in helping the California Air Resources Board (ARB) achieve its AB32 goals. As we have demonstrated across the two electric utilities, targeting high marginal price consumers with this education could induce a 3 to 5% decline in electricity consumption. As electric utilities such as Southern Utility and Northern Utility fall under the cap, they will have an incentive to broadly offer such courses.

Suppose the price of a ton of $CO_2$ rises to $20 each. Suppose these electric utilities have an emissions factor of 700 pounds of carbon dioxide per megawatt-hour of energy. Given that natural gas power plants release roughly 930 pounds per megawatt-hour. Given these assumptions, 1 MWh of consumption reduced is worth $7 to the utility. Roughly 1/3 of California's electricity is consumed by the residential sector, which approximately 80,000,000 MWh per year. Assuming that widespread deployment of our information treatment results in a reduction of 1 to 2 percent of residential electricity consumption in California, implies hundreds of thousands of tons $CO_2$ emissions savings per year and valuing these savings at $20 per ton, implies significant cost savings.

## Summary and Conclusions

In co-operation with two major California electric utilities, we have designed and implemented an educational field experiment to quantify how increased knowledge about nonlinear pricing and how the household's appliance use translates into electricity use impacts the household's electricity consumption.

At both electric utilities in late 2011, 2012 households were enrolled to take a 30 minute Internet educational experience focused on teaching participants the precise details about the non-linear pricing tariff they face and the implications for how day to day actions affect the monthly electricity bill. Households were divided into three sets. The first set was the control group. This group of single family home residents was chosen at random and received no communications from us. By partnering with the electric utilities, we were able to access their electricity consumption data before and after the treatment began. The second group of households are households who were randomly assigned to receive a "treatment invitation letter". Members of this group received a letter inviting them to go to the Internet website to take the 30 minute course. The third group is the subset of invited households who took the treatment. For each of these three groups of households, we track their electricity consumption before and after the treatment date.

The goal of the Internet treatment was to educate households to become more sophisticated consumers of electricity. Households are major consumers of electricity but are unlikely to be sophisticated consumers of this essential input in daily life. A sophisticated consumer has a strong understanding of what is the price per unit of electricity consumed and how the use of different products ranging from lights to air conditioning to computers affects a household's electricity bill. Armed with both of these pieces of information, a household will make its optimal choices as it trades-off the benefits of electricity consumption as an input in

engaging in household production and leisure activities against the marginal cost of increased electricity. In reality, it is unlikely that the vast majority of households are sophisticated electricity consumers. Unlike other consumption goods, households only receive a single bundled electricity bill once a month. Households face a complex increasing block tariff structure for electricity and households are unlikely to be able to link "cause and effect" of how certain actions such as changing their thermostat setting affect their electricity bill. If households seek to be "better" electricity consumers but lack the knowledge of key pieces of information that would allow them to achieve their goals, then there is a positive potential role for information interventions that educate households with respect to the prices they face and the mapping from actions to total kilowatt consumption consequences.

The major finding of our study can be seen in Figures 3 and 4. These figures highlight that households who learn that they face a high marginal price for electricity consumption respond by reducing their consumption while households who learn that they face a low marginal price for electricity consumption respond by increasing their consumption. From the perspective of the Air Resources Board with its focus on achieving AB32's greenhouse gas mitigation goals, this main finding suggests that resources should be invested in educating high marginal price consumers about the pricing schedule they face and offering specific advice for how to reduce their consumption. Our field experiments highlight that consumers do change their behavior when educated.

## Recommendations

1. The ARB should work with the state's electric utilities to scale up information interventions targeted to those households who face high marginal prices. Each California electric utility's administrative database can be used to identify this subset of customers and then these households can be randomly assigned to a treatment group and a control group to quantify average behavioral changes.
2. Each electric utility has a demand side management team investigating different incentives and nudges to encourage energy conservation. The ARB should encourage the state's utilities to form a research consortium to identify the best practices and to encourage research academics to work more closely with the electric utilities while guaranteeing consumer confidentiality. Such a research team could identify the most cost-effective strategies for achieving AB32's goals where cost effectiveness would be measured by kilowatt-hour of power reduced per dollar invested in the demand side management tool.
3. Given the diversity of California's households, some households will be more responsive to an Internet Educational experience than others. Future research should explore the hypothesis that more educated households are more responsive to information treatments.
4. As California's electric utilities roll out the introduction of Smart Meters in more homes, the ARB should commission research that investigates how households use this new technology and examine potential nudges to help households become more sophisticated electricity consumers.
5. This field experiment has reported results from a one time information intervention. Many households may require further information reinforcement such as being nudged to return to the site. Future research could study the persistence of interventions such as

ours and the extra benefits enjoyed by households who receive information reinforcement.

