Using Information to Improve the Effectiveness of Nonlinear Pricing: Evidence from a Field Experiment

by

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Abstract

This paper reports on the results of two field experiments examining the impact of providing information on how a consumer's own electricity use translates into its monthly electricity bill on how that consumer responds to a nonlinear retail price schedule for electricity. Across the two utilities, over 2,000 consumers participated in a customized on-line interactive educational program that taught them how their monthly electricity bill was determined from nonlinear retail price schedule they face. Each consumer was also told where their typical consumption monthly places it on this nonlinear pricing schedule. Consumers were also shown how changes in their major electricity-consuming activities would affect their monthly bill under the nonlinear price schedule. Using data from before and after this intervention for consumers that took the educational program (our treatment) and a randomly selected set of control consumers, we estimate the overall treatment effect associated with our educational program as well as a treatment effect for consumers on each specific pricing tier on the nonlinear price schedule during the pre-intervention period. For both utilities, we find that the overall impact of our treatment is a reduction in the consumer's daily average consumption. In addition, our price tier-specific treatment effect results are that consumers that learn they face a higher marginal price for consuming electricity reduce their electricity consumption and consumers that learn they face the lowest marginal price increase their electricity consumption. These results emphasize that the need to provide timely and actionable information to consumers in order to maximize the effectiveness of nonlinear retail price schemes.

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 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 kilowatt-hours (KWhs) 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 KWhs 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 know how their monthly electricity bills are determined from an IBT. Second, consumers must determine where on the IBT schedule they are likely to end the month in order to determine the appropriate marginal price to use for their electricity consumption decisions during the month. Third, and perhaps most important, consumers need to understand how their electricity-using actions translate into KWhs of electricity consumption, because depending on where the customer is on the nonlinear price schedule the cost of a given electricity consuming action can differ by more than a factor of two for many IBT schedules.

Electricity demand is derived from a consumer's demand for air conditioning, space heating, water heating, lighting, television watching, computer use, and use of electricity-consuming appliance services in general. Although most consumers are able to predict the dollar amount of their typical summer and winter monthly electricity bills based on previous experience, there is considerable debate among industry observers whether: (1) consumers understand how their electricity bills are determined from an IBT, (2) what their marginal price for the month is likely to be, and (3) how their appliance-using actions translate into KWhs of consumption and dollars on their monthly electricity bill.

For example, suppose a consumer did not know how much electricity it was likely to consume in the month. Even if a consumer understood how his monthly bill was computed under IBT pricing, he would not know the marginal price of electricity for that month and would therefore be forced to use less efficient approaches to managing his 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 consumers to adopt rules of thumb for determining their monthly electricity consumption. Shin postulates that consumers respond to the monthly average price—the consumer's monthly electricity bill divided by his monthly electricity consumption. Shin then presents empirical evidence consistent with this hypothesis. Borenstein (2009) argues that lack of information about the monthly marginal price, because the consumer cannot accurately forecast his monthly electricity consumption, causes him not to respond to the monthly marginal price. Ito (2012) proposes an empirical test of whether consumers respond to the monthly marginal price versus the monthly average price and finds evidence consistent with the hypothesis that consumers respond to the monthly average price.

Possible explanations for the empirical results of Shin (1985) and Ito (2012) are that consumers 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 consumers 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 consumers that are provided with information about their monthly marginal price and how this price impacts their monthly electricity bill change their behavior. 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 consumers 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 often lack the information that would allow them to do so. Our experiment provides empirical evidence that our on-line educational treatment provides the basic information that allows consumers to respond to an IBT pricing structure.

Starting in the Spring of 2011, we partnered with two California electric utilities and implemented a field experiment with consumers from each utility that resulted in roughly 2,000 consumers taking 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 residential customers. We randomly assigned the vast majority of these customers to the intent-to-treat (ITT) group and the remaining consumers to the control group. All customers 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 consumer with: (1) information about how its electricity bill is determined from its IBT pricing function, (2) the value of its typical monthly marginal price of electricity, and (3) information about how the customer's appliance-using actions translate into dollars on its monthly electricity bill.

After completing the Internet course, we tracked the changes in electricity consumption for the ITT group, which is composed of consumers that were offered the opportunity to take our educational course but refused (the offered-but-refused-treatment group) and consumers that were offered the opportunity to take the course and actually took it, and the control group. Besides estimating the treatment effect of our intervention across all consumers, we also specify a measurement framework that allows the treatment effect of our education program on electricity consumption to differ by the level of the consumer's typical monthly marginal price. This econometric approach is justified by an appeal to the static theory of consumer utility-maximizing choice subject to an IBT presented in Section 2 which implies that the level of this marginal price should impact a consumer's electricity consumption choices.

For both utilities, the overall the average treatment effect for our educational program is negative, implying that on-average customers that took our treatment reduced their consumption relative to customers in our sample that did not take the treatment. We also estimate pricing-tier-specific treatment effects regressions for our educational program. Consistent with the view that customers armed with information about their typical monthly marginal price will use this information to use electricity more efficiently, we find that customers that learn they face a higher marginal price for electricity *reduce* their consumption while customers that learn that they face the lowest marginal price for electricity *increase* their consumption.

This result is consistent with the view that the consumers 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. Both of our utilities assess a monthly fixed charge for providing service, so consumers whose marginal price is the first price step on the IBT face a marginal price that is less than their average price. A unique feature of our study is that we ran the same experiment at two independent locations and obtained qualitatively the same results at both locations. There are also crucial differences across the two utilities in terms of their IBT pricing structures, climate conditions and the type of data, which strengthens the case for our results being valid for other utilities where customers pay according to IBTs.

This paper adds to an emerging literature on educating consumers about non-linear incentives such as the tax code and evaluating the impact of providing this information on consumer 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. Liebman and Luttmer (2011) use a field experiment to document how information about the Social Security system impacts older women's labor force participation.

This literature and our field experiments assess the impact of lowering the cost of information acquisition on economic behavior. In our case, the on-line educational course lowers the cost to the consumer of learning the information that will allow it to respond to an IBT for electricity. 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, it is therefore reasonable to assume that any change in behavior between the treatment and control groups is caused by the information provided. In our case, making consumers 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 consumers making beneficial use of this information.

Although our results are directly relevant to the impact of information provision on the behavior of consumers subject to IBT pricing structures, it does not seem to be a stretch to extend them to case of marginal prices that differ over time. Specifically, our results suggest that notifying consumers that they face an hourly price that is higher than their annual average retail price will cause them to reduce their consumption and notifying consumers 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 consumers 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 making more efficient use of the existing electricity industry infrastructure.

2. Impact of Marginal Price Information

To understand how notifying consumers of their typical monthly marginal price is likely to impact their electricity consumption, consider the following two models of utility-maximizing consumer-level electricity consumption behavior. The first assumes linear pricing where the consumer faces the same marginal price for all units consumed and the second assumes nonlinear or IBT pricing where the consumer pays higher marginal prices for higher levels of monthly consumption. For simplicity, we assume that the consumer faces an IBT for electricity with two pricing tiers and a monthly fixed charge, F. For consumption between zero and E_1 the consumer faces a marginal price of $p_{1.}$ For consumption greater than E_1 the consumer faces a marginal price of p_2 that is strictly greater than p_1.

Suppose that the consumer is only told its monthly electricity bill is B dollars and that its consumption is E KWhs. Suppose that based on this information, the consumer concludes that it faces a price of $p_A \equiv B/E$ for electricity. Assume the consumer has a budget constraint of M dollars and that the only other good available to the consumer is a composite good X, that has a price of $p_{X.}$ The consumer'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 customer-level electricity consumption subject to a linear price of electricity set equal to the average price faced by the consumer, $p_{A.}$ In this case the consumer'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 $p_1 < p_A < p_2$, because $p_A = (p_2 \max((E - E_1),0) + p_1 \min(E_1,E) + F)/E$. Now suppose that the consumer receives our information treatment and is notified that its monthly marginal price is p_2 and that it faces an IBT. In this case, the consumer's utility-maximization problem is:

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

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 consumer 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 (the marginal utility of X is decreasing in X and increasing in E). This result implies that telling a consumer 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 has a marginal price of $p_2 > p_A$, will result in that consumer reducing its electricity consumption. By similar logic, telling the consumer it faces an IBT and a marginal price of $p_1 < p_A$ will result in that consumer increasing its electricity consumption.[1] 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 California electric utilities. For confidentiality reasons, we never accessed data that identified the consumer's name or street address. However, by partnering with these electric utilities we were able to access consumer-level data on electricity consumption before and after our intervention took place for a large random sample of consumers from each utility and a subsample of the consumers from each utility that have taken our educational program.

