Contents

List of Tables

List of Figures

1 Introduction

Increasing-Block Pricing (IBP) is one of the most common electricity rate plans.[1] Under the pricing scheme, the marginal price increases, in a nonlinear way, with the customer's usage. Specifically, the price consumers pay for their marginal electricity consumption is a step function of their aggregate consumption in a billing cycle.

Economists have studied how residential consumers respond to nonlinear electricity pricing. Ito (2014) demonstrates that when faced with IBP, households respond to average prices rather than marginal prices. More recently, Shaffer (2020) shows that not all households uniformly respond to average prices. To be specific, this paper exhibits that most residential consumers respond to average prices, but their response can be veiled by the response of a small number of households mistakenly applying the marginal price to all inframarginal units of consumption, not the last unit. And in both papers, it is stressed that households' misunderstanding of nonlinear electricity pricing leads to their inefficient electricity consumption, such as over- or under-consumption.

Electricity bills, usually issued every month, have been a primary, perhaps for some households the only, source of information about their electricity consumption (e.g., the total charges, the amount of consumption, and the marginal price). Inherently, the consumption-relevant information on a monthly electricity statement is not up to date—a statement principally includes information about the previous billing cycle. Household electricity consumption, however, is affected, at least partly, by the intermittent bills. As illustrated in Gilbert and Graff Zivin (2014), households change their consumption behavior after receiving a monthly bill. And in addition to the key finding discussed above, Ito (2014) presents convincing evidence that households respond more to lagged average prices, which are available in monthly electricity statements, than contemporaneous ones.

There are two issues when residential consumers change their electricity consumption according to price signals delivered through monthly electricity bills. The first issue is that they respond to the incorrect prices. Whatever households' perceived price of nonlinear price schedules is, the price signals are false because these signals reflect not their contemporaneous consumption level but their past one. And households' exaggerated responses to the price signals are the second issue. Suppose that residential consumers adjust their electricity consumption according to the lagged prices. In that case, the behavioral change implies that all consumption in a billing cycle is subject to the previous billing cycle's prices. Importantly, such an implication is analogous with households' over-responses to the (current) marginal price discussed in Shaffer (2020).

On both those fronts, this paper examines households' responses to the marginal price again. For residential consumers under IBP, I measure how much electricity consumption they reduced in a billing month in response to the discontinuous increase in the marginal price at the lower base usage quantity in the immediately preceding billing month, which was not accompanied by any discontinuous change in average prices. In other words, focusing on two consecutive billing cycles, I investigate how households responded to the sharp increase in the *lagged* marginal price signaled through their monthly electricity bills.

[1] As of the end of December 2022, about 40% of the residential consumers of Pacific Gas and Electric Company (PG&E), which is one of the largest utilities in California, were on the IBP.

To estimate the impact of the change in the marginal price due to surpassing a base usage quantity in a billing cycle on household electricity consumption in the following billing cycle, I adopt a Regression Discontinuity (RD) approach that exploits the sharp discontinuity in the marginal price at the threshold. Under IBP, a household's (within-billing-cycle) aggregate electricity consumption at some point completely determines the price the household pays for the marginal unit of consumption at that point. Under the known-to-consumer price determination mechanism, my identification relies on the assumption that households cannot manipulate whether they fall on one side of the cutoff or the other conditional on their monthly consumption being close to the cutoff point. In my empirical setting, the assumption is convincing for two reasons. First of all, the households in my sample had no practical way to know how much electricity they had consumed from the first day of a billing cycle to the point of marginal electricity consumption, especially before installing smart meters. They were able to find out whether their total consumption in a billing cycle surpassed the threshold only after receiving their monthly bills at the beginning of the subsequent billing cycle. On top of that, it is not feasible for them to adjust their electricity consumption precisely to avoid crossing the cutoff point due to their indispensable consumption (e.g., consumption for refrigerators and lighting) and too high information cost imposed when micromanaging electricity demand according to the change of outdoor conditions. Thus, the two points demonstrate that my RD design clearly satisfies the fundamental assumption required for identification: around the threshold, the treatment assignment is random.

Implementing the RD design to monthly billing records from hundreds of thousands of residential consumers in Sacramento, CA, I find households' interesting behavioral change with respect to electricity consumption: around the lower base usage quantity, the households that were subject to a higher marginal price because their aggregate electricity consumption in a billing month exceeded the cutoff point reduced their average daily electricity consumption by about 0.16% in the following billing month, compared to the households experiencing no change in the marginal price. Because only the marginal price discontinuously increased, not the average price, at the threshold, this result is convincing evidence that households, conservatively at least some of them, respond to marginal prices. In line with Shaffer (2020), if the identified reduction in household electricity consumption is entirely attributable to behavioral changes of a subset of residential consumers, my estimates imply that approximately 11% of households in my sample reacted to the discontinuous jump in the marginal price. More importantly, the result suggests other inefficiencies stemming from households' responses to nonlinear electricity pricing: 1) households also respond to the lagged marginal price, which is irrelevant to their present consumption level; and 2) the lagged marginal price is applied to all units of electricity consumption, not the last unit, during a billing cycle.

I also examine the heterogeneity in household responsiveness to the lagged marginal price across rate codes and seasons. In addition, my investigation of the multi-period impact of the discontinuous increase in the lagged marginal price on household electricity consumption shows whether households' use of electric heating drove the impact.

The rest of this paper proceeds as follows. In Section 2, I discuss my empirical approach and data. Section 3 presents the results from my empirical analysis. Section 4 describes the policy implications of my key findings, and Section 5 concludes.

2 Data and Research Design

This section provides a detailed description of the data utilized for my empirical analysis. Furthermore, this section demonstrates a key feature of my research design.

2.1 Background of Residential Rates of Sacramento Municipal Utility District

Sacramento Municipal Utility District (SMUD), which is the nation's sixth-largest community-owned electric utility, provides electricity to most of Sacramento County and small portions of adjoining Placer and Yolo Counties.[2] As of December 31, 2020, the total number of accounts served by SMUD is 644,723.

Before the default residential rate switched to the Time-Of-Day (TOD) rate, most SMUD residential customers chose residential rates having an increasing nonlinear block-tier structure.[3] The three most popular rates for SMUD residential customers were Standard General Service (RSGH), Standard Closed Electric-Heated Service (RSCH), and Standard Open Electric-Heated Service (RSEH).[4] For those residential rates, the marginal price of the energy charge was a step function of monthly consumption relative to a base usage quantity per month, which varies seasonally. Figure 1 illustrates variations in price and base usage quantity over time. Two points are noteworthy from this figure: first, both tier rates and base usage quantities of the energy charges showed substantial seasonality; second, the structure of the residential rates changed from three-tier to two-tier since September 2009.

In addition to the variable charge (i.e., the energy charge), households choosing one of the three rates should pay a per-month fixed charge, called the System Infrastructure Fixed Charge. As shown in Figure 7, the unit price of the fixed charge significantly increased between 2009 and 2014.

2.2 Data and Summary Statistics

From SMUD, I obtain household-level monthly billing history of residential consumers in the Sacramento area from 2004 to 2013. For each monthly record, account ID, premise ID, rate code, billing start and end dates, monthly consumption with its breakdown into each tier, monthly fixed charge, monthly variable charge only for kWh usage, total monthly bill, and an indicator related to solar adoption are included in the data. Of note, in

[2] According to the company information presented on SMUD's website, the size of this utility's service area is about 900 square miles.

[3] In my sample, only 5% of residential customers adopted the TOD rate, although SMUD already offered it.

[4] Specifically, more than 75% of SMUD residential customers in my dataset chose the RSGH rate, whereas 2% and 20% of households in my dataset adopted the RSCH and RSEH rate, respectively.

my empirical analysis, I assume that a pair of account and premise IDs corresponds to an individual household. And because the monthly billing data contain no price and base usage quantity information, I append historical price schedules and base usage quantities presented by SMUD. Unfortunately, my monthly billing data also lack any socioeconomic and demographic information.

For my empirical analysis throughout this paper, I construct a sample from the monthly billing data for SMUD residential customers. My sample satisfies the following criteria. First, I focus on households that consistently used one of the three major residential rates (i.e., RSGH, RSCH, and RSEH) in their billing history. Second, I only utilize pre-2010 billing records to rule out the potential undermining of the validity of my identification assumption, which will be discussed in a later section. Third, I focus on households whose number of billing periods is greater than or equal to 24. Fourth, I focus on SMUD residential customers with reliable billing records only.[5] Fifth, my sample only includes households that crossed the lower threshold at least once in their billing history.[6] The procedure results in 16,322,353 billing records for 365,975 households. Table 1 provides summary statistics for my sample. Furthermore, Figure 8 shows, for each rate code, households' average daily electricity consumption by month of the year.

To take account of the impact of weather conditions, especially outdoor temperatures, on household electricity consumption, I utilize the Local Climatological Data (LCD) for the Sacramento International Airport, published by the National Oceanic and Atmospheric Administration (NOAA). Using daily heating degree days (HDDs) and daily cooling degree days (CDDs) in the LCD between 2004 and 2009, I calculate each monthly billing period's accumulated HDDs and CDDs, which are used to compute the average daily HDDs and CDDs.

2.3 Research Design

2.3.1 Monthly Bill as the Only Source of Electric Usage Information for Households

Before 2009, there was no feasible way for SMUD residential customers to access real-time information related to their electricity use. SMUD initiated installations of smart meters, allowing its residential and business customers to view their electricity usage online when they want, in late 2009. The electric service completed it in the first quarter of 2012. Also, the three types of bill alert SMUD are offering were introduced in 2017.[7] Therefore, for households using SMUD-delivering electricity, the only practical source of information about their electricity consumption had been their monthly bill statements, which send out (either e-mail or U.S. mail) after

[5] To be specific, I exclude, from the sample used for my empirical analysis, households that have billing records being applied to any of the following conditions: 1) observations whose length of the billing period is either less than 27 or greater than 34; 2) observations with negative values for either quantities or charges; 3) observations having overlapping billing periods within a pair of account and premise IDs; and 4) the length of the period between two consecutive billing months was greater than 14 at least once.

[6] In other words, I drop always-light- and always-heavy-users from my sample.

[7] SMUD provides its customers with three types of bill alerts, via text or e-mail, as a billing service: 1) Mid-Bill Alerts send an alert on the 16th day of a customer's billing period and advise what his usage has been and what the cost is as of that day, 2) High Bill Alters compare a customer's current billing cycle to the same billing cycle in the previous year and alerts the customer if their current usage is running higher than before, and 3) Bill Threshold allows a customer to know when his bill has reached a certain amount set in advance by himself.

3 or 4 business days from the last day of each billing cycle.

The issue of households' welfare losses due to their response to discontinuous changes in the lagged marginal price suggests the importance of providing seemly price information in an appropriate manner. Many studies about various time-varying electricity pricing show that households changed their consumption behavior in response to the information about consumption and prices (Faruqui and Sergici, 2011; Jessoe and Rapson, 2014; Pon, 2017; Bollinger and Hartmann, 2020). My empirical finding demonstrates that even under IBP, such information, though lagged, still plays a role in household electricity consumption. In this respect, providing household-specific as well as current price information for residential consumers, via text messages or app notifications regularly, could encourage them to respond to *true* price signals rather than lagged ones, which in turn avoid the negative impact on household welfare. Based on the dissipating effect of intermittently salient information discussed in Gilbert and Graff Zivin (2014), a high frequency of informing the latest tailored price information might maximize households' behavior change in electricity consumption. In addition, because sending such information-bearing notifications is available at a very low cost these days, this type of information provision would be a practical policy instrument for utilities, especially in developing countries where the transition toward dynamic electricity pricing is difficult due to substantial investments in installing smart metering systems.