## References


Arrellano, M. (1987) “Practitioner’s Corner: Computing Robust Standard Errors for Within Groups Estimators,” Oxford Bulletin of Economics and Statistics, 49(4): 431-434.

Bertrand, M., Esther Duflo, and Sendhil Mullainathan (2004) “How Much Should We Trust Differences-In-Differences Estimates,” Quarterly Journal of Economics, 119(1), 249-275.

Borenstein, Severin. 2009. ‘“To What Electricity Price Do Consumers Respond? Residential Demand Elasticity Under Increasing-Block Pricing.”

Chetty, Raj and Emmanuel Saez. 2013. "Teaching the Tax Code: Earnings Responses to an Experiment with EITC Recipients," American Economic Journal: Applied Economic, vol. 5(1), pages 1-31,

Ito, Koichiro. "Do Consumers Respond to Marginal or Average Price? Evidence from Nonlinear Electricity Pricing." Energy Institute at Haas Working Paper 210 (2012).

Reiss, Peter and Matthew White (2008). “What Changes Energy Consumption? Prices and Public Pressure.” Rand Journal of Economics, 39, 636-663.

Shin, Jeong-Shik (1985). “Perception of Price When Price Information is Costly: Evidence from Residential Electricity Demand.” The Review of Economics and Statistics, 67(4) 591-598.Varian, Hal R. (1992) *Microeconomic Analysis (Third Edition)*, W.W. Norton & Company.

Wolak, Frank A. (2010) "An Experimental Comparison of Critical Peak and Hourly Pricing: The PowerCentsDC Program,, available at http://www.stanford.edu/~wolak .

**Table 1: Experiment Design Parameters for Southern Utility and Northern Utility**

| Experimental Design at the Southern Utility | |
|---|---|
| Intent-to-Treat Group Size (Invited) | 12,273 customers |
| Treatment Group Size (Invited and Accepted) | 1,227 customers |
| Control Group Size | 10,964 customers |
| 1st Letter Sent | August 1, 2011 |
| 2nd Letter Sent | August 18, 2011 |
| 3rd Letter Sent | September 26, 2011 |
| Period for Consumption Data | 12/2/2010 to 6/30/2012 (monthly) |

| **Experimental Design at the Northern Utility** | |
|---|---|
| Intent-to-Treat Group Size (Invited) | 5,715 |
| Treatment Group Size (Invited and Accepted) | 785 |
| Control Group Size | 1,000 |
| 1st E-mail Sent | October 18, 2011 |
| 2nd Letter Sent | October 26, 2011 |
| Period for Consumption Data | 4/1/2011 to 3/29/2012 (hourly) |

**Table 2:** Southern Utility Gift Card Amounts and Response Rates

| Amazon Amount ($) | Number Offered | Cards Sent | Sent/Offered % |
|---|---|---|---|
| 10 | 700 | 34 | 4.9% |
| 20 | 3437 | 283 | 8.2% |
| 25 | 3161 | 291 | 9.2% |
| 30 | 3053 | 298 | 9.7% |
| 35 | 2949 | 299 | 10.1% |
| 50 | 200 | 22 | 11.0% |
| SUM | 13500 | 1227 | 9.1% |

**Table 3:** Northern Utility Gift Card Amounts and Response Rates

| Northern Utility Gift Card Amounts and Response Rates | | | |
|---|---|---|---|
| Amazon Amount ($) | Number Offered | Cards Sent | Sent/Offered % |
| 0 | 1800 | 108 | 6.0% |
| 10 | 1500 | 181 | 12.1% |
| 20 | 1100 | 142 | 12.9% |
| 30 | 900 | 150 | 16.7% |
| 40 | 700 | 121 | 17.3% |
| 50 | 500 | 83 | 16.6% |
| Overall | 6500 | 785 | 12.1% |