We now describe 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 customers 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 consumers

[1] Note that even with only two pricing tiers, p_A, is greater than p_1 because customers must pay a F, the monthly fixed charge, regardless of how much they consumer, that make the average price of customers on the first pricing tier greater than p_1.

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 that the customer 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.

Utility A Experiment Specifics

Utility A provided a third party with the confidential data for 1,407,500 single family homeowners in its service area.[2] This third-party had to be provided with the name and street address of each of these homeowners because it sent out the invitation letters that we describe below. These consumers all faced the most common residential rate structure used by Utility A.

This third party was employed to guarantee data confidentiality. It created a unique customer identifier and provided data to us only using this identifier. This procedure guaranteed the privacy of all customers in our treatment group and control group. From the population of Utility A single-family residential customers, 25,000 customers were drawn at random. The control group received no correspondence from us.

Each member of the intent-to-treat group was randomly assigned one of the following Amazon Gift Card Amounts: \$10, \$20, \$25, \$30, \$35, and \$50. The third-party incorporated this information in the invitation letter that was sent out to each member of the treatment group. We use this consumer-specific randomized payment amount as an instrument for the decision of a consumer to take our treatment to compute a local average treatment effect for our educational program.

[2] The sample provided by Utility A includes single family residences, domestic tariff only, continuously on a domestic rate for one year, no tariff riders such as an air conditioning cycling program and no reduced payment tariffs that were income based or voluntary.

The third-party 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 consumers that took our treatment logged into an Internet website and used a customer-specific ID (rather than their name) and password to login. Their customer ID and password were provided in their invitation letter. Once participating individuals logged in, they received customized information about their electricity consumption that we describe below and they answered a set of survey questions. Figure 1 gives a sample screenshot from our education program showing the IBT for an inland customer of Utility A. The grey shaded area under the curve shows how much the customer must pay for amount of energy shown on the horizontal axis under this IBT.

Upon finishing the Internet Education Program, each customer was e-mailed the promised Amazon gift card and a printable file that could be posted in a prominent place in the customer's residence containing a set of tips for reducing the customer's electricity bills customized based on the consumer's answers to a number of survey questions.[3] At this point, those in the treatment group did not interact with us again.

Utility B Specifics

While the general content and intent of the Internet Education Program was identical at both sites, there are some important differences in how we implemented the experiment at Utility B relative to the Utility A. In choosing the treatment group and control group, we selected a random sample of single-family homeowners that had an electronic account with Utility B.

[3] The third-party handled the processing of the Amazon Gift Cards so at no point did we have access to treated customers' e-mail addresses. The third-party also e-mailed the customized electricity conservation tips.

Such customers receive their communications from the utility via e-mail rather than through the United States Postal Service. According to Utility B, roughly 20% of residential customers have electronic accounts. We were told by Utility B that these customers are a bit younger and more ethnically diverse than the utility's overall service population. We focused our experiment on this population of Utility B customers because of cost considerations. The marginal cost of sending an e-mail asking a customer to take our treatment is virtually zero versus almost a dollar per letter for contacting a customer by regular mail.

The Utility B experiment population is composed of all electronic account customers that had an interval meter (that records the customer's hourly consumption) installed as of the Autumn of 2011. At that time, roughly 50% of the Utility B's customers had interval meters 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 is randomly drawn from the population of customers that had electronic accounts and whose geographic area had smart meters in place as of Autumn 2011.

We followed the same steps at Utility B that we did at Utility A to assign customers randomly 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, $10, 20, $20, $30, $40 and $50 to all treatment group customers for completing the course. A $0 Amazon amount 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 Utility B experiment by sending out the solicitation e-mails with randomly assigned Amazon amounts, including a solicitation e-mail with no promise of payment. On October 26th 2011 another 4,500 emails were sent out to those who did not open the first e-mail. After a customer completed our on-line education program, the third party e-mailed the customer their Amazon Gift card and the customized electricity consumption tips. The third party worked with Utility B to provide us with anonymous customer-level electricity consumption data with an anonymous numerical identifier assigned to each customer in the intent-to-treat group and control group.

Table 1 gives the details of the experiment design for the Utility A and Utility B experiments. The breakdown for the intent-to-treat, treatment, and control groups reflects that fact that data errors after receiving the final data from Utility A and Utility B required deleting a number of customers from each of the three groups. Table 2 gives 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.

4. Valid Randomization and Potential Endogenous Selection

` This section analyzes pre-intervention data on monthly consumption from Utility A and monthly consumption from Utility B aimed at demonstrating: (1) our procedure for randomizing customers into the intent-to-treat (ITT) group and the control group is statistically valid and (2) that the pre-intervention distribution of consumption for customers in the ITT sample that took the treatment is no different from the pre-intervention distribution for those that did not take the treatment.

Our analysis relies on the two-sample Kolmogorov-Smirnov test of equality of two distributions. Specifically, let Q_{im}^{k} equal the average daily consumption of customer i of type k during month m, where k denotes one of four groups: ITT, control, treatment, and ITT-declined (the customer is in the ITT group but declined to take the treatment). We express all monthly consumption in terms of average daily consumption during that month to account for the fact that there are different numbers of days during different months of the year.

Suppose there are M months during the pre-intervention period, which ends during the month that first letter was send out in the case of Utility A and the month the first e-mail was sent out in the case of Utility B. Suppose there are N_k customers in group k. Define the empirical distribution of average daily consumption in month m for group k as:

$$F_m^k(t) = \frac{1}{N_k}\sum_{i=1}^{N_k} I(Q_{im}^k \leq \mathrm{t}),$$

where $I(X \leq t)$ is an indicator variable that takes on the value 1 if X is less than or equal to t and zero otherwise. Under the assumption that the Q_{im}^k, i=1,2,…,N_k are independent and identically distributed within month m for each group k with population distribution equal to $G_m^k(t)$, we can perform the hypothesis test:

$$H\colon\ G_m^k(t) = G_m^h(t) \text{ versus } K\colon\ G_m^k(t) \neq G_m^h(t),$$

using the two-sample Kolmogorov-Smirnov statistic

$$\mathrm{KS} = sup_{\ t} \,|\, F_m^k(t) - F_m^h(t)|.$$

Table 3A reports the KS statistic and the associated probability value (p-value) for month m for the test that the population distribution of average daily consumption for month m for the control group is equal to the population distribution of average daily consumption for month m for the ITT group during the pre-intervention period for Utility A. The p-value gives the probably of obtaining a draw from the null asymptotic distribution of the test statistic greater than the realized value of the KS statistic. The table also gives number of observations in both the ITT and control groups. For the months January to July of 2011, the probability value is never less than 0.05, indicating that a size $\alpha = 0.05$ test of the null hypothesis would not be rejected for any of these months during the pre-sample period.

Table 3B reports the KS statistic and the associated probability value (p-value) for month m for the test that the population distribution of average daily consumption for month m for the treatment group is equal to the population distribution of average daily consumption for month m for the subset of the ITT group that declined treatment for Utility A. The table also gives number of observations in both the treatment and ITT-but-declined-treatment groups. For the months of January to July of 2011, the probability value is never less than 0.05, indicating that the null hypothesis would not be rejected for any of these months during the pre-sample period.

These results provide no evidence against the null hypothesis that the average daily consumption distributions for each month of the pre-intervention period for the ITT sample and control sample are equal and no evidence against the null hypothesis that the average daily consumption distributions of the treatment and ITT-but-declined-treatment groups are equal during each of the month of the pre-intervention period. These results provide evidence consistent with the hypothesis that Utility A customers did not self-select into the treatment group based on their pre-invention consumption levels.

Table 4A repeats the analysis in Table 3A for Utility B for the months of May to September of 2011. Because of metering errors and other data recording problems throughout our sample period for Utility B, there were different numbers of customers in the control and ITT groups for each month. Because the data we obtained from Utility B was during its transition from monthly metering to interval metering for the customers in our sample, there were many measurement errors and data recording problems that were never resolved. These problems did not arise for Utility A, because we had access to billing quality data for the entire sample period.

Nevertheless, the results in Table 4A provide no evidence against the null hypothesis that the pre-intervention distributions of average daily consumption for the control group and the ITT group are equal for the months of May to September 2011.