2.3.2 Regression Discontinuity Design

In this paper, I employ a Regression Discontinuity (RD) design to examine how households' electricity consumption responds to the marginal price informed via monthly energy statements under Increasing-Block Pricing (IBP). In previous studies, a common challenge in measuring consumption responses to price changes has been discussed repeatedly: constructing a well-defined control group is difficult due to that consumers typically experience the same price variation. However, the setting I exploit in this paper enables me to address the identification challenge.

The RD design I implement in this paper relies on three points. First, the marginal price is a step function of consumption level in the increasing block-tier rate plans chosen by SMUD residential customers. That is, under IBP, the price a household pays for the marginal electricity consumption increases discontinuously at some pre-determined aggregate consumption in a billing cycle. Second, as discussed in Section 2.3.1, before 2009, SMUD residential customers had practically no way to know the marginal price in a billing cycle within the very cycle. They were informed of the price they paid for the marginal electricity consumption in a billing cycle only through their electricity bills delivered in the following cycle. Third, it is not generally feasible for households to consume only a pre-targeted amount of electricity within a billing cycle. In general, households have limited capability to control their electricity consumption due to the minimal essential demand (e.g., usage for refrigerators and lighting). In addition, because household electricity consumption heavily depends on outdoor temperature variation, managing one's own electricity usage not to exceed the target amount of electricity consumption could incur too high information cost, which might result in rational inattention (Sallee, 2014), even if households are available to adjust their consumption behavior with complete flexibility.

Regarding the first point, the discontinuities under the nonlinear electricity schedules allow utilizing a RD design. In my RD design, the running variable is the level of electricity consumption in a household during a billing period (denoted as Period 0), whereas the outcome variable corresponds to the household's average daily electricity consumption during the subsequent billing period (denoted as Period 1). So, in this quasi-experimental setting, I compare SMUD residential customers just above and below the thresholds of the tier rates, called base usage quantities. Under IBP, surpassing a threshold leads to an increase in the marginal price households pay for electricity consumption mechanically. Here, the discontinuous increase in the marginal price, which accompanies *no discontinuous change in the average price*, applies only to Period 0, not to Period 1.[8] Moreover, information about whether households were subject to a higher marginal price in a billing period is delivered early in the subsequent billing period through their monthly electricity bills. Therefore, any changes with respect to the electricity consumption of households just above the threshold (i.e., households in the treatment group) in Period 1, compared to households just below the threshold (i.e., households in the control group), can be understood as their short-term behavioral responses stemming from the sharp jump in the marginal price in Period 0. Figure 3, showing how the mean of households' average daily electricity consumption in Period 1 evolves around the lower base usage quantity, seems to indicate the existence of such behavioral responses.

The last two points demonstrate that the fundamental identifying assumption of the RD design is reasonable. The fundamental identifying assumption is that SMUD residential customers just below a base usage quantity are expected to be very similar to those just above it, along with observed and unobserved characteristics. In other words, a group of households in the small neighborhood of the threshold is not different from one obtained from a randomized experiment. In my setting for empirical analysis, SMUD residential customers were unable to be aware of how far away they were from a given cutoff point in real time. Furthermore, as discussed above, it is not convincing that they can perfectly control their electricity consumption during a billing cycle to use exactly a target amount of electricity by the end of the last day of the billing cycle. Hence, it is highly unlikely that the customers precisely adjusted their consumption behavior so as to avoid surpassing the cutoff point, which in turn prevented them from leading to a higher marginal price. That is, it seems plausible that households were not able to sort themselves around the threshold strategically. Therefore, any discontinuity gap in the outcome variable can be attributed to the discontinuous increase in the marginal price at the threshold in Period 0.

2.3.3 The Validity of the Regression Discontinuity Design

Two pieces of evidence support the assumption that base usage quantities do not correspond to jumps in household characteristics. First, as illustrated in Figure 2, each density plot of the running variable is very smooth, without any bump (i.e., excess mass), around base usage quantities at which marginal prices jump. The

[8] The average price smoothly grows around the cutoff point.

set of density plots that show apparent continuity at the thresholds suggests households' inability to precisely adjust their electricity consumption in order not to be subject to a higher marginal price.

Second, Figure 4 demonstrates that households' average daily electricity consumption during Period 0 evolved smoothly around the lower cutoff point. This figure allows me, at a minimum, not to reject the assumption of local randomization around the base usage quantity, even though examining an observed covariate around the thresholds is not also a direct test for the validity of the assumption.

3 Empirical Analysis and Results

3.1 Household Responses to the Lagged Marginal Prices

3.1.1 Econometric Model

Exploiting the sharp Regression Discontinuity (RD) design described earlier, I estimate the following econometric specification to measure how SMUD residential customers respond, in terms of their electricity consumption in a billing month (i.e., Period 1), to the discontinuous change in the marginal prices due to exceeding the lower base usage quantity in the previous billing month (i.e., Period 0):

$$ADC_{i,1} \;=\; \beta\, \mathbb{1}[Treatment]_{i,0} \;+\; f\left(\overline{NC}_{i,0}\right) \;+\; \boldsymbol{X}'\boldsymbol{\alpha} \;+\; \delta_{ym} \;+\; \epsilon_{i,1} \tag{1}$$

The dependent variable $ADC_{i,1}$ is the average daily consumption by household i in Period 1. $\overline{NC}_{i,0}$ corresponds to the running variable, household i's normalized consumption in Period 0:

$$\overline{NC}_{i,0} \;=\; kWh_{i,0} \;-\; BUQ_{i,0} \tag{2}$$

where $kWh_{i,0}$ and $BUQ_{i,0}$ are, in Period 0, household i's aggregate electricity consumption and the lower base usage quantity, respectively. The binary indicator variable $\mathbb{1}[Treatment]_{i,0}$ is equal to 1 only if household i's aggregate electricity consumption in Period 0 exceeded the lower base usage quantity:

$$\mathbb{1}[Treatment]_{i,0} \;=\; \begin{cases} 0 & \text{if } \overline{NC}_{i,0} \;\leqslant\; 0 \\ 1 & \text{if } \overline{NC}_{i,0} \;>\; 0 \end{cases} \tag{3}$$

For $f\left(\overline{NC}_{i,0}\right)$, which is a continuous function of $\overline{NC}_{i,0}$, I utilize a variety of functional forms to show the robustness of my estimates. $\boldsymbol{X}$ are covariates, such as average daily Cooling Degree Days (CDDs) and average daily Heating Degree Days (HDDs). δ_{ym} is billing year-by-month fixed effects (FEs).[9] The last term $\epsilon_{i,0}$ is a stochastic error term. In this model, the coefficient of interest β captures the treatment effect. I cluster the

[9]For a given billing observation, the mid-date of the observation determines the billing month-by-year.

standard errors at the household ID as well as billing year-by-month levels to allow correlations across households in a given month.

In the specification, each household's average daily electricity consumption, instead of the aggregate consumption, in a billing cycle is utilized as the dependent variable. My sample contains household-level monthly billing records. But because of the fact that each billing month consists of a different number of days, I use each billing month's average daily consumption for my empirical analysis. For the same reason, average daily CDDs and HDDs are exploited in later analysis.

3.1.2 Regression Discontinuity Results

Table 2 summarizes the regression results of several alternate specifications for the bandwidth of 10%. Column (1) reports estimates from the most straightforward RD specification, controlling linearly for $\overline{NC}_{i,0}$, without any control and FEs. Column (2) adds controls for households' cooling and heating needs, significantly driving household electricity consumption. In addition to those two controls, column (3) uses billing year-by-month FEs. Adding the FEs attenuates the estimate of interest. Moreover, the standard errors of the estimated treatment effect are substantially smaller, suggesting that controlling for time-varying factors is important.[10] In this specification, the estimated treatment effect indicates a discontinuous reduction in households' electricity demand by 0.040 kWh, which amounts to 0.16% of their average daily electricity consumption. This estimate is statistically different from 0 at the 5% level. Columns from (4) to (6) additionally include the interaction term between the binary indicator and the running variable. Adding the interaction term to the specifications has only minimal impact on estimates.

The identified reduction in household electricity consumption provides strong evidence that households respond to lagged marginal prices. As discussed in Section 2.3.2, the discontinuous increase in the marginal price at the lower base usage quantity was not followed by any discontinuous change in the average price. Moreover, the households in my sample were able to notice the price jump only through their monthly bill statements, which were delivered a few days after the first day of the new billing month. Collectively, my estimates reveal an inefficiency stemming from households' responses to nonlinear electricity pricing because the lagged marginal price reflects their consumption history, not their contemporaneous consumption. In other words, under IBP, the untimely price signals drive, at least partly, households' electricity consumption.

Importantly, the estimated discontinuous decrease in residential electricity consumption also suggests that SMUD residential customers overreacted to the lagged marginal price under nonlinear electricity pricing. The discontinuous change in the marginal price at the lower base usage quantity occurred in a billing cycle (i.e., in Period 0). And my estimates show that in the following billing cycle (i.e., in Period 1), the customers reduced their electricity consumption as a response to the price variation. Consequently, the sharp increase in the

[10] Table 8 shows the RD estimates of the treatment effect from specifications without the billing year-by-month FEs. From this table, it is convincing that including the FEs is necessary to reduce sampling variance.

marginal price at the cutoff point in Period 0 affected all consumption, not the marginal one, in Period 1. That is, households excessively applied the lagged marginal price to every unit of electricity consumption during a billing month.

Inspired by Shaffer (2020), the estimates could be interpreted differently. The paper finds that a subgroup of less than 10% of households, which applies the marginal price to all consumption, was driving the seemingly overall response, in which the primary response to the average price is masked. If this is also true in my setting, then the measured decrease in household electricity consumption would be attributed to a subset of my sample. Suppose that there are two distinct types of SMUD residential customers: households over-responding to the lagged marginal price and those not responding to it.[11] My back-of-the-envelope calculation suggests that about 11% of over-responders produce the estimated treatment effect.[12] The share of over-responding households is obtained from the following steps: 1) computing the price elasticity of household electricity consumption by using the estimated treatment effect (i.e., the measured reduction in households' average daily electricity consumption), the average daily electricity consumption, the size of the price jump at the lower base usage quantity, and the average price at the cutoff point; and then 2) for a given price elasticity, which is available from other papers or reports, estimating how much households would have to respond to the lagged marginal price to obtain the price elasticity implied by my RD estimate. Moreover, for this computation, I exploit billing records only from non-electric-heating households (i.e., households choosing the RSGH rate plan.) Interestingly, my calculation, which indicates the reduction in electricity consumption by a subset of households in my sample, parallels the finding in the paper. Figure 5 visualizes, for different price elasticities of residential electricity consumption, how the proportion of over-responding households varies with the magnitude of the RD estimates identified.