**Figure 1: IBT for Southern Utility Households**

**Figure 2: IBTs for Southern Utility and Northern Utility Service Areas**

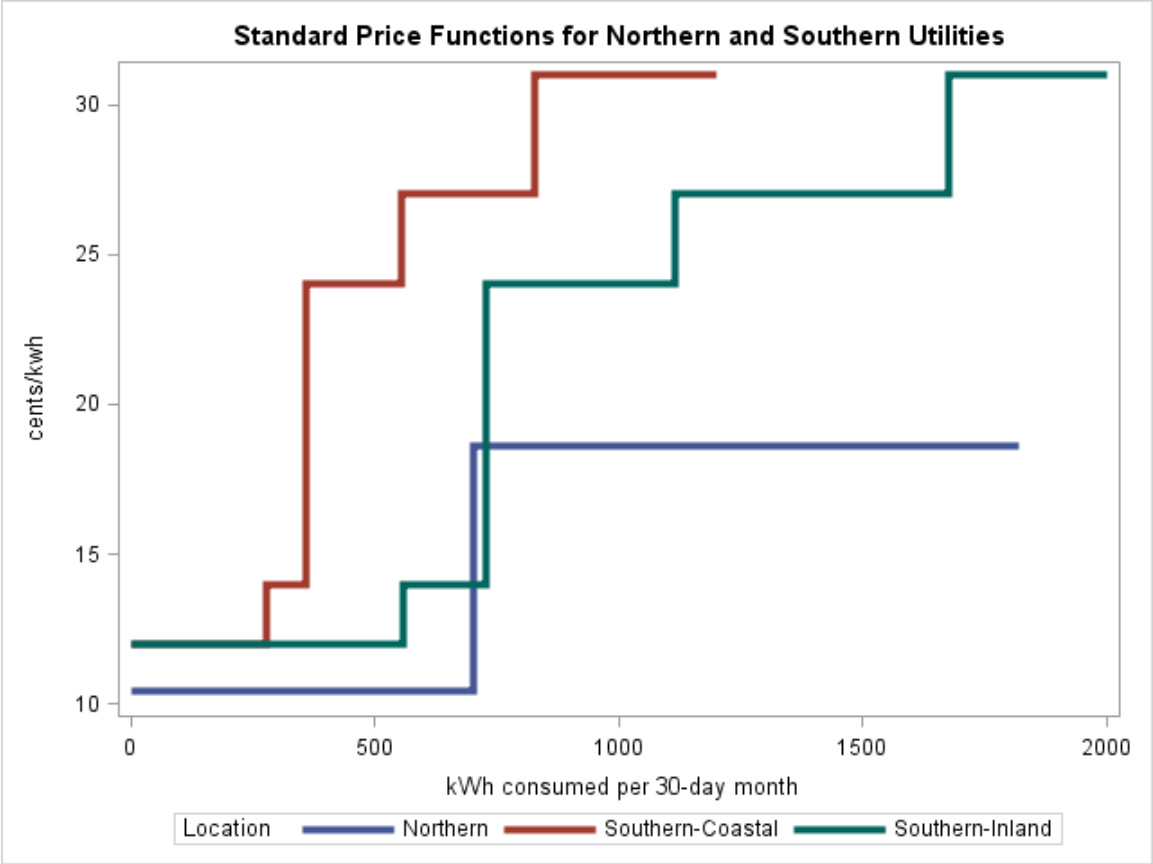


**Figure 3: Tier-Specific Treatment Effects**
**Southern Utility Treatment versus Control Sample**

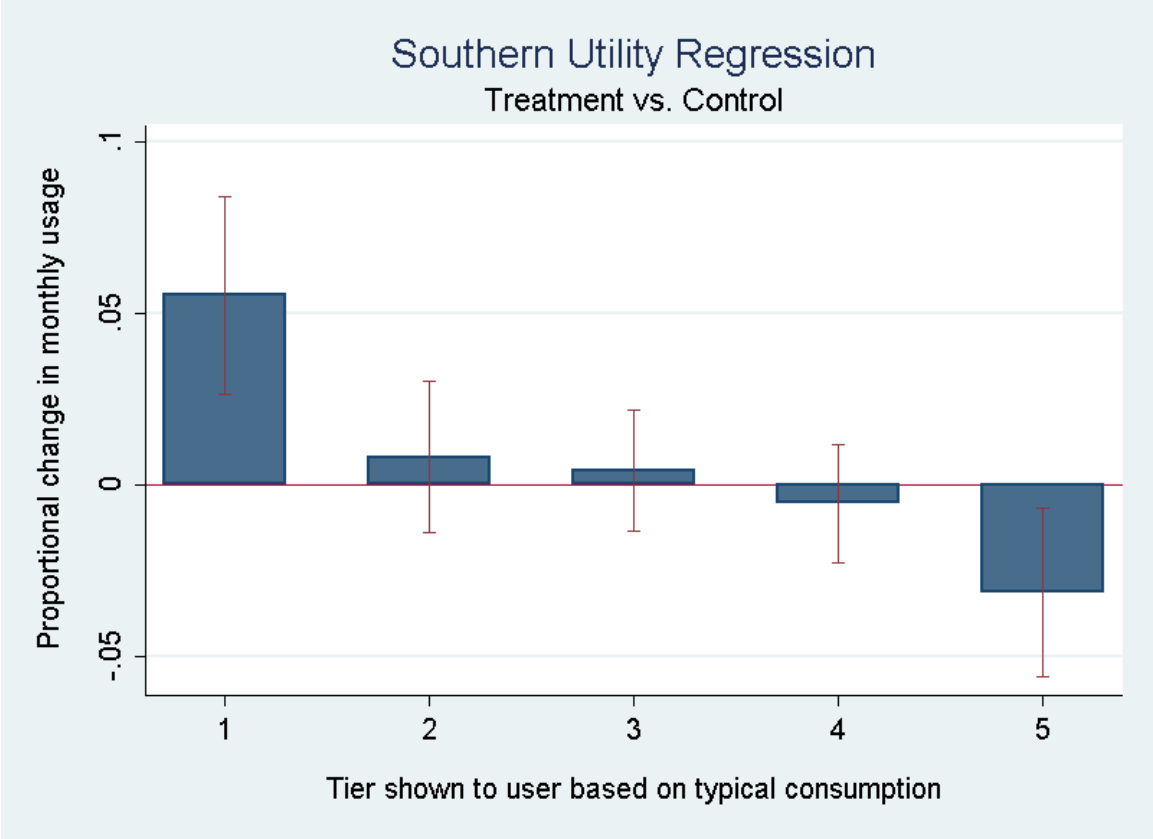


**Figure 4: Tier-Specific Treatment Effects**
**Northern Utility Treatment versus Control Sample**

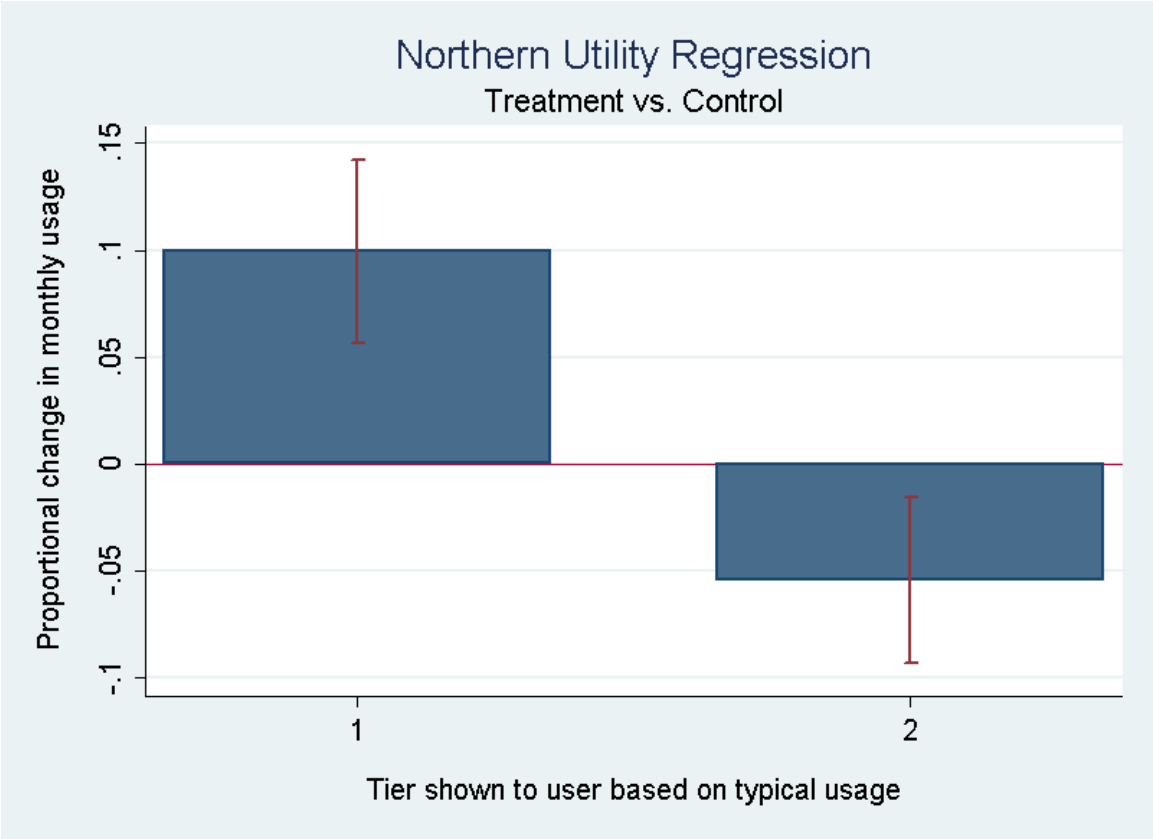