Table 4B repeats the analysis in Table 3B for Utility B for the months of May to September 2011. For the reasons described above, there are different numbers of customers in the treatment group and the ITT-but-declined-treatment group each month. Different from the case of Utility A, there is substantial evidence against the null hypothesis of equality of the two distributions for the majority of months of the pre-intervention period. However, we are unable to determine if data errors is primary the reason for the p-values below 0.05 for a number of the months, or if the two monthly distributions are in fact different.

Taken as whole, the results of this section suggest that our randomization of customers into the ITT and control groups is statistically valid for both Utility A and Utility B. In addition, the pre-intervention distributions of average daily consumption for the treatment and ITT-but-declined-treatment groups were the same for all months during this time period for Utility A, and that the KS statistics provide evidence against this null hypothesis for Utility B, but it is unclear if this result is being driven by data issues or failure of null hypothesis to hold.

The next section summarizes the basic features of our educational program and the three key pieces of information that it conveys to customers that should cause them to become more efficient consumers of electricity.

5. Internet Educational Treatment Specifics

The basic goal of the Internet Education Course was to familiarize the individual with the three pieces of information described earlier: (1) the customer's typical monthly marginal price, (2) how the customer's bill was determined from its IBT, and (3) how the customer's monthly electricity bill changes in response to changes in how the customer uses its electricity-consuming appliances.

The survey was organized in three sections. Section 1 demonstrates how the customer's monthly bill is determined from the IBT and where the customer's monthly consumption is typically located on the schedule during the three months before each survey was administered. This section also shows how the customer's marginal price of electricity and monthly bill change depending on how much electricity is consumed in the month. Section 2 surveys the customer about the characteristics of its home and the appliances in it. Section 3 uses the answers provided in Section 2 to determine how changes in the utilization of these appliances would impact the customer's monthly electricity bill and provides information tailored the customer's appliance stock to assist them in becoming more sophisticated electricity consumers. Specifically, the likely monthly bill increase or decrease associated with changes in these customer's major electricity consuming actions given the customer's current marginal price are presented.

Differences in IBT Pricing Between the Two Utilities

Figure 2 displays the IBT for Utility A for the inland and coastal portion of its service area. This is the dominant rate structure for single family homeowners in its 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 Utility A is the length of each price step. Because of the more extreme temperatures in the inland region of Utility A's service territory, the length of each pricing step in the IBT is longer for the inland versus coastal region.

Customers in the intent-to-treat group that took our Internet course were presented with their IBT schedule and shown the locational of their typical month's usage in KWhs 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 customer'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. Utility A has five pricing tiers with marginal prices that differ by almost a factor of three from the lowest to highest-priced tier. As shown in Figure 2, the other retailer, Utility B, has only 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 customer's typical monthly marginal price yields the anticipated behavioral response described in Section 2.

Data

This section discusses the data the utilities have provided to us. For both utilities, our unit of analysis is a customer/month. For Utility A, we have billing cycle level-data that we converted to average daily electricity consumption data for each month of our sample starting in July 2010 and running through June 2012. For both utilities, we assumed that the treatment took place day the first letter was send for Utility A or the day the first e-mail was sent for utility B. For Utility A, we use data for 6 months before the treatment and 6 months after the treatment.

Although we had hourly billing cycle-level data available for Utility B, for comparability with the results for Utility A, we converted this data to average daily values for each month of our sample period, similar to how the data used for Utility A. Different from the Utility A setup, we use this average daily consumption monthly data for 5 months before and after the first e-mail was sent.

For both Utility A and Utility B, we also re-ran our analysis with the treatment dates for customers in the treatment group set equal to the actual date they took the treatment rather that the first day a letter was mailed for Utility A or the first day an e-mail was sent for Utility B and obtained very similar results to the ones reported below.

6. Econometric Modeling Framework and Empirical Results

This section presents our treatment effect and tier-specific treatment effects econometric modeling framework that we use to estimate the impact of our informational intervention on the customer's electricity consumption for each utility. We then present results of our model estimation for both Utility A and Utility B for the control and ITT (treatment plus ITT-but-declined-treatment) sample. We obtain very similar results to those reported below when we use the treatment plus the control sample and exclude the ITT-but-declined-treatment customers from the sample. However, we report treatment versus control and ITT-but-declined-treatment ordinary least squares results below so that they can be compared to the local average treatment effect (LATE) estimates that we present using the ITT indicator variable as instrument for the Treatment indicator variable. The LATE estimator can only be computed for the combined ITT and control sample.

Let Q_{im} equal the average daily electricity consumption in month m for customer i. This data is constructed from the customer-level billing cycle-level data by computing an average daily consumption for each billing cycle and then taking a weighted average of the average daily consumption of each billing cycle in month i, where the weights are the shares of the days of the 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 the next billing cycle, then the weights are

2/3 and 1/3. Let Treat(i) equal 1 if customer i is in the treatment group and 0 for all other customers.

Rather than attempt to model how a customer's consumption of electricity varies across months in the sample, we instead decided to estimate all of our treatment effects off of the cross-section of differences between average daily consumption after the intervention versus before the intervention. Define Q_i^{pre} as the mean average daily consumption for all months during the pre-intervention time period for customer i. Define Q_i^{post} as the mean average daily consumption for all months during the post-intervention time period for customer i. Define $Y_i = Q_i^{post} - Q_i^{pre}$, which is the difference between average daily consumption during the post-intervention period minus the average daily consumption during the pre-intervention period for customer i.

In terms of this notation our overall treatment effect model is:

$$Y_i = \alpha + \beta * Treat(i) + \varepsilon_i,$$

where β is the overall average treatment effect. Our tier-specific treatment effects model for tier j assumes:

$$Y_{ij} = \alpha_j + \beta_j * Treat(i) + \varepsilon_{ij},$$

where β_j is the treatment effect for customers typically on tier j. We estimate β_j by restricting our sample to customers whose typical pre-intervention consumption was on tier j The pre-intervention typical consumption price tier is computed for all customers in both the control and ITT samples, but only customers in the treatment group are told this information during our educational program. We estimate the same two models for Utility B. The only difference is that Utility B only has two pricing tiers, so we estimate two tier-specific treatment effects.

We also estimate these equations by instrumental variables using the instrument ITT_i, which equals 1 if customer i is in the ITT sample—it receives a letter asking it to take the treatment in the case of Utility A or an e-mail asking it to take the treatment in the case of Utility B. ITT_i equals zero if customer i is in the control group and therefore did not receive a letter in the case of Utility A or an e-mail in the case of Utility B. We estimate both the overall treatment effect equation and the tier-specific equations using ITT_i as an instrument for Treat(i). Using the full set of indicator variables for the Amazon gift card—6 indicator variables for Utility A and 7 indicator variables for Utility B—interacted with the value of ITT_i yields parameters estimates for the overall and tier-specific local average treatment effects that are very similar to the ones presented below for the single indicator variable ITT_i for both Utilities.

Because our treatment effects model is simply estimating the difference in means of $Y_{i,}$ the difference between the post-intervention versus pre-intervention average consumption, more informative graphical presentation of the results is possible. Figure 3 plots the histogram on Y_i for the treatment sample and the histogram of Y_i for the control and ITT-but-declined-treatment sample. The distribution of Y_i for the treatment sample is almost a uniformly negative shift across all percentiles of the distribution of Y_i for the control and ITT-but-declined-treatment sample. The regression result in Table 5-1 demonstrates that the average treatment effect associated with our educational program is precisely estimated to be -0.723 KWhs per day.

Figures 4-1 to 4.5 plot the histograms on Y_i for the treatment sample and the histogram of Y_i for the control and ITT-but-declined-treatment sample for each of the five pricing tiers. Consistent the logic of Section 2, for the first pricing tier, distribution of Y_i, pre- versus post-intervention daily-average consumption difference, is a slight positive shift relative to the distribution of Y_i for the control and ITT-but-declined-treatment sample. Table 5-1 confirms that the tier-specific treatment effect of our educational program for the first tier is precisely estimated to be 0.136 KWhs per day. For the remaining 4 tiers, the treatment distribution of Y_i is an increasingly negative shift relative to the distribution of Y_i for the control and ITT-but-declined-treatment sample. Table 5-1 shows that these tiers specific treatment effects are all precisely estimated to be negative and range from -0.461 KWhs per day for Tier 3 to -1.201 KWhs per day for Tier 5.