3.1.3 Robustness Checks

Regression Discontinuity Results for Different Bandwidths and Functional Forms — Table 3 summarizes the regression results for a set of different bandwidths. The estimated treatment effect for the households in a very narrow range from the lower base usage quantity (i.e., the households within the bandwidth of 5%) is not statistically significant even at the 10% level. Except for the bandwidth of 5%, the treatment estimates range from -0.038 to -0.069 and statistically differ from zero at least at the 5% level. The estimated treatment effect is almost identical for the bandwidths of 10% and 15%. For wider bandwidths falling between 20% and 40%, the magnitude of the estimated treatment effect increases and remains stable.[13] Interestingly, this table

[11] Here, I do not consider the type of households that respond to the average price because the change in the lagged marginal price at the threshold does not accompany any discontinuous change in the average price.

[12] To obtain the proportion of over-responding households, I exploit the following values: 1) the daily price elasticity for default non-EAPR customers (i.e., -0.030), which is presented in *Section 7.2 Price Elasticity Estimates* of Potter, George and Jimenez (2014); and 2) the treatment effect, estimated with the value of bandwidth 10%, for households selecting the RSGH rate plan (i.e., -0.060), which is given in Table 9.

[13] The number of observations increases with the size of the bandwidth exploited, except the two widest ones. The exceptions are because I drop observations crossing the higher base usage quantity to avoid picking up the effect of surpassing the higher cutoff

clearly shows that the wider the bandwidth employed, the larger the estimated treatment effect. In other words, the treatment estimates approach zero as I move even closer to the lower base usage quantity.

There are several possible explanations for this monotonic trend in the treatment effect. First, it may be more difficult or demanding for SMUD residential customers near the threshold to notice, from their monthly bill statements, that their electricity consumption in the previous billing month barely exceeded the lower base usage quantity, which in turn made them experience a discontinuous increase in the marginal price. Second, households whose electricity consumption just surpassed the cutoff point in a billing cycle could intentionally ignore the lagged price signal in the subsequent billing cycle. Some of them likely understood that their immediate electricity consumption was utterly irrelevant to the signal. And it is also possible that adjusting their electricity consumption pattern against the lagged marginal price during a whole billing month led to too much cost for some treated households very near the threshold compared to its benefit. Third, households near the lower base usage quantity may respond differently to the lagged marginal price compared to those farther from the threshold. Specifically, conditional on a given magnitude of the increase in the lagged marginal price, heavy electricity consumers could be more responsive to the price signal.

Tables 4 and 5 present the regression results from other specifications having different functional forms. As illustrated in Figure 9, a linear regression function seems highly reasonable on both sides of the threshold, even for broader bandwidth. The robustness of the results from the first four columns in Table 4 confirms that the linear approximation of the regression line does not induce considerable biases in my RD estimates. In addition, the RD estimates in the two tables suggest that for wider bandwidths, adding higher-order polynomials of the running variables is still reasonable for the estimates to be precise.

Falsification Test — Figure 6 summarizes the results from falsification tests that examine treatment effects at two placebo cutoff points (i.e., at −30% and 40% of the normalized electricity consumption in Period 0 from the *true* lower base usage quantity).[14] In the falsification tests, I only use bandwidths less than the distance between a false threshold and the (actual) lower base usage quantity to avoid capturing some of the treatment effect. As clearly demonstrated, no estimate is different from zero at the 5% level, suggesting that my RD design is valid.

3.1.4 Heterogeneity in Household Responses to the Lagged Marginal Prices

Treatment Effects by Season — Table 6 summarizes how households responded differently to the lagged marginal price in different seasons. In this table, based on the billing month of Period 0, the summer season is from June to September, while the winter season is from December to March. Of note, there was no change

point.

[14] That is, the two false thresholds are at 70% and 140% of the normalized consumption in Period 0. Following the suggestion in Imbens and Lemieux (2008), I select those false cutoff points that are close to the median of the running variable on each side of the *true* cutoff point.

in the lower base usage quantity during each season. For each of the three rate codes (i.e., RSCH, RSEH, and RSGH), the first columns (i.e., columns (1), (4), and (7) in the table) present the treatment effect obtained by exploiting meter readings from all months.

The two rate groups for households with electric heating (i.e., RSCH and RSEH) shared identical base usage quantities in my sample. The only difference between them was that households choosing the RSCH rate plan paid a much lower price in the winter season. Generally, households with electric heating show very similar consumption changes, though the large standard errors of the coefficient of interest make it difficult to say anything conclusive about any difference between the two rate groups.

Residential customers adopting the RSGH rate plan, which experienced relatively small seasonal changes in base usage quantities, show similar reductions in daily electricity consumption in both seasons, except that the RD estimate for the summer season demonstrates much larger standard errors.

Treatment Effects at the Higher Base Usage Quantity — Table 7 presents the results of applying the RD design to the higher base usage quantity. In other words, the RD estimates shown in this table demonstrate how SMUD residential customers responded to the lagged marginal price at the higher base usage quantity. Interestingly, no estimated treatment effect is statistically significant at the 5% level. In other words, the table highlights that households did not respond to the lagged marginal price at the higher base usage quantity.

There is a number of possible reasons for the empirical finding. First, considering the consumption reductions around the lower base usage quantity, this finding may indicate that households' responsiveness to the lagged marginal price varies with the level of electricity consumption. If heavy electricity consumers, presumably high-income households, tend to pay less attention to how much they are paying for their marginal electricity consumption, no response at the higher cutoff point seems reasonable. Second, no change in households' consumption behavior near the higher base usage quantity could be attributed to the relatively small magnitude of the increases in the marginal price at the threshold. Specifically, the average marginal price increase at the lower base usage quantity was about 74%, whereas it was only about 18% at the higher threshold.

3.2 Multi-Period Household Responses to the Lagged Marginal Prices

Section 3.1 presents the empirical evidence that SMUD residential customers under IBP reduced their average daily electricity consumption in a billing cycle (i.e., in Period 1) as a response to the increase in the marginal price in the immediate previous billing period (i.e., in Period 0). In this section, I examine how their electricity consumption responded to the lagged price signals in a prolonged time interval—the relationship between Period -1 and Period 1 as well as Period -2 and Period 1. In other words, I study the impact of the lagged marginal price on household electricity consumption in two- and three-month intervals. Clearly, the conditions on which my RD design relies, which are described in Section 2.3.2, still hold in the multi-period setting here. Nevertheless, the seasonal variation in the lower base usage quantity might significantly alter households' consumption behavior over a longer time frame. To rule out this potential confounding factor, I focus on the summer and winter seasons, during which the cutoff point for each season remained at the same level.

Figure 7 shows the estimated multi-period treatment effects for a set of bandwidths. The two panels on the left side of this figure are for the summer season, whereas those on the right are for the winter season. The upper and lower panels present the estimated multi-period treatment effects for households with either one of the two electric-heating rate plans and those with the RSGH rate plan, respectively.

The households choosing electric heating rate plans, whose base usage quantities moved together seasonally, demonstrated vastly different responses in the two seasons. In the summer season, they reacted to the discontinuous increases in the lagged marginal price by reducing their electricity consumption. Interestingly, the lagged price signals persisted over multiple billing cycles. Furthermore, their consumption reductions were more considerable for earlier price signals. In addition to the summer season's higher prices and much lower base usage quantity, the salience of Period -2's winter-to-summer transition in marginal prices and base usage quantities, compared to Period -1 and Period 0, could affect their responsiveness to the lagged marginal price. As described in the upper right panel, the SMUD residential customers did not respond to the lagged price signals in the winter season. Similar to the no response in the higher base usage quantity, the significantly higher cutoff point at which the first discontinuous price jump occurred in the winter season may explain this response.

In both seasons, the households selecting the RSGH rate plan showed similar responses. One notable point from their responses is that the marginal price's discontinuous increase in Period -2 had minimal impact on their electricity consumption in Period 1. In other words, the impact of the discontinuous increases on household electricity consumption tends to dissipate gradually over time.[15]

4 Policy Implications

Utilizing the Regression Discontinuity (RD) design described in Section 2.3.2, I show that under Increasing-Block Pricing (IBP), residential electricity consumption responded to the lagged marginal prices, informed by their monthly bill statements. Before 2010, SMUD residential customers had no feasible way to know, in real time, how much electricity they had consumed since the beginning of a billing cycle, how much they paid for the marginal unit, and so on. In such a situation, it seems reasonable for them to use the available information—for example, the information contained in their monthly bills, which are delivered after several days after the last day of each billing cycle—as much as possible to make decisions about their electricity use.

Nevertheless, it is undeniable that their electricity consumption responding to the lagged marginal price is suboptimal. As discussed, the marginal price to which households responded is not for the marginal unit in

[15] The salience of the winter-to-summer transition, accompanying relatively small price increases and growths in base usage quantities, seems not to play an important role in altering households' consumption behavior.

the current billing period but for the last unit in the previous one. In response to *wrong* price signals, SMUD residential customers reduced their electricity consumption. Moreover, they applied the lagged price signals to all units of electricity consumption in a billing month, not just the last unit in a billing month. In other words, the *informed* consumption decisions made by households, based on the lagged marginal prices, caused them welfare losses.

The issue of household welfare losses due to their response to the discontinuous change in the lagged marginal prices suggests the importance of providing seemly price information in an appropriate manner. Many studies about various time-varying electricity pricing show that households changed their consumption behavior in response to the information about consumption and prices (Faruqui and Sergici, 2011; Jessoe and Rapson, 2014; Pon, 2017; Bollinger and Hartmann, 2020). My empirical finding demonstrates that even under IBP, such information, though lagged, still plays a role in household electricity consumption. In this respect, providing household-specific as well as current price information to residential consumers, via text messages or app notifications, could encourage them to respond to *true* price signals rather than lagged ones, which in turn avoids the negative impact on household welfare. Based on the dissipating effect of intermittently salient information discussed in Gilbert and Graff Zivin (2014), a high frequency of advising the latest tailored price information might maximize the behavioral change of households in electricity consumption.

My empirical results also suggest the significance of ensuring people understand the information provided correctly. Using an up-to-date machine learning technique, Prest (2020) shows that the most critical driver of households' response to Time-Of-Use electricity pricing is their awareness of intraday price changes under the dynamic pricing. Given the empirical evidence suggested in Shaffer (2020), a subset of households in my sample may be driving the identified response to the lagged marginal prices.[16] If this is the case, the household group perceived the variation in the lagged marginal prices informed by their monthly billing statements. However, their identified response to the lagged price signals clearly indicates that they misunderstood it as price information for right now. Herefore, in my empirical context, the result of my empirical analysis could suggest that it is crucial not only to get residential consumers to be aware of price changes, but also to get them to interpret the price signals correctly.

5 Conclusion

In this paper, I examine how the electricity consumption of SMUD residential customers responded to the marginal price informed through monthly bill statements under Increasing-Block Pricing (IBP). In a setting with a valid regression discontinuity design, my empirical analysis shows that households, on average, reduced their electricity consumption in response to the discontinuous price change in the marginal price in the immediately

[16]For the households showing no response to the lagged price signals, there are two possible explanations: 1) they interpreted the signals correctly; or 2) they did not pay attention to it.

preceding billing cycle. In other words, the empirical results of my analysis reveal an inefficiency of IBP. But at the same time, the interesting response demonstrates the potential to induce desired behavioral changes in household electricity consumption by providing appropriate, even lagged, price information. On top of that, the identified response, which may be driven by a subset of households in my sample, suggests that it is also important for households to correctly understand price-related information provided in order to make optimal decisions about electricity consumption.