**Figure 5: Tier-Specific Treatment Effects**
**Southern Utility Intent-to-Treat Sample**

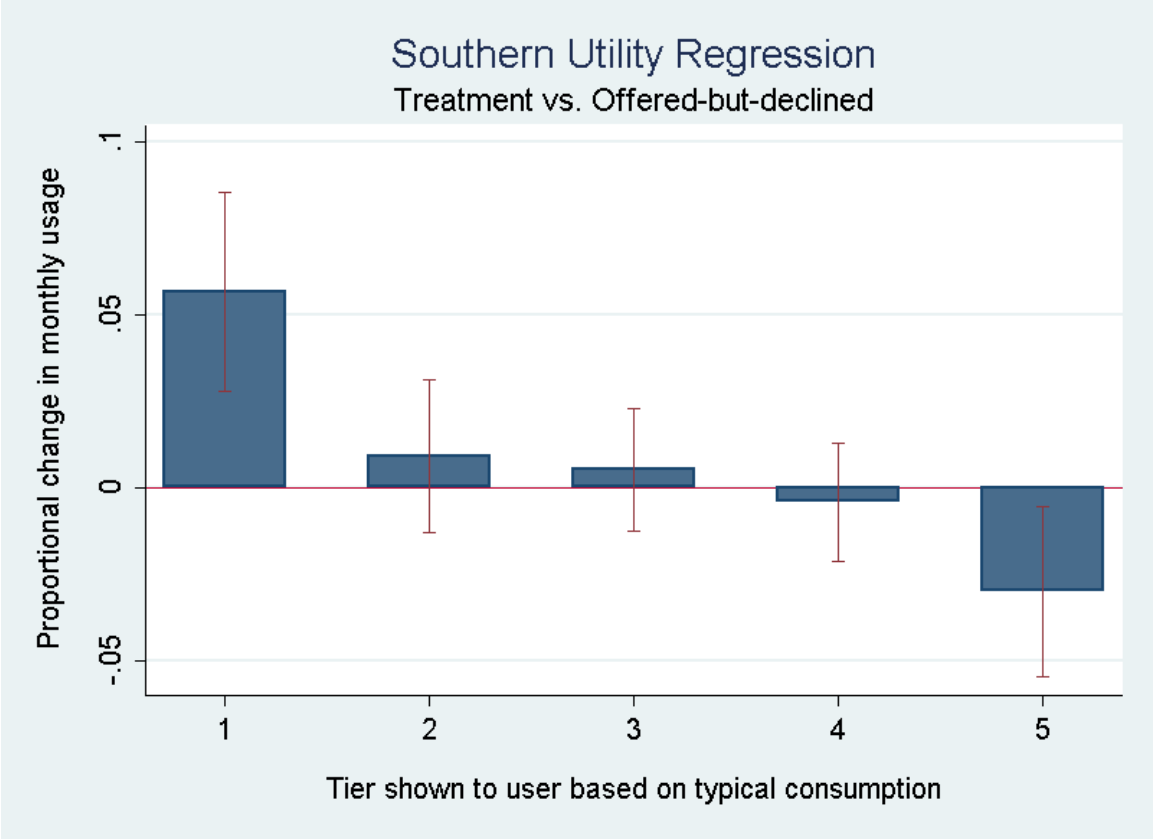
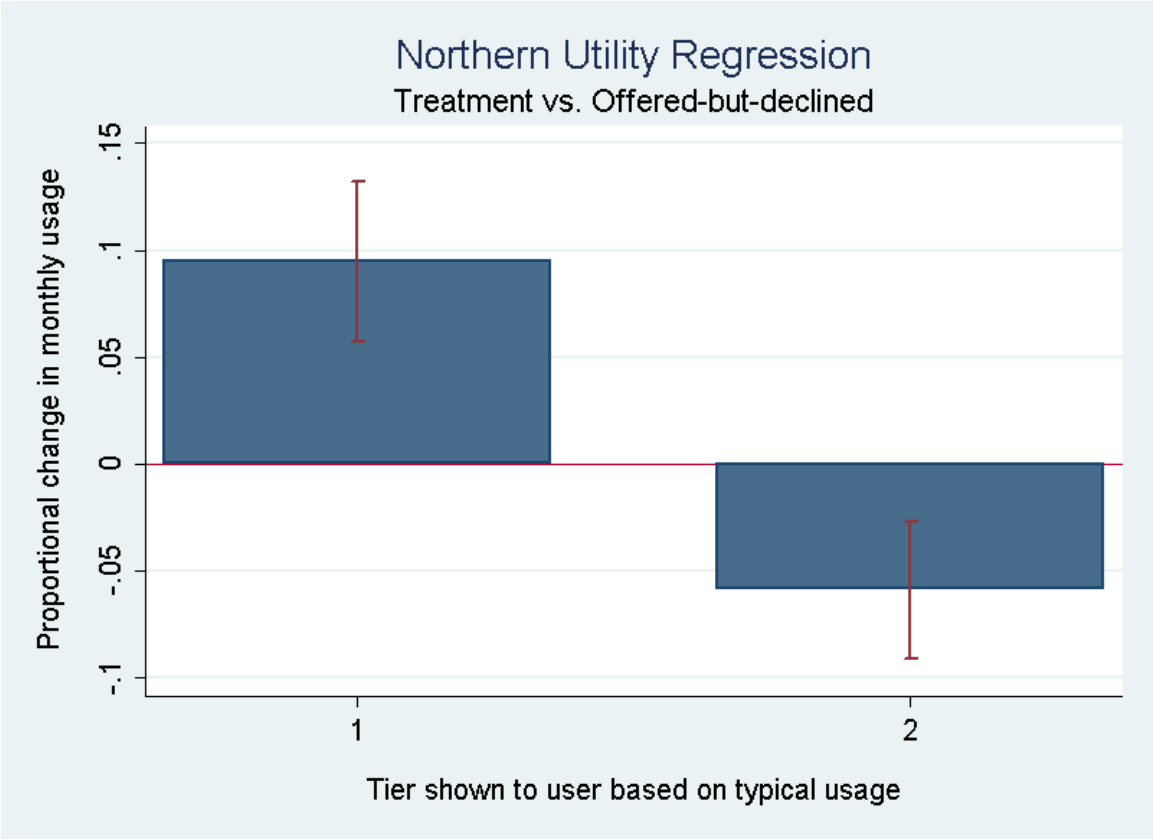


**Figure 6: Tier-Specific Treatment Effects**
**Northern Utility Intent to Treat Sample**



Appendix 1

Dear [insert name],

Northern Utility is partnering with researchers from Stanford University and UCLA to develop a home energy savings workshop. Your valuable input will help Northern Utility create similar educational tools in the future. This online workshop is a 15-20 minute tutorial that could help you save money on your next electricity bill. For completing the workshop, you will receive a **$50 gift card to Amazon.com.**

The workshop starts by showing how your electricity use affects your electricity bill. Then, using a brief survey of your household's characteristics, the workshop generates the customized suggestions you can use to reduce your household's electricity bills.

We hope you will try this innovative program today. To begin the workshop simply click the link below or paste it into your browser. If you have any questions, please contact me at the number below.

[insert link]

Sincerely,

Mr. XX
Northern Utility

P.S. You will receive your Amazon Gift Card by e-mail within 10 days of completing the survey. If you do not receive the card within this time period, please check your spam filter.