Table 5-2 reports the local average treatment effect estimate and tier-specific local average treatment effect estimates using the indicator variable ITT_i as an instrument for Treat(i). The instrumental variable estimates are significantly larger in absolute value that the corresponding estimates reported in Table 5-2. It is important to bear in mind that the sample the overall and tier-specific local average treatment effect can be written as:

$$LATE = [E(Y_i \mid ITT_i=1) – (E(Y_i \mid ITT_i=0)]/E(Treat(i)=1 \mid ITT_i = 1),$$

for the sample analogues to these population conditional expectations. This expression points to two possible explanations for the significantly larger in absolute value estimate of the local average treatment effects in Table 5-2 versus Table 5-1. First, although the difference between the mean of Y_i for the ITT sample versus the control sample is negative and roughly the same order of magnitude as the difference between the mean of Y_i for the treatment sample versus the control plus ITT-but-declined-treatment sample, from Table 2 $E(Treat(i)=1 \mid ITT_i = 1) = 0.12$ for the entire sample, so that this difference is divided by 0.12 to produce the LATE. Second, the fact that a customer received our letter asking them to take our education program may have caused them to reduce their consumption of electricity, because the letter (reproduced in Appendix A) emphasizes that the educational program will help the customer reduce its electricity consumption. This difference in parameter estimates emphasizes the well-known result that the instrumental variables estimate and ordinary least squares estimates of a slope coefficient rarely are consistent for the same population magnitude.[4]

Figure 5 plots the density of Y_i for the treatment group and the control plus ITT-but-declined-treatment samples for Utility B. Again, the treatment density appears to be a negative shift of the control plus ITT-but-declined-treatment density. The coefficient estimate in Table 6-1 confirms that the treatment effect of our educational program for Utility B is -0.328 KWhs per day, although this point estimate is not precisely estimated. Figures 6-1 and 6- 2 plot the tier-specific density comparisons for Utility B. Consistent with the logic in Section 2, the Tier 1 treatment density for Y_i appears to be a positive shift of the control plus ITT-but-declined-treatment density and the Tier 2 treatment density for Y_i is a larger negative shift. The parameter estimates in Table 6-1 find a precisely estimated Tier 1 treatment effect of our educational program of 0.670 KWhs per day and a more precisely estimated Tier 2 treatment effect of -1.922 KWhs per day.

Similar to the case of Utility A, the local average treatment effects shown in Table 6-2 are larger in absolute value than the corresponding coefficient estimates reported in Table 6-1. However, the LATE coefficient estimates in Table 6-2 are not estimated with sufficient precision to draw any firm conclusions about their magnitude.

Although the coefficients for Utility B are not as precisely estimated as those for Utility A, the signs are consistent with the view that our educational program provides useful marginal price information that allows the customer to become a more sophisticated consumer. Although in the aggregate, customers reduced their electricity consumption in response to this marginal price information, our results suggest that customers on the lowest marginal price tier responded to this information by increasing their consumption. As discussed in Section 2, if customers are

[4] Reiss and Wolak (2007) provide detailed discussion of this point.

using rules of thumb to determine their monthly electricity consumption based on an average price computed from their total monthly bill and total electricity consumed, providing marginal price information is likely to have this response.

7. Conclusion

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

Our experiment demonstrated that providing information to customer about the IBT they face and where they are on that schedule can help electric utilities reduce residential electricity consumption and reduce greenhouse gas emissions. The average daily consumption of customers for both utilities during our sample periods for both utilities is approximately 25 KWh. Our overall treatment effect of -0.724 KWh per day for Utility A is approximately 3 percent of average daily consumption, whereas the overall treatment effect for Utility B is -0.328 KWh day which is approximately 1.5 percent of average daily consumption.

Our findings emphasize that the timely provision of actionable information to final electricity consumers is crucial 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 customer-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 tangible 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 customers 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. Customers with interval meters that are also provided with information on the hourly retail price 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.

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Table 1: Experiment Design for Utility A and Utility B

Experimental Design Utility A	
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 of Analysis	2/1/2011 to 1/31/2012 (monthly data)

Experimental Design Utility B	
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 of Analysis	5/1/2011 to 2/29/2012 (monthly data)

Table 2: Treatment Response Rates for Utility A and B

Utility A Gift Card Amounts and Response Rates				
Amazon Amount ($)	**Number Offered**	**Cards Sent**	**Sent/Offered %**	**Standard Error %**
10	700	34	4.90%	0.82%
20	3437	283	8.20%	0.47%
25	3161	291	9.20%	0.51%
30	3053	298	9.70%	0.54%
35	2949	299	10.10%	0.55%
50	200	22	11.00%	2.21%
Overall	13500	1227	9.10%	0.25%

Utility B Gift Card Amounts and Response Rates				
Amazon Amount ($)	**Number Offered**	**Cards Sent**	**Sent/Offered %**	**Standard Error %**
0	1800	108	6.00%	0.56%
10	1500	181	12.10%	0.84%
20	1100	142	12.90%	1.01%
30	900	150	16.70%	1.24%
40	700	121	17.30%	1.43%
50	500	83	16.60%	1.66%
Overall	6500	785	12.10%	0.40%

Table 3: Kolomogorov-Smirnov Test of Equality of Pre-Invention Distributions of Average Daily Consumption by Month for Utility A

Table 3A: Test of Equality of Monthly ITT and Control Distributions During Pre-Invention Period for Utility A Number in Control Group = 11,500 Number in ITT Group = 13,500		
Month of 2011	**KS Statistic**	**P-Value**
January	0.0137	0.193
February	0.0172	0.051
March	0.0131	0.236
April	0.0170	0.052
May	0.0152	0.115
June	0.0149	0.126
July	0.0167	0.061

Table 3B: Test of Equality of Monthly Treatment and ITT-But-Declined Treatment Distributions During Pre-Intervention Period for Utility A Number in Treatment Group = 1,227 Number in ITT-But-Declined Treatment Group = 12,273		
Month of 2011	**KS Statistic**	**P-Value**
January	0.0238	0.551
February	0.0303	0.256
March	0.0296	0.283
April	0.0265	0.415
May	0.0318	0.208
June	0.0195	0.789
July	0.0317	0.211

Table 4: Kolomogorov-Smirnov Test of Equality of Pre-Invention Distributions of Average Daily Consumption by Month for Utility B

Table 4A: Test of Equality of Monthly ITT and Control Distributions During Pre-Invention Period for Utility B				
Month of 2011	**KS Statistic**	**P-Value**	**Number in Control**	**Number in ITT**
May	0.0232	0.742	993	6,461
June	0.0234	0.732	996	6,474
July	0.0175	0.968	914	5,986
August	0.0223	0.823	916	5,997
September	0.0284	0.542	917	5,992
Table 4B: Test of Equality of Monthly Treatment and ITT-But-Declined Treatment Distributions During Pre-Intervention Period for Utility B				
Month of 2011	**KS Statistic**	**P-Value**	**Number in Treatment**	**Number in ITT-But-Declined**
May	0.0531	0.038	783	5,678
June	0.0455	0.110	782	5,692
July	0.0551	0.033	747	5,239
August	0.0581	0.005	747	5,250
September	0.0541	0.042	747	5,245

Table 5-1: Overall and Tier-Specific Treatment Effects Estimates for Utility A

Overall Treatment Effect		
Variable	Estimate	Standard Error
Treat	-0.723	0.082
Constant	-0.668	0.019
Tier 1 Treatment Effect		
Treat	0.136	0.060
Constant	-0.184	0.040
Tier 2 Treatment Effect		
Treat	-0.483	0.175
Constant	-0.291	0.046
Tier 3 Treatment Effect		
Treat	-0.461	0.134
Constant	-0.528	0.032
Tier 4 Treatment Effect		
Treat	-0.912	0.155
Constant	-0.786	0.378
Tier 5 Treatment Effect		
Treat	-1.201	0.220
Constant	-1.200	0.052

Table 5-2: Overall and Tier-Specific Local Average Treatment Effects Estimates for Utility A Using ITT Indicator as Instrument

Overall Treatment Effect		
Variable	Estimate	Standard Error
Treat	-12.77	0.516
Constant	-0.621	0.025
Tier 1 Treatment Effect		
Treat	1.136	0.051
Constant	-0.184	0.056
Tier 2 Treatment Effect		
Treat	-5.32	0.974
Constant	-0.043	0.060
Tier 3 Treatment Effect		
Treat	-9.84	0.842
Constant	-0.072	0.042
Tier 4 Treatment Effect		
Treat	-14.39	1.024
Constant	-0.070	0.051
Tier 5 Treatment Effect		
Treat	-22.31	1.635
Constant	-0.080	0.071