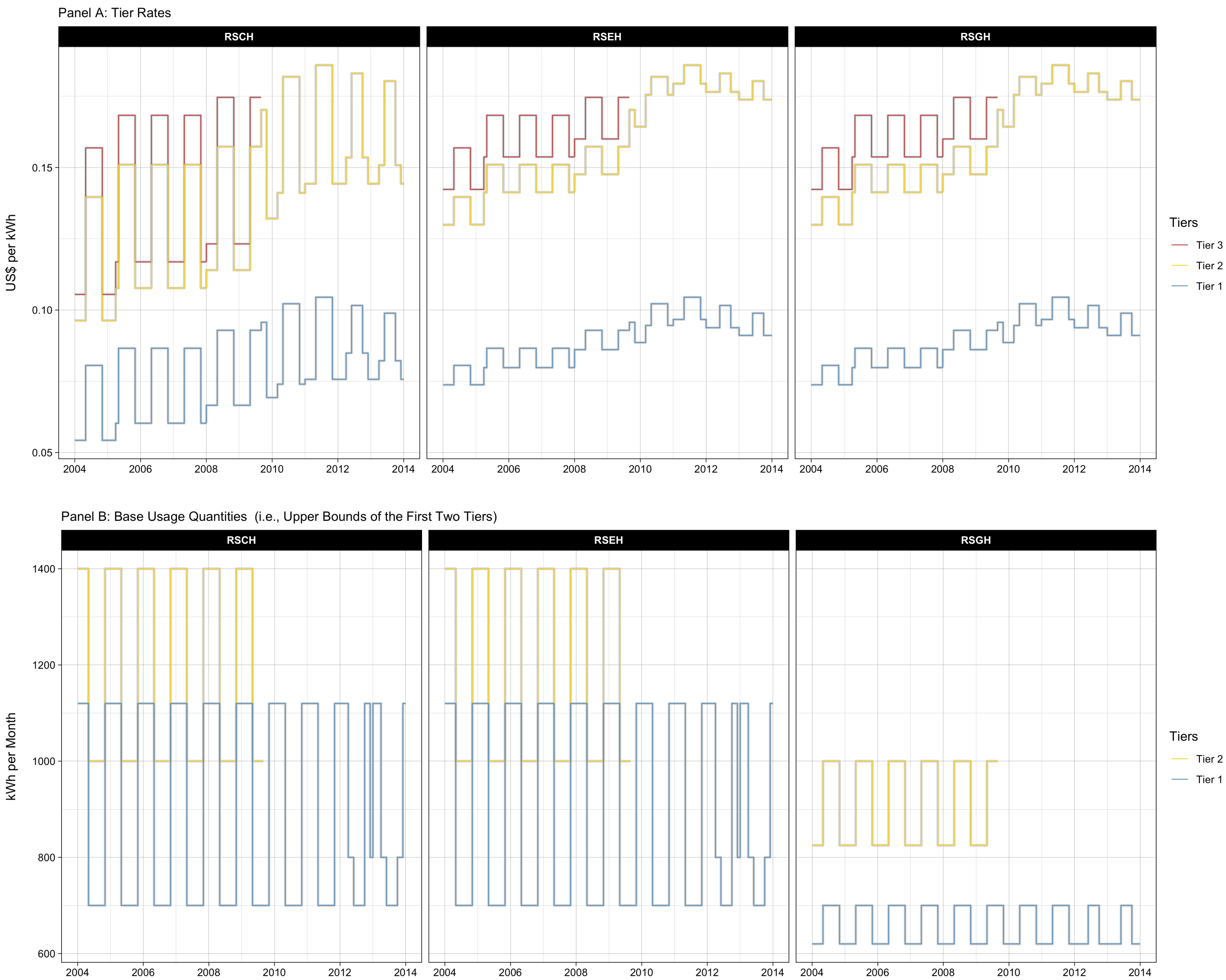

Figure 1: Tier Rates and Base Usage Quantities of SMUD Residential Rates

Note: The figure illustrates how SMUD changed tier rates and base usage quantities of the three major residential rate plans (i.e., RSCH, RSEH, and RSGH) over time. Both tier rates and base usage quantities show significant seasonality. The two rate plans for electric-heating households (i.e., RSCH and RSEH) had the same base usage quantities. There have been only two tiers since September 2009.

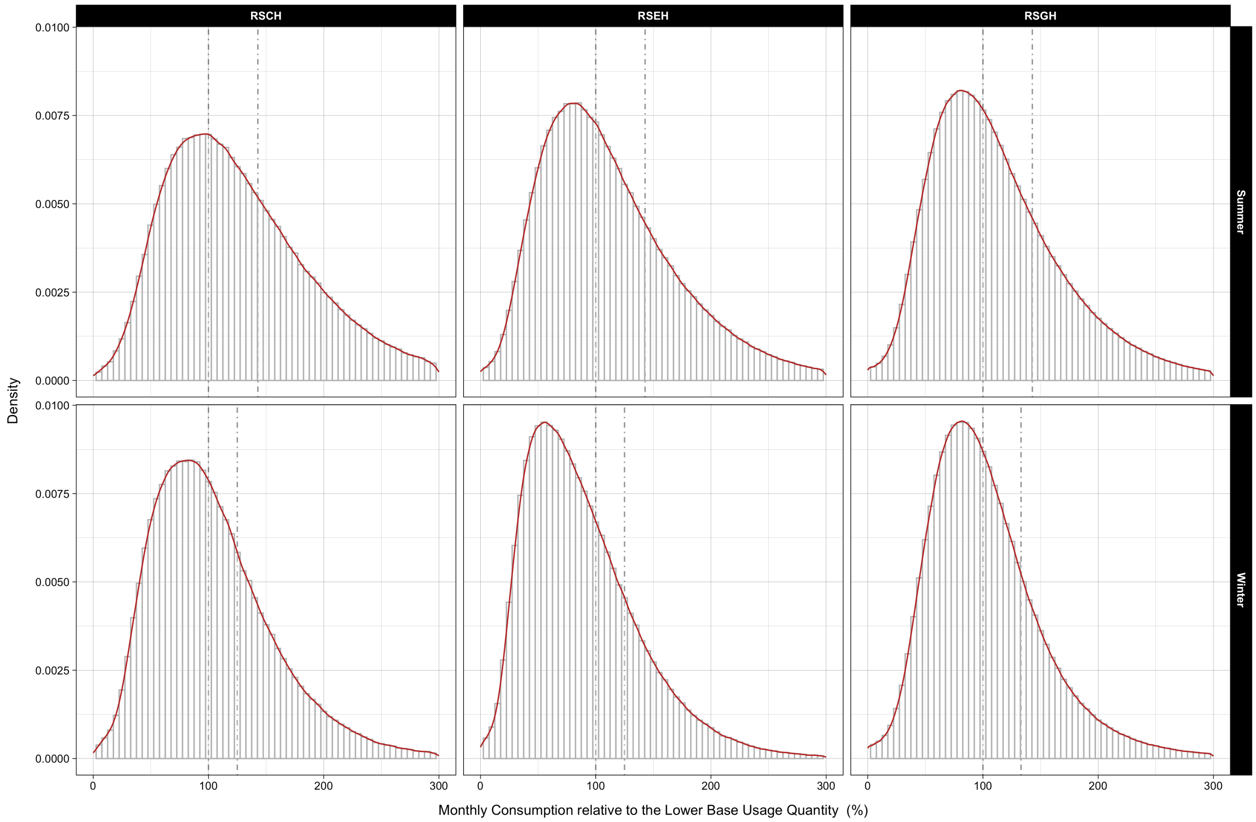

Figure 2: Distribution of Electricity Consumption by SMUD Residential Customers

Note: This figure presents histograms, with kernel density estimates, for electricity consumption by SMUD residential customers. Each of the six panels in the figure is for a pair of three major residential rates (i.e., RSCH, RSEH, and RSGH) and two seasons (i.e., summer and winter). Dot-dashed vertical lines in each panel are base usage quantities for the corresponding rate code and season.

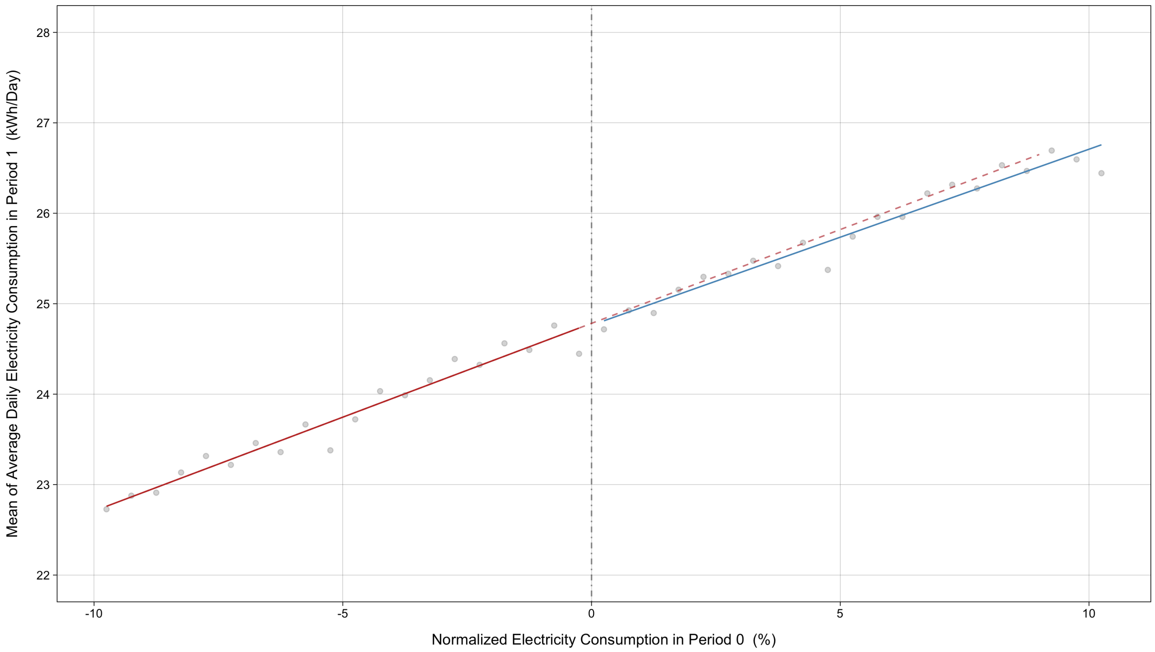

Figure 3: Mean of Average Daily Electricity Consumption in Period 1 over $\overline{NC}_0$

Note: This figure's scatter points correspond to the average daily electricity consumption in Period 1, computed by bins with a bandwidth of 1% of $\overline{NC}_0$. The solid line on each side of the vertical dot-dash line is a parametric fit obtained from the regression of the average daily electricity consumption on $\overline{NC}_0$. The dashed red line is an extension of the solid red line. The gap between the dashed red and solid blue lines seems to indicate a non-negligible treatment effect.