Table 6-1: Overall and Tier-Specific Average Treatment Effects Estimates for Utility B

Overall Treatment Effect		
Variable	Estimate	Standard Error
Treat	-0.328	0.282
Constant	-4.830	0.084
Tier 1 Treatment Effect		
Treat	0.670	0.271
Constant	-3.077	0.086
Tier 2 Treatment Effect		
Treat	-1.922	0.419
Constant	-6.276	0.128

Table 6-2: Overall and Tier-Specific Local Average Treatment Effects Estimates for Utility B Using ITT Indicator as Instrument

Overall Treatment Effect		
Variable	Estimate	Standard Error
Treat	-1.712	1.834
Constant	-4.676	0.218
Tier 1 Treatment Effect		
Treat	1.509	1.710
Constant	-3.183	0.234
Tier 2 Treatment Effect		
Treat	-5.122	3.200
Constant	-5.963	0.336

Figure 1: IBT for Utility A Inland Customers

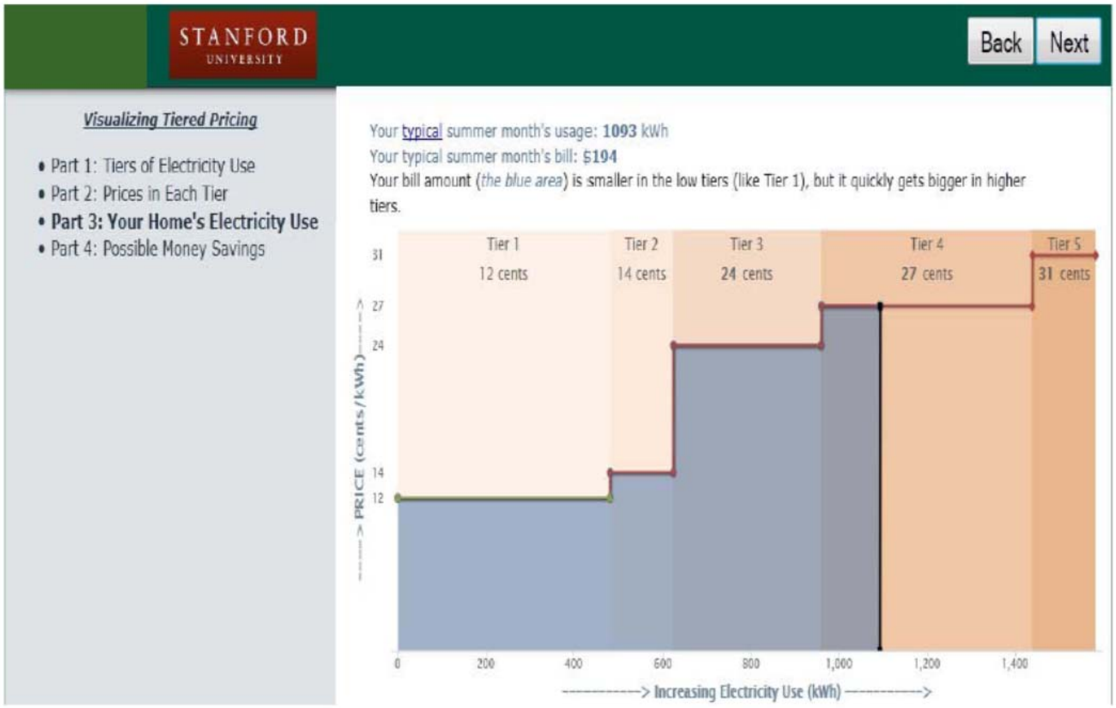


Figure 2: IBTs for Utility A and Utility B

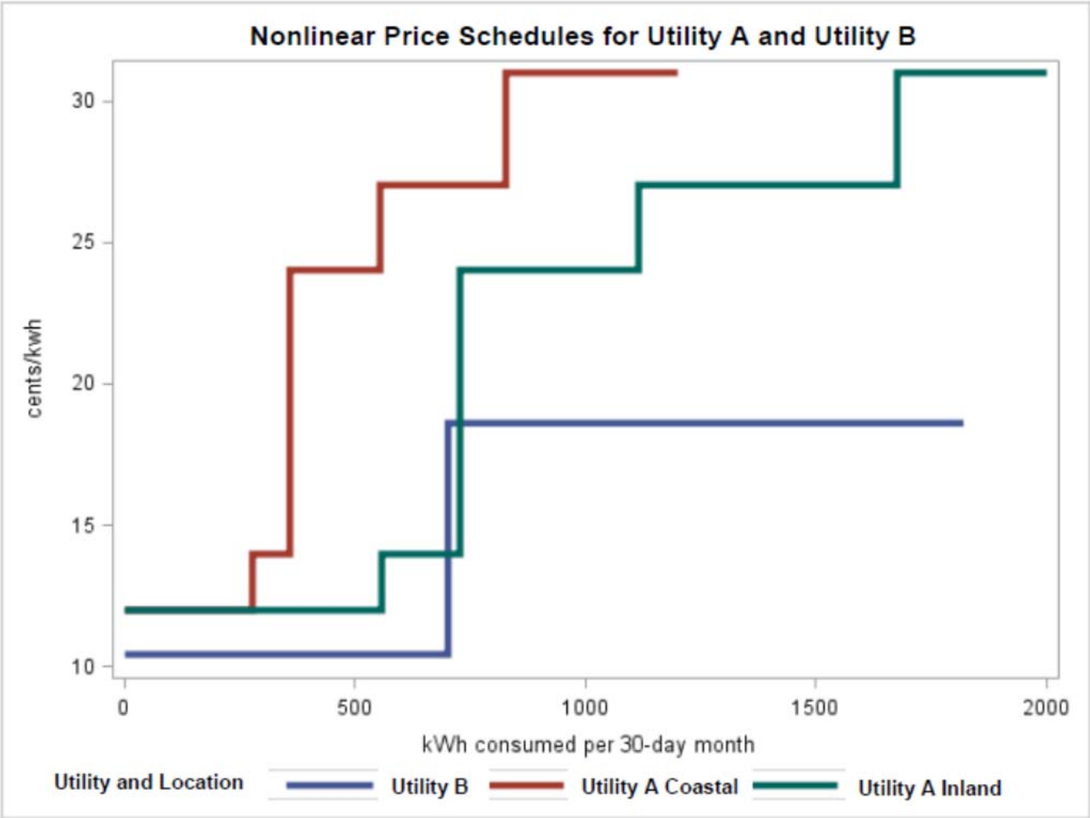


Figure 3: Densities of Post- Minus Pre-Intervention Average Consumption for Treatment and Control plus ITT-But-Declined Treatment Samples for Utility A