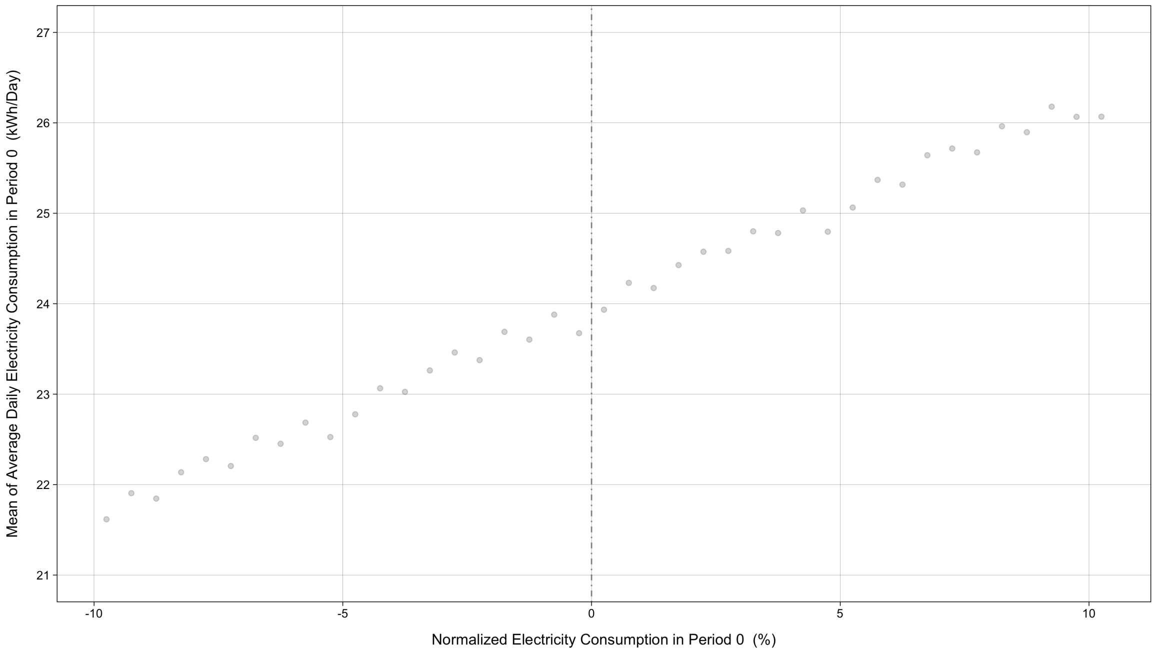

Figure 4: Mean of Average Daily Electricity Consumption in Period 0 over $\overline{NC}_0$

Note: In this figure, the scatter points correspond to the average daily electricity consumption in Period 0, calculated by binds with a bandwidth of 1% of $\overline{NC}_0$. As can be seen, the average daily electricity consumption evolves smoothly around the cutoff point (i.e., $\overline{NC}_0 = 0$).

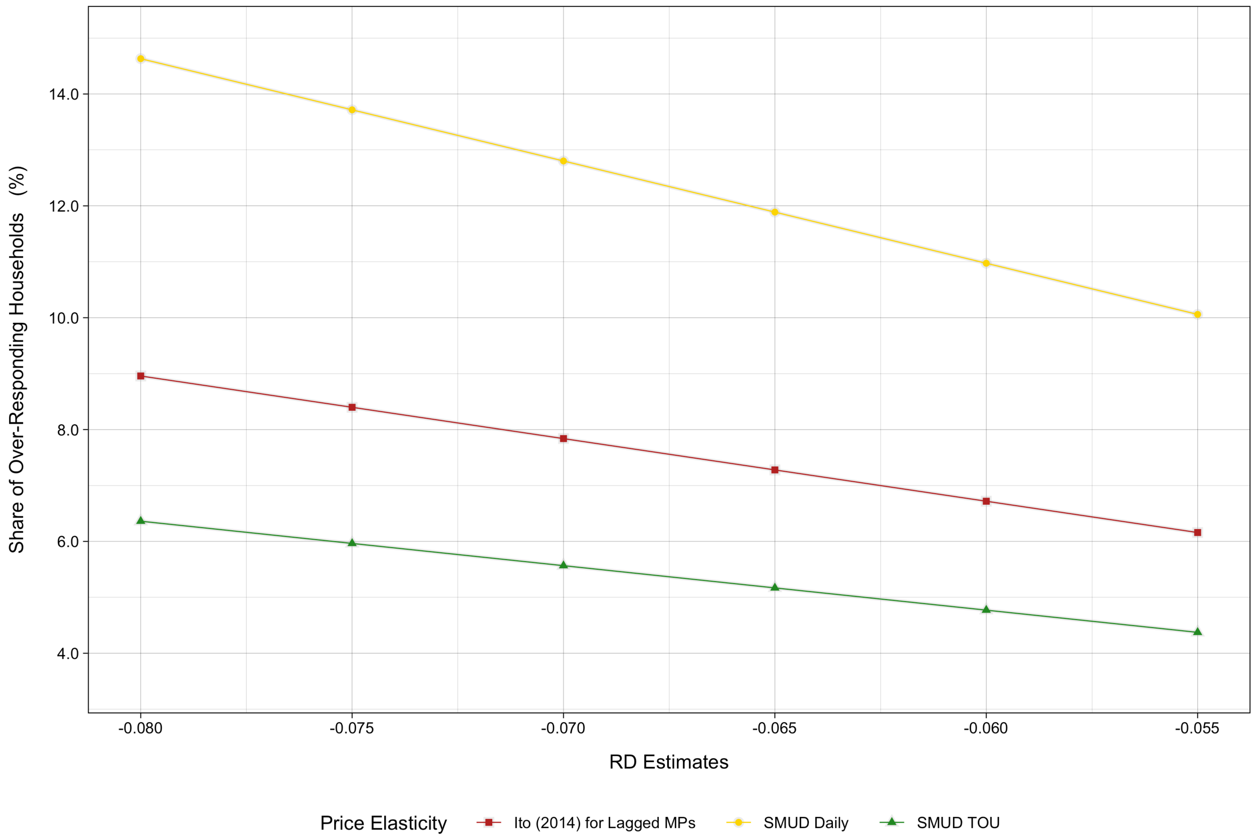

Figure 5: The Share of Over-Responding Households

Note: This figure shows, for different price elasticities of household electricity consumption, how the share of over-responding households varies with the value of the RD estimates. Two price elasticities for SMUD residential customers are in Potter, George and Jimenez (2014), whereas the remaining price elasticity, estimated from PG&E residential customers' billing data, is from Ito (2014). See the text for details.

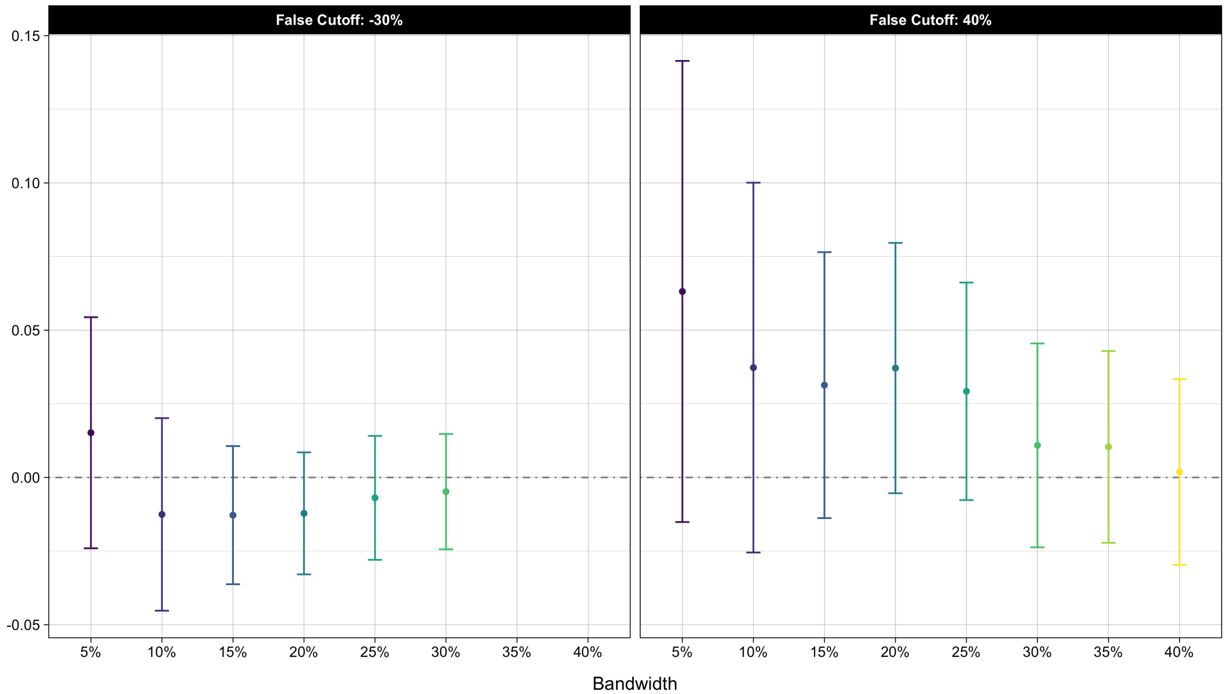

Figure 6: Robustness Checks: Falsification Tests

Note: This figure shows the results of falsification tests exploiting two placebo thresholds at -30% and 40% from the point $\overline{NC}_0 = 0$. As depicted, no RD estimate is statistically different from zero. See the text for details.

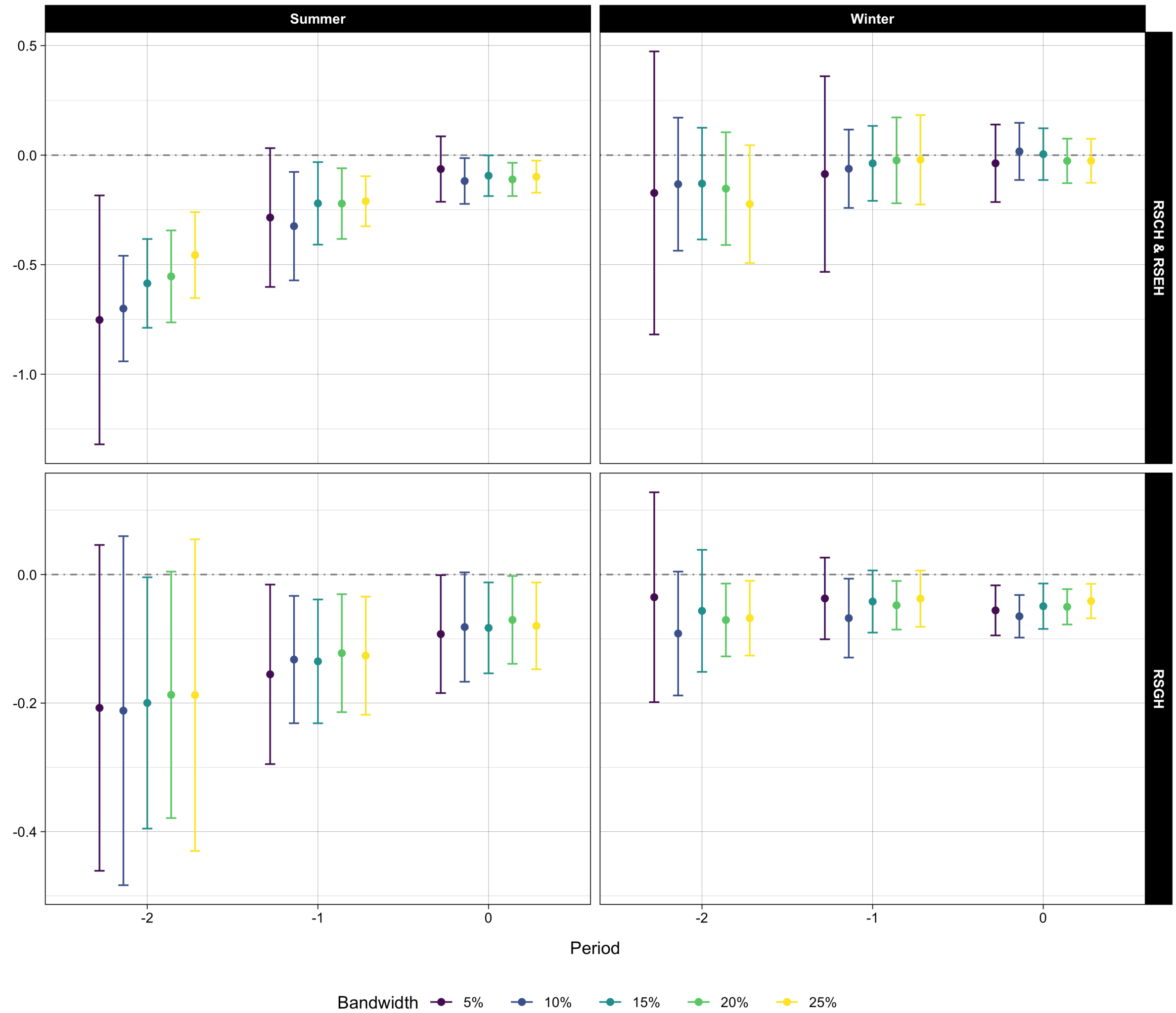

Figure 7: Multi-Period Treatment Effects

Note: This figure summarizes the estimated multi-period treatment effects. The over-period evolving pattern of the estimates for electric-heating households (i.e., households selecting either the RSCH or RSEH rate plan) is significantly different from that of the estimates for non-electric-heating households (i.e., households choosing the RSGH rate code). See the text for details.

Table 1: Summary Statistics

Bandwidth	Households	Observations	Control		Treatment	
			Mean	(S.D.)	Mean	(S.D.)
Normalized Electricity Consumption in Period 0 (%)						
5%	286,671	1,186,630	−2.454	1.444	2.485	1.407
10%	318,880	2,378,864	−4.993	2.885	4.918	2.847
15%	331,605	3,566,318	−7.543	4.324	7.357	4.322
20%	338,470	4,702,081	−10.085	5.756	9.617	5.718
25%	343,139	5,816,854	−12.612	7.184	11.870	7.144
30%	341,917	6,276,579	−15.054	8.597	14.063	8.559
Average Daily Electricity Consumption in Period 1 (kWh/Day)						
5%	286,671	1,186,630	24.329	7.922	25.296	8.143
10%	318,880	2,378,864	23.776	7.786	25.782	8.290
15%	331,605	3,566,318	23.231	7.674	26.270	8.450
20%	338,470	4,702,081	22.681	7.582	26.744	8.624
25%	343,139	5,816,854	22.140	7.509	27.202	8.805
30%	341,917	6,276,579	20.674	6.560	26.517	7.874

Note: This table presents summary statistics for household electricity consumption. Including this table, all following tables are generated using the *stargazer* package for *R* (Hlavac, 2022).

Table 2: Regression Discontinuity Results

	Dependent Variable					
	Average Daily Electricity Consumption (kWh/Day)					
	(1)	(2)	(3)	(4)	(5)	(6)
𝟙[Treatment]	-0.047^{*}	-0.054^{*}	-0.040^{**}	-0.047^{*}	-0.054^{*}	-0.038^{**}
	(0.027)	(0.030)	(0.018)	(0.027)	(0.030)	(0.018)
NC0	0.207^{***}	0.197^{***}	0.219^{***}	0.207^{***}	0.197^{***}	0.222^{***}
	(0.007)	(0.006)	(0.005)	(0.007)	(0.007)	(0.005)
𝟙[Treatment] × NC0				0.0002	0.001	-0.006
				(0.004)	(0.004)	(0.004)
Average Daily CDDs		0.753^{***}	1.146^{***}		0.753^{***}	1.146^{***}
		(0.121)	(0.106)		(0.121)	(0.106)
Average Daily HDDs		0.281^{***}	0.428^{***}		0.281^{***}	0.428^{***}
		(0.078)	(0.106)		(0.078)	(0.106)
(Constant)	24.810^{***}	19.974^{***}		24.810^{***}	19.973^{***}	
	(0.542)	(0.941)		(0.542)	(0.941)	
Bandwidth	10%	10%	10%	10%	10%	10%
FEs: Billing Year-by-Month	No	No	Yes	No	No	Yes
Observations	2,378,864	2,378,864	2,378,864	2,378,864	2,378,864	2,378,864
Adjusted R^2	0.021	0.120	0.293	0.021	0.120	0.293

Note: The table shows, for the bandwidth of 10%, the regression results from different econometric specifications. Standard errors in parentheses are clustered at the household and billing year-by-month levels to allow correlations across households in a given month; * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$.

Table 3: Robustness Checks: For Different Bandwidths

	Dependent Variable							
	Average Daily Electricity Consumption (kWh/Day)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
𝟙[Treatment]	−0.026	−0.038**	−0.039**	−0.064***	−0.060***	−0.061***	−0.060***	−0.069***
	(0.027)	(0.018)	(0.017)	(0.015)	(0.014)	(0.012)	(0.020)	(0.023)
NC0	0.207***	0.222***	0.224***	0.225***	0.225***	0.221***	0.236***	0.229***
	(0.009)	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)	(0.008)	(0.009)
𝟙[Treatment] × NC0	0.017*	−0.006	−0.010***	−0.009***	−0.009***	−0.015***	−0.019***	−0.017***
	(0.010)	(0.004)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.004)
Average Daily CDDs	1.146***	1.146***	1.146***	1.146***	1.145***	1.135***	1.102***	1.133***
	(0.105)	(0.106)	(0.106)	(0.105)	(0.105)	(0.109)	(0.115)	(0.129)
Average Daily HDDs	0.427***	0.428***	0.429***	0.431***	0.433***	0.375***	0.691***	0.742***
	(0.108)	(0.106)	(0.105)	(0.104)	(0.103)	(0.128)	(0.128)	(0.202)
Bandwidth	5%	10%	15%	20%	25%	30%	35%	40%
FEs: Billing Year-by-Month	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,186,630	2,378,864	3,566,318	4,702,081	5,816,854	6,276,579	4,093,259	3,904,120
Adjusted R^2	0.282	0.293	0.311	0.334	0.361	0.536	0.550	0.592

Note: This table shows the results of robustness checks for a range of bandwidths using the regression in the specification (6) in Table 2. Standard errors in parentheses are clustered at the household and billing year-by-month levels to allow correlations across households in a given month. See the text for details; * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$.

Table 4: Robustness Checks: For Different Functional Forms, 1st- and 2nd-Order Polynomial Models

	Dependent Variable							
	Average Daily Electricity Consumption (kWh/Day)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
𝟙[Treatment]	−0.038**	−0.064***	−0.061***	−0.069***	−0.018	−0.028	−0.068***	−0.082***
	(0.018)	(0.015)	(0.012)	(0.023)	(0.028)	(0.020)	(0.014)	(0.021)
NC0	0.222***	0.225***	0.221***	0.229***	0.223***	0.222***	0.216***	0.224***
	(0.005)	(0.005)	(0.006)	(0.009)	(0.011)	(0.006)	(0.006)	(0.010)
𝟙[Treatment] × NC0	−0.006	−0.009***	−0.015***	−0.017***	−0.020	−0.013**	−0.004**	−0.003*
	(0.004)	(0.002)	(0.002)	(0.004)	(0.014)	(0.005)	(0.002)	(0.002)
NC0^2					0.0001	−0.0002	−0.0001**	−0.0001*
					(0.001)	(0.0002)	(0.0001)	(0.0001)
𝟙[Treatment] × NC0^2					0.001	0.001***	−0.0001	−0.0001
					(0.001)	(0.0002)	(0.0001)	(0.0001)
Average Daily CDDs	1.146***	1.146***	1.135***	1.133***	1.146***	1.146***	1.135***	1.133***
	(0.106)	(0.105)	(0.109)	(0.129)	(0.106)	(0.105)	(0.109)	(0.129)
Average Daily HDDs	0.428***	0.431***	0.375***	0.742***	0.428***	0.431***	0.375***	0.742***
	(0.106)	(0.104)	(0.128)	(0.202)	(0.106)	(0.104)	(0.128)	(0.202)
Bandwidth	10%	20%	30%	40%	10%	20%	30%	40%
FEs: Billing Year-by-Month	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,378,864	4,702,081	6,276,579	3,904,120	2,378,864	4,702,081	6,276,579	3,904,120
Adjusted R^2	0.293	0.334	0.536	0.592	0.293	0.334	0.536	0.592

Note: This table reports the results of robustness checks for different functional forms, specifically the first- and second-order polynomial models. For each functional form, I run regressions with four different bandwidths (i.e., 10%, 20%, 30%, and 40%). Standard errors in parentheses are clustered at the household and billing year-by-month levels to allow correlations across households in a given month; * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$.

Table 5: Robustness Checks: For Different Functional Forms, 3rd- and 4th-Order Polynomial Models

	Dependent Variable							
	Average Daily Electricity Consumption (kWh/Day)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
𝟙[Treatment]	0.049	−0.022	−0.056***	−0.101***	0.129**	0.019	−0.049**	−0.068**
	(0.042)	(0.025)	(0.017)	(0.028)	(0.051)	(0.037)	(0.021)	(0.027)
NC0	0.143***	0.211***	0.215***	0.225***	0.111**	0.207***	0.213***	0.217***
	(0.022)	(0.010)	(0.006)	(0.010)	(0.043)	(0.016)	(0.008)	(0.011)
𝟙[Treatment] × NC0	0.056	0.005	−0.007	0.0003	−0.035	−0.027	−0.008	−0.001
	(0.035)	(0.013)	(0.005)	(0.005)	(0.079)	(0.021)	(0.008)	(0.010)
$NC0^2$	−0.020***	−0.002	−0.0003	−0.0001	−0.035**	−0.003	−0.001	−0.001*
	(0.005)	(0.001)	(0.0002)	(0.0002)	(0.017)	(0.003)	(0.001)	(0.001)
𝟙[Treatment] × $NC0^2$	0.022***	0.001	0.0004	−0.0004	0.092***	0.010**	0.001	0.001**
	(0.008)	(0.001)	(0.0003)	(0.0003)	(0.024)	(0.005)	(0.001)	(0.001)
$NC0^3$	−0.001***	−0.00005	−0.00000	0.00000	−0.004	−0.0001	−0.00002	−0.00003*
	(0.0003)	(0.00003)	(0.00001)	(0.00000)	(0.002)	(0.0002)	(0.00004)	(0.00002)
𝟙[Treatment] × $NC0^3$	0.001**	0.0001	−0.00000	0.00000	−0.005	−0.0005*	−0.00001	−0.00000
	(0.001)	(0.00005)	(0.00001)	(0.00001)	(0.005)	(0.0003)	(0.0001)	(0.00004)
$NC0^4$					−0.0001	−0.00000	−0.00000	−0.00000*
					(0.0001)	(0.00000)	(0.00000)	(0.00000)
𝟙[Treatment] × $NC0^4$					0.001***	0.00002*	0.00000	0.00000**
					(0.0002)	(0.00001)	(0.00000)	(0.00000)
Average Daily CDDs	1.146***	1.146***	1.135***	1.133***	1.146***	1.146***	1.135***	1.133***
	(0.106)	(0.105)	(0.109)	(0.129)	(0.106)	(0.105)	(0.109)	(0.129)
Average Daily HDDs	0.428***	0.431***	0.375***	0.742***	0.428***	0.431***	0.375***	0.742***
	(0.106)	(0.104)	(0.128)	(0.202)	(0.106)	(0.104)	(0.128)	(0.202)
Bandwidth	10%	20%	30%	40%	10%	20%	30%	40%
FEs: Billing Year-by-Month	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,378,864	4,702,081	6,276,579	3,904,120	2,378,864	4,702,081	6,276,579	3,904,120
Adjusted R^2	0.293	0.334	0.536	0.592	0.293	0.334	0.536	0.592

Note: This table reports the results of robustness checks for different functional forms, specifically third- and fourth-order polynomial models. For each functional form, I run regressions with four different bandwidths (i.e., 10%, 20%, 30%, and 40%). Standard errors in parentheses are clustered at the household and billing year-by-month levels to allow correlations across households in a given month; * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$.