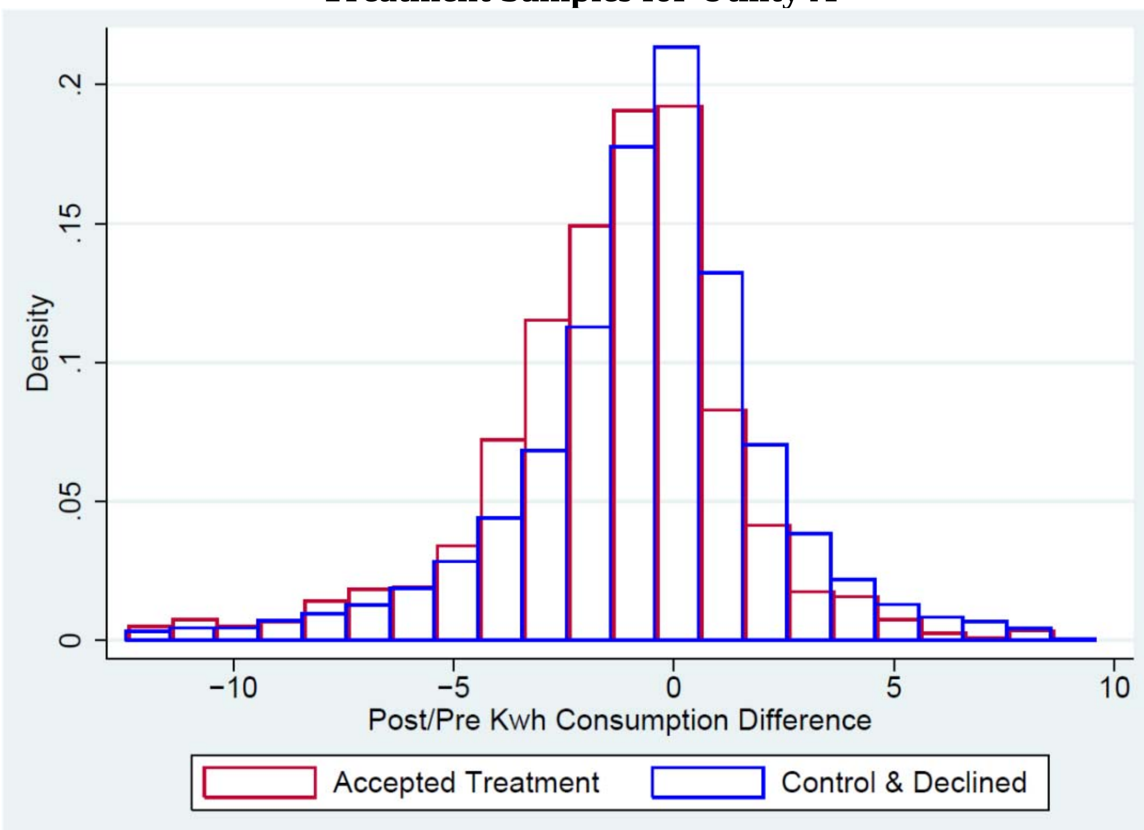


Figure 4-1: Densities of Post- Minus Pre-Intervention Average Consumption for Tier 1 Treatment and Control plus ITT-But-Declined Treatment Samples for Utility A

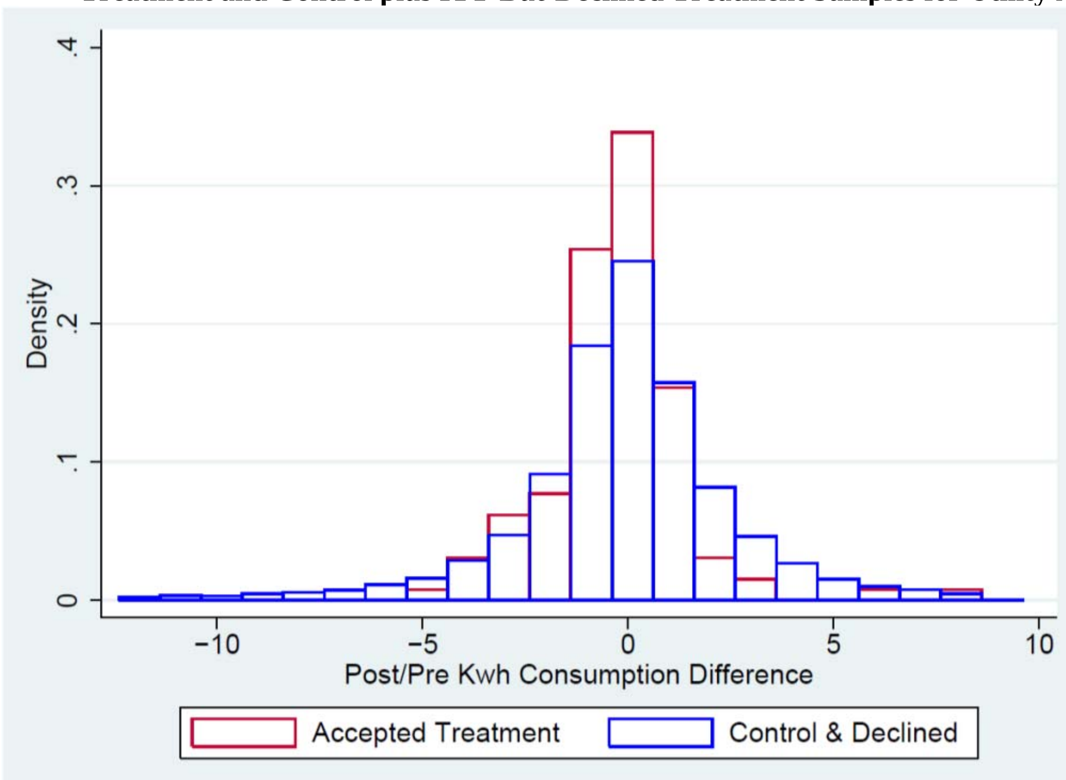


Figure 4-2: Densities of Post- Minus Pre-Intervention Average Consumption for Tier 2 Treatment and Control plus ITT-But-Declined Treatment Samples for Utility A

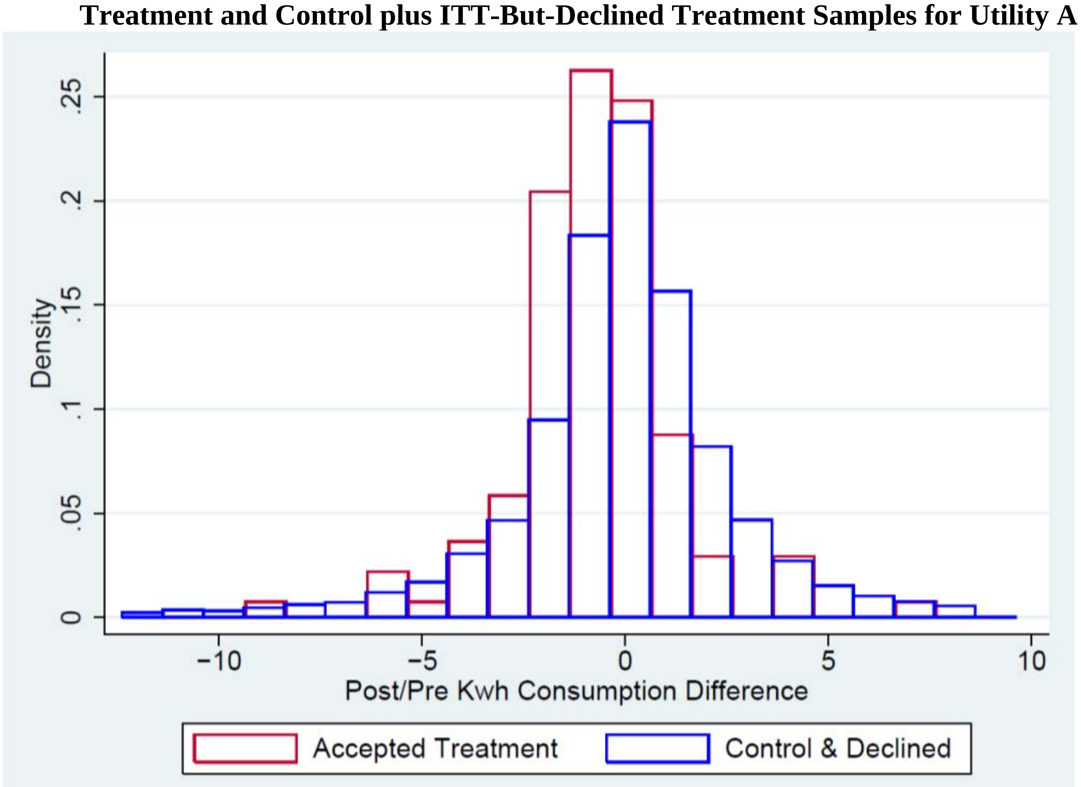


Figure 4-3: Densities of Post- Minus Pre-Intervention Average Consumption for Tier 3 Treatment and Control plus ITT-But-Declined Treatment Samples for Utility A