Table 6: Heterogeneity in Household Responses: Treatment Effects by Season

	Dependent Variable								
	Average Daily Electricity Consumption (kWh/Day)								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\mathbb{1}$[Treatment]	−0.129**	−0.101	−0.127	−0.127***	−0.148**	−0.052	−0.060***	−0.074**	−0.070***
	(0.064)	(0.134)	(0.082)	(0.044)	(0.062)	(0.091)	(0.016)	(0.035)	(0.015)
NC0	0.308***	0.234***	0.332***	0.283***	0.209***	0.309***	0.215***	0.208***	0.191***
	(0.012)	(0.021)	(0.016)	(0.011)	(0.010)	(0.012)	(0.006)	(0.012)	(0.003)
$\mathbb{1}$[Treatment] × NC0	−0.030**	−0.014	−0.043*	0.004	0.020**	−0.0004	−0.010***	−0.007	−0.006**
	(0.012)	(0.013)	(0.021)	(0.009)	(0.010)	(0.017)	(0.003)	(0.006)	(0.003)
Average Daily CDDs	0.845***	1.270***	4.291***	0.928***	1.372***	4.763***	1.172***	1.502***	1.320***
	(0.161)	(0.165)	(0.850)	(0.171)	(0.154)	(0.963)	(0.108)	(0.167)	(0.290)
Average Daily HDDs	1.212***	2.421***	0.833***	1.226***	2.283***	0.856***	0.227**	2.089***	0.037
	(0.212)	(0.218)	(0.191)	(0.213)	(0.231)	(0.230)	(0.090)	(0.243)	(0.080)
Rate Code	RSCH	RSCH	RSCH	RSEH	RSEH	RSEH	RSGH	RSGH	RSGH
Season	All	Summer	Winter	All	Summer	Winter	All	Summer	Winter
Bandwidth	10%	10%	10%	10%	10%	10%	10%	10%	10%
FEs: Billing Year-by-Month	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	130,757	35,948	46,731	306,775	106,231	102,522	1,941,332	575,228	695,162
Adjusted R^2	0.535	0.414	0.259	0.571	0.418	0.301	0.486	0.540	0.167

Note: This table shows how the treatment effect varies across seasons. I run three regressions for each of the three major residential rate plans (i.e., RSCH, RSEH, and RSGH). I utilize the observations from June through September for the summer season, whereas I use the observations from December through March for the winter season. The first columns for each rate plan report the regression results exploiting all available observations. Standard errors in parentheses are clustered at the household and billing year-by-month levels to allow correlations across households in a given month; * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$.

Table 7: Heterogeneity in Household Responses: Treatment Effect at the Higher Base Usage Quantity

	Dependent Variable							
	Average Daily Electricity Consumption (kWh/Day)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\mathbb{1}$[Treatment]	0.045	−0.009	0.002	0.003	−0.007	−0.022*	−0.006	−0.011
	(0.037)	(0.028)	(0.024)	(0.022)	(0.018)	(0.012)	(0.015)	(0.018)
NC0	0.299***	0.300***	0.296***	0.297***	0.299***	0.287***	0.315***	0.310***
	(0.010)	(0.007)	(0.007)	(0.007)	(0.007)	(0.008)	(0.011)	(0.013)
$\mathbb{1}$[Treatment] × NC0	−0.037**	−0.012***	−0.009***	−0.013***	−0.016***	−0.021***	−0.029***	−0.028***
	(0.014)	(0.004)	(0.003)	(0.003)	(0.003)	(0.004)	(0.005)	(0.006)
Average Daily CDDs	1.604***	1.598***	1.586***	1.573***	1.559***	1.526***	1.518***	1.535***
	(0.149)	(0.148)	(0.147)	(0.145)	(0.144)	(0.144)	(0.151)	(0.163)
Average Daily HDDs	0.500***	0.504***	0.500***	0.493***	0.484***	0.418**	0.927***	1.019***
	(0.153)	(0.151)	(0.148)	(0.144)	(0.141)	(0.165)	(0.203)	(0.306)
Bandwidth	5%	10%	15%	20%	25%	30%	35%	40%
FEs: Billing Year-by-Month	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,008,265	2,024,211	3,056,688	4,098,107	5,173,016	5,699,991	3,865,674	3,926,154
Adjusted R^2	0.368	0.378	0.395	0.416	0.442	0.605	0.610	0.648

Note: This figure reports the results of regressions at the higher base usage quantity (i.e., the higher cutoff point) for a range of different bandwidths. Except for the bandwidth of 30%, the estimated treatment effects are not statistically significant even at the 10% level. Standard errors in parentheses are clustered at the household and billing year-by-month levels to allow correlations across households in a given month. See the text for the details; * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$.

A Appendixes

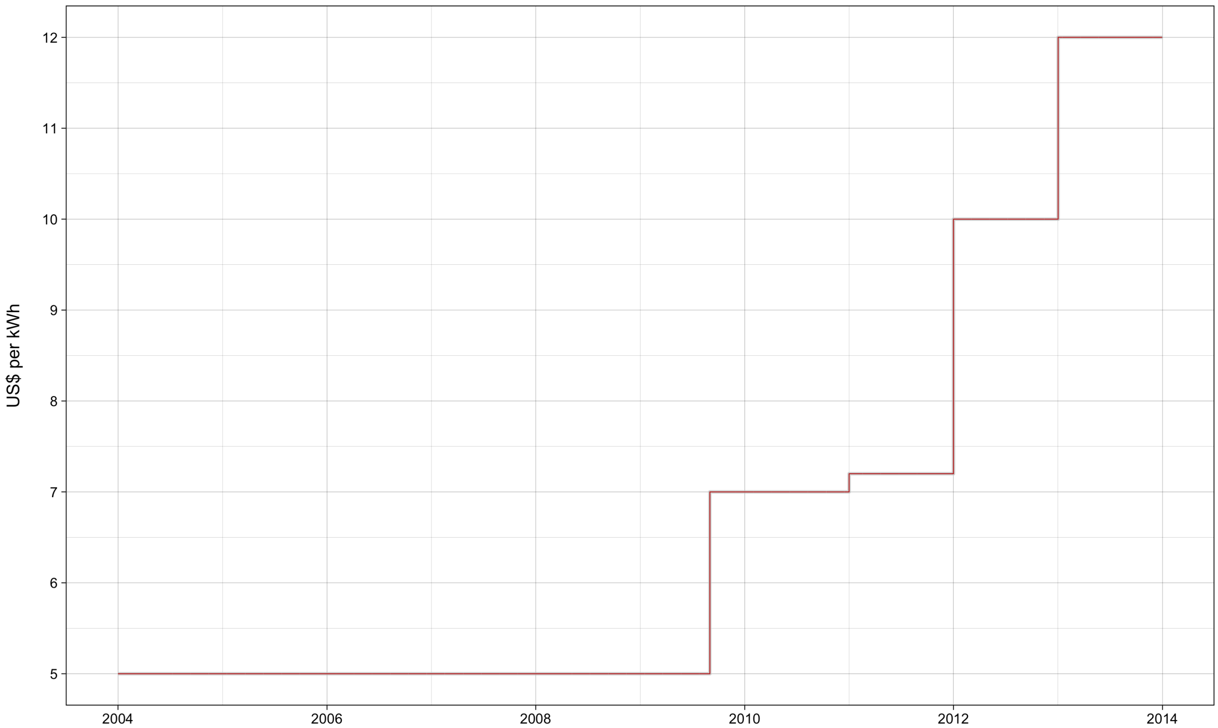

Figure 7: Fixed Charge of SMUD Residential Rates

Note: The figure shows how SMUD changed the monthly fixed charge over time. The same fixed charge applies to households that choose one of the three major residential rate plans (i.e., RSCH, RSEH, and RSGH).

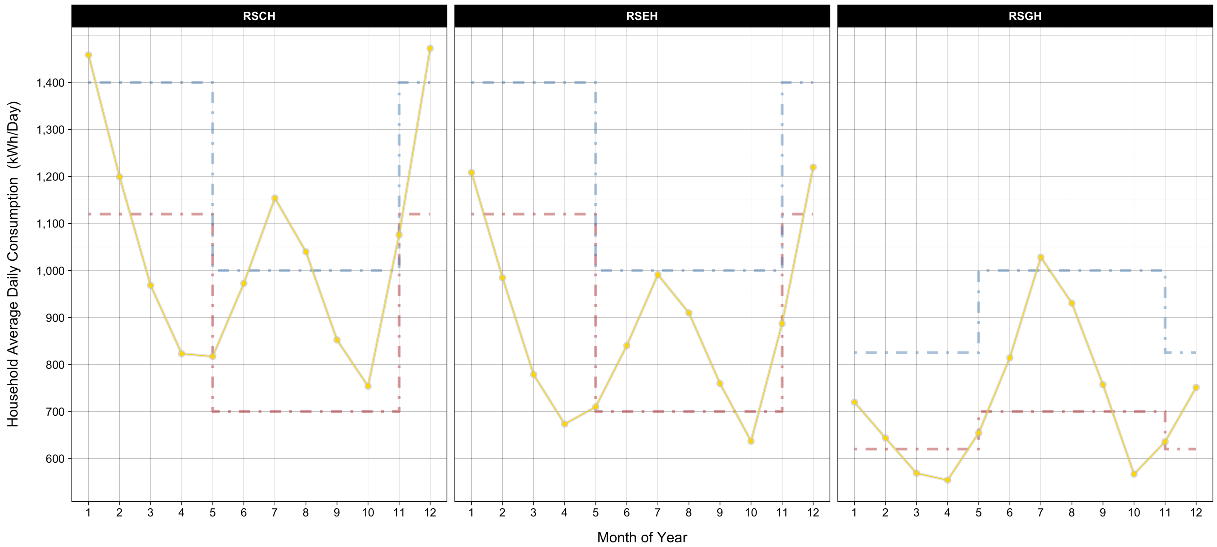

Figure 8: Household Average Daily Electricity Consumption by Month of Year

Note: This figure depicts, for each of SMUD residential rate plans, how households' average daily electricity consumption varied across months of the year. The red and blue dot-dash lines represent the lower and higher base usage quantities in each month of the year, respectively. The three rate plans show similar consumption and seasonal patterns.