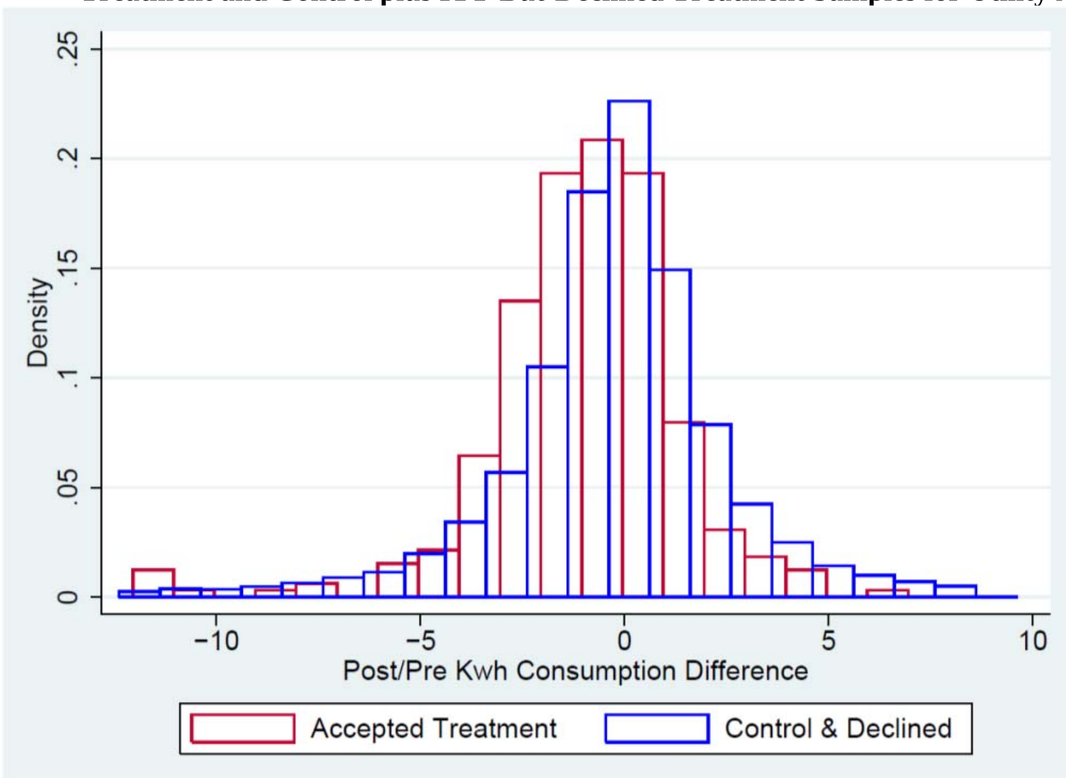


Figure 4-4: Densities of Post- Minus Pre-Intervention Average Consumption for Tier 4 Treatment and Control plus ITT-But-Declined Treatment Samples for Utility A

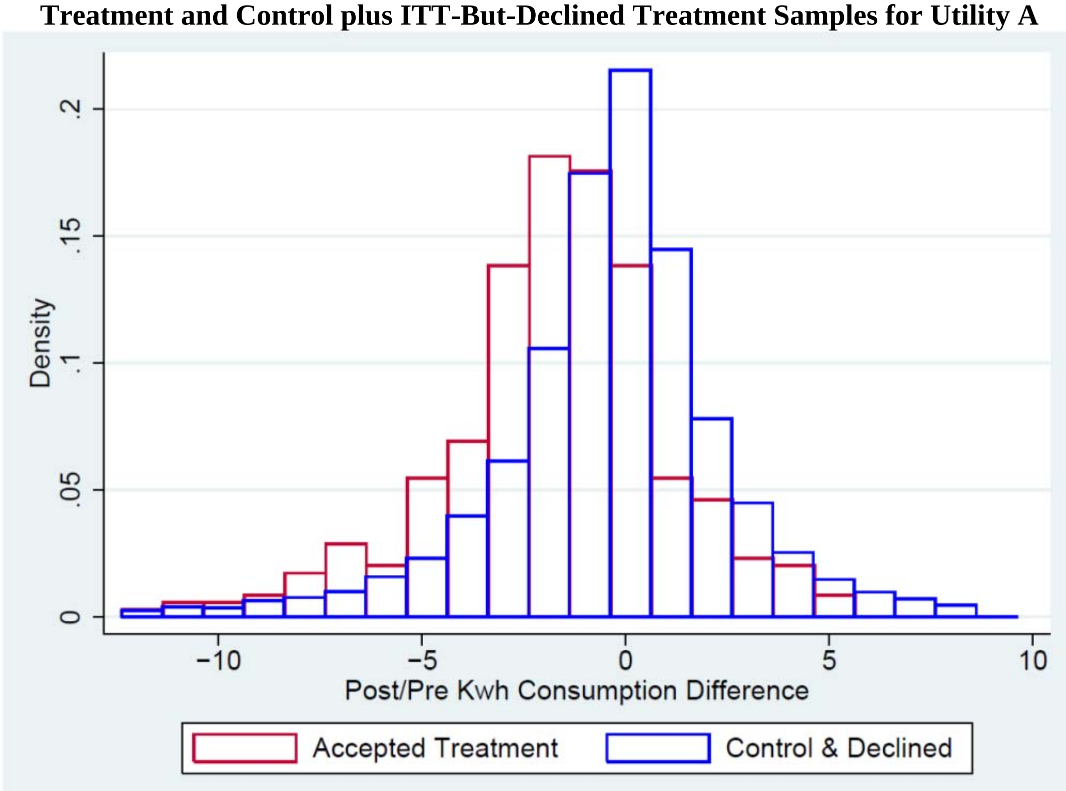


Figure 4-5: Densities of Post- Minus Pre-Intervention Average Consumption for Tier 5 Treatment and Control plus ITT-But-Declined Treatment Samples for Utility A

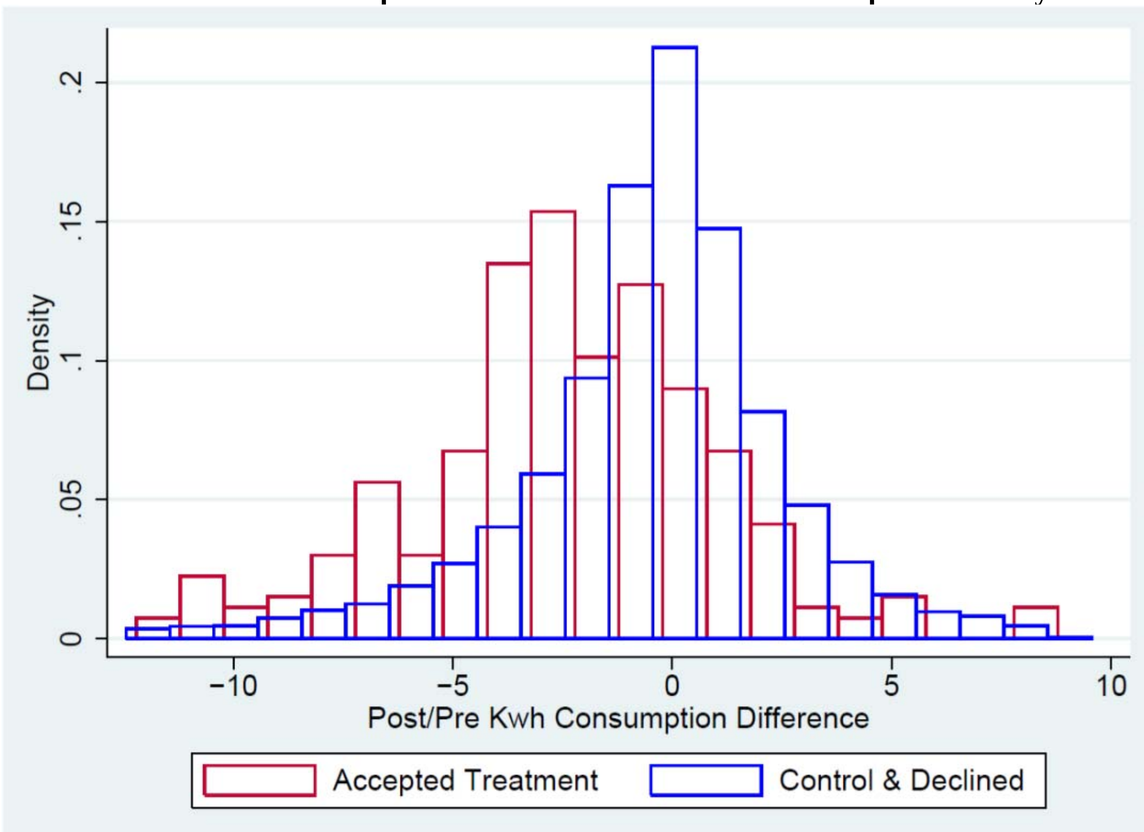


Figure 5: Densities of Post- Minus Pre-Intervention Average Consumption for Treatment and Control plus ITT-But-Declined Treatment Samples for Utility B

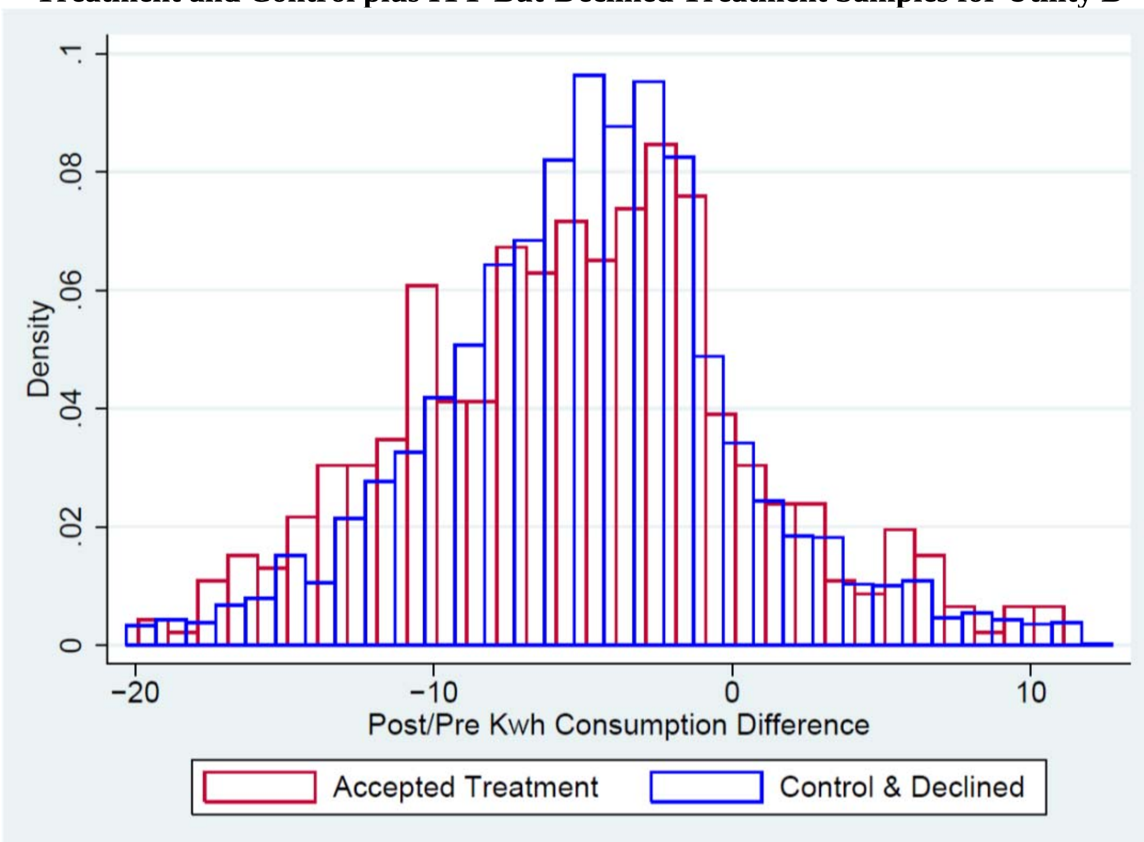


Figure 6-1: Densities of Post- Minus Pre-Intervention Average Consumption for Tier 1 Treatment and Control plus ITT-But-Declined Treatment Samples for Utility B

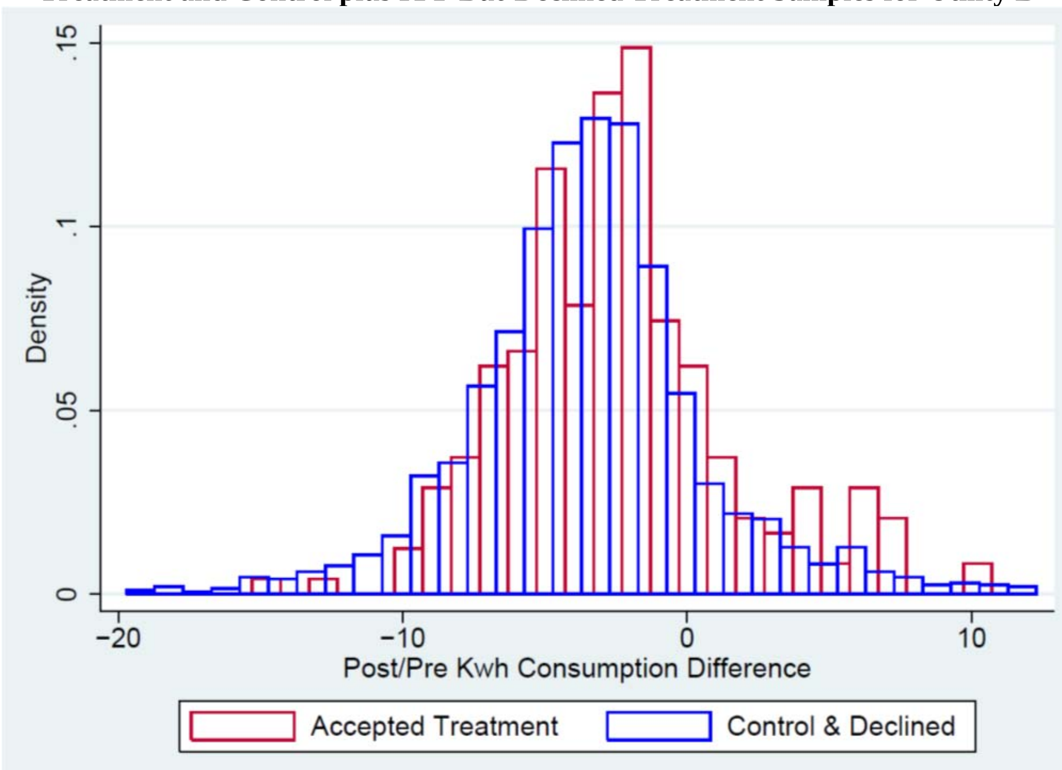
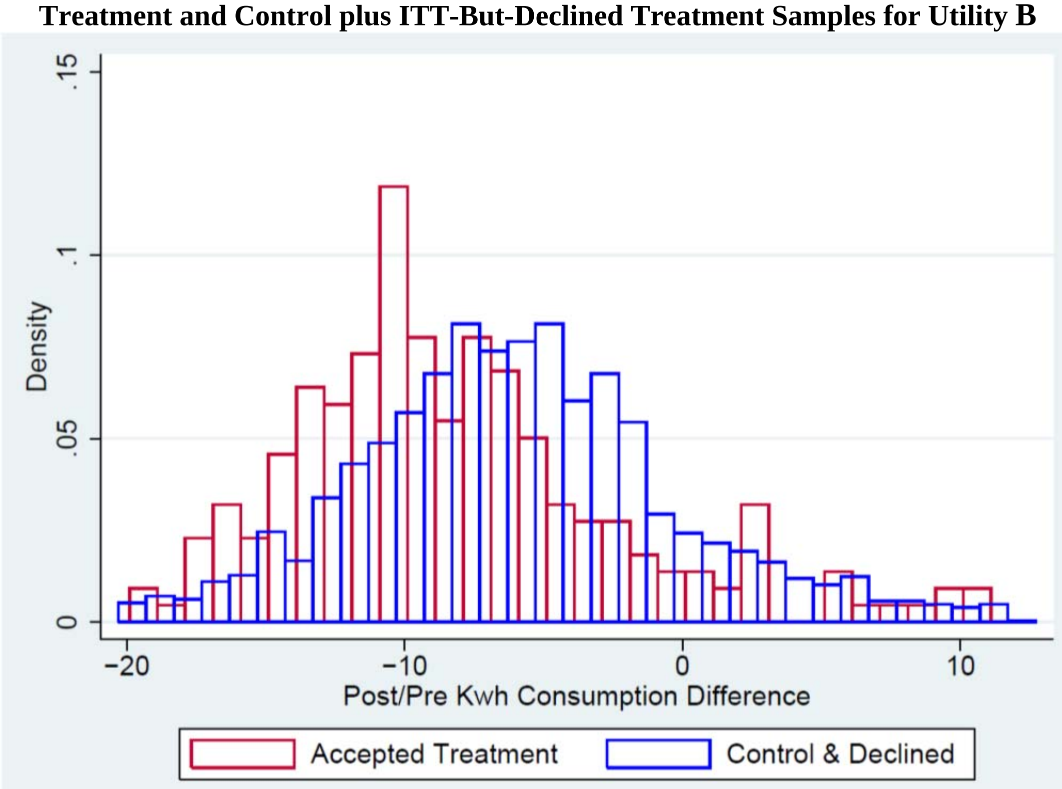


Figure 6-2: Densities of Post- Minus Pre-Intervention Average Consumption for Tier 2 Treatment and Control plus ITT-But-Declined Treatment Samples for Utility B



Appendix A

Dear [insert name],

Utility A is partnering with researchers from Stanford University and UCLA to develop a home energy savings workshop. Your valuable input will help Utility A 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 customer's characteristics, the workshop generates the customized suggestions you can use to reduce your customer'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. Smith
Utility A

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.