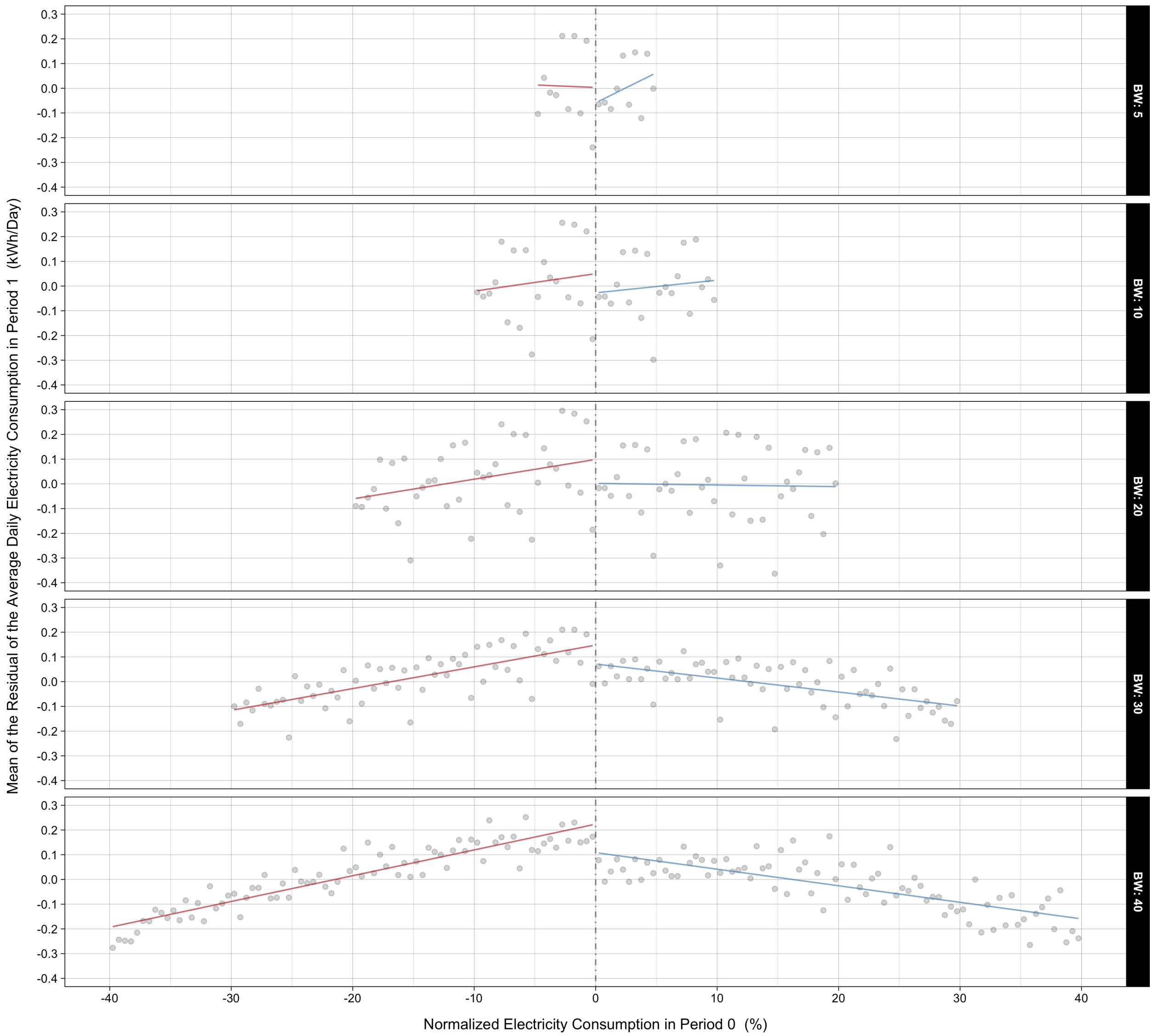

Figure 9: The Impact of the Change in the Marginal Price due to Surpassing the Lower Base Usage Quantity

Note: In this figure, scatter dots correspond to the mean of residuals, computed by bins with a bandwidth of 0.5%, from a regression of households' average daily electricity consumption in Period 1 on $\overline{NC}_0$, HDDs and CDDs. As described, a linear model fits those scatter points well, even for a wide bandwidth.

Table 8: Robustness Checks: For Different Bandwidths, Without FEs

	Dependent Variable							
	Average Daily Electricity Consumption (kWh/Day)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\mathbb{1}$[Treatment]	−0.014	−0.054*	−0.053*	−0.084***	−0.076***	−0.072**	−0.097*	−0.118*
	(0.032)	(0.030)	(0.028)	(0.028)	(0.029)	(0.031)	(0.056)	(0.064)
NC0	0.169***	0.197***	0.202***	0.204***	0.204***	0.199***	0.214***	0.211***
	(0.010)	(0.007)	(0.006)	(0.006)	(0.006)	(0.006)	(0.009)	(0.009)
$\mathbb{1}$[Treatment] × NC0	0.038***	0.001	−0.010***	−0.008***	−0.009***	−0.014***	−0.018***	−0.017***
	(0.012)	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.005)
Average Daily CDDs	0.749***	0.753***	0.755***	0.757***	0.758***	0.767***	0.932***	1.143***
	(0.122)	(0.121)	(0.120)	(0.119)	(0.118)	(0.114)	(0.124)	(0.124)
Average Daily HDDs	0.280***	0.281***	0.282***	0.284***	0.286***	0.152**	0.637***	1.033***
	(0.079)	(0.078)	(0.078)	(0.077)	(0.077)	(0.066)	(0.101)	(0.131)
(Constant)	19.947***	19.973***	19.972***	19.965***	19.937***	19.720***	17.769***	15.117***
	(0.948)	(0.941)	(0.937)	(0.932)	(0.926)	(0.829)	(1.082)	(1.159)
Bandwidth	5%	10%	15%	20%	25%	30%	35%	40%
FEs: Billing Year-by-Month	No	No	No	No	No	No	No	No
Observations	1,186,630	2,378,864	3,566,318	4,702,081	5,816,854	6,276,579	4,093,259	3,904,120
Adjusted R^2	0.105	0.120	0.144	0.175	0.210	0.349	0.394	0.468

Note: Contrary to Table 3, this table reports the results of robustness checks for a range of bandwidths using the regression in the specification (5) in Table 2. Standard errors in parentheses are clustered at the household and billing year-by-month levels to allow correlations across households in a given month; * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$.

Table 9: Robustness Checks: For Different Bandwidths, Only RSGH Rate Code

	Dependent Variable							
	Average Daily Electricity Consumption (kWh/Day)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\mathbb{1}$[Treatment]	-0.055^{***}	-0.060^{***}	-0.055^{***}	-0.065^{***}	-0.064^{***}	-0.058^{***}	-0.068^{***}	-0.080^{***}
	(0.020)	(0.016)	(0.015)	(0.014)	(0.013)	(0.013)	(0.021)	(0.024)
NC0	0.211^{***}	0.215^{***}	0.215^{***}	0.216^{***}	0.216^{***}	0.217^{***}	0.234^{***}	0.229^{***}
	(0.008)	(0.006)	(0.005)	(0.005)	(0.005)	(0.006)	(0.008)	(0.010)
$\mathbb{1}$[Treatment] × NC0	-0.005	-0.010^{***}	-0.013^{***}	-0.012^{***}	-0.014^{***}	-0.016^{***}	-0.021^{***}	-0.020^{***}
	(0.006)	(0.003)	(0.002)	(0.001)	(0.002)	(0.002)	(0.003)	(0.004)
Average Daily CDDs	1.170^{***}	1.172^{***}	1.174^{***}	1.174^{***}	1.172^{***}	1.171^{***}	1.162^{***}	1.190^{***}
	(0.106)	(0.108)	(0.108)	(0.107)	(0.107)	(0.106)	(0.114)	(0.126)
Average Daily HDDs	0.224^{**}	0.227^{**}	0.227^{**}	0.228^{**}	0.228^{**}	0.229^{**}	0.547^{***}	0.708^{***}
	(0.090)	(0.090)	(0.090)	(0.089)	(0.088)	(0.087)	(0.133)	(0.186)
Rate Code	RSGH	RSGH	RSGH	RSGH	RSGH	RSGH	RSGH	RSGH
Bandwidth	5%	10%	15%	20%	25%	30%	35%	40%
FEs: Billing Year-by-Month	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	967,546	1,941,332	2,909,164	3,832,683	4,738,070	5,604,830	3,396,312	3,191,411
Adjusted R^2	0.475	0.486	0.503	0.524	0.547	0.571	0.576	0.613

Note: This table shows the results of regressions with observations only for households selecting the RSGH rate plan. Standard errors in parentheses are clustered at the household and billing year-by-month levels to allow correlations across households in a given month; * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$.

References

Bollinger, Bryan K., and Wesley R. Hartmann. 2020. "Information vs. Automation and Implications for Dynamic Pricing." *Management science*, 66(1): 290–314.

Faruqui, Ahmad, and Sanem Sergici. 2011. "Dynamic pricing of electricity in the mid-Atlantic region: econometric results from the Baltimore gas and electric company experiment." *Journal of regulatory economics*, 40(1): 82–109.

Gilbert, Ben, and Joshua Graff Zivin. 2014. "Dynamic salience with intermittent billing: Evidence from smart electricity meters." *Journal of Economic Behavior and Organization*, 107: 176–190.

Hlavac, Marek. 2022. "stargazer: Well-Formatted Regression and Summary Statistics Tables." Bratislava, Slovakia, Social Policy Institute, R package version 5.2.3.

Imbens, Guido W., and Thomas Lemieux. 2008. "Regression discontinuity designs: A guide to practice." *Journal of econometrics*, 142(2): 615–635.

Ito, Koichiro. 2014. "Do Consumers Respond to Marginal or Average Price? Evidence from Nonlinear Electricity Pricing." *American Economic Review*, 104(2): 537–563.

Jessoe, Katrina, and David Rapson. 2014. "Knowledge is (Less) Power: Experimental Evidence from Residential Energy Use." *American Economic Review*, 104(4): 1417–1438.

Pon, Shirley. 2017. "The Effect of Information on TOU Electricity Use: An Irish Residential Study." *Energy Journal*, 38(6): 55–79.

Potter, Jennifer M., Stephen S. George, and Lupe R. Jimenez. 2014. "SmartPricing Options Final Evaluation."

Prest, Brian C. 2020. "Peaking Interest: How Awareness Drives the Effectiveness of Time-of-Use Electricity Pricing." *Journal of the Association of Environmental and Resource Economists*, 7(1): 103–143.

Sallee, James M. 2014. "Rational Inattention and Energy Efficiency." *The Journal of Law and Economics*, 57(3): 781–820.

Shaffer, Blake. 2020. "Misunderstanding Nonlinear Prices: Evidence from a Natural Experiment on Residential Electricity Demand." *American Economic Journal: Economic Policy*, 12(3).