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Nonlinear Pricing in Energy and Environmental Markets

by

Koichiro Ito

A dissertation submitted in partial satisfaction of the

requirements for the degree of

Doctor of Philosophy

in

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in the

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of the

University of California, Berkeley

Committee in charge:

Professor Severin Borenstein, Co-chair
Professor W. Michael Hanemann, Co-chair
Professor Maximilian Auffhammer
Professor Catherine Wolfram

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Abstract

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Professor Severin Borenstein, Co-chair

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This dissertation consists of three empirical studies on nonlinear pricing in energy and environmental markets. The first investigates how consumers respond to multi-tier nonlinear price schedules for residential electricity. Chapter 2 asks a similar research question for residential water pricing. Finally, I examine the effect of nonlinear financial rewards for energy conservation by applying a regression discontinuity design to a large-scale electricity rebate program that was implemented in California.

Economic theory generally assumes that consumers respond to marginal prices when making economic decisions, but this assumption may not hold for complex price schedules. The chapter “Do Consumers Respond to Marginal or Average Price? Evidence from Nonlinear Electricity Pricing” provides empirical evidence that consumers respond to average price rather than marginal price when faced with nonlinear electricity price schedules. Nonlinear price schedules, such as progressive income tax rates and multi-tier electricity prices, complicate economic decisions by creating multiple marginal prices for the same good. Evidence from laboratory experiments suggests that consumers facing such price schedules may respond to average price as a heuristic. I empirically test this prediction using field data by exploiting price variation across a spatial discontinuity in electric utility service areas. The territory border of two electric utilities lies within several city boundaries in southern California. As a result, nearly identical households experience substantially different nonlinear electricity price schedules. Using monthly household-level panel data from 1999 to 2008, I find strong evidence that consumers respond to average price rather than marginal or

expected marginal price. I show that even though this sub-optimizing behavior has a minimal impact on individual welfare, it can critically alter the policy implications of nonlinear pricing.

The second chapter "How Do Consumers Respond to Nonlinear Pricing? Evidence from Household Water Demand" provides similar empirical evidence in residential water markets. In this paper, I exploit variation in residential water pricing in Southern California to examine how consumers respond to nonlinear pricing. Contrary to the standard predictions for nonlinear budget sets, I find no bunching of consumers around the kink points of their nonlinear price schedule. I then explore whether consumers respond to marginal price, expected marginal price, or average price when faced with nonlinear water price schedules. The price schedule of one service area was changed from a linear price schedule to a nonlinear price schedule. This policy change led to an increase in marginal price and expected marginal price but a decrease in average price for many consumers. Using household-level panel data, I find strong evidence that consumers respond to average price rather than marginal or expected marginal price. Estimates of the short-run price elasticity for the summer and winter months are $-.127$ and $-.097$, and estimates of the long-run price elasticity for the summer and winter months are $-.203$ and $-.154$.

I conclude with "The Effect of Cash Rewards on Energy Conservation: Evidence from a Regression Discontinuity Design" to examine the effect of an alternative form of nonlinear pricing that was developed to provide an explicit financial incentive for conservation. In the summer of 2005, California residents received a 20% discount on their summer electricity bills if they could reduce their electricity consumption by 20% relative to 2004. Nearly all households automatically participated in the program, but the eligibility rule required households to have started their electricity service by a certain cutoff date in 2004. This rule generated an essentially random assignment of the program among households that started their service right before and after the cutoff date. Using household-level monthly billing records from the three largest California electric utilities, I find evidence that the rebate incentive reduced consumption by 5% to 10% in the areas where summer temperature is persistently high and income-level is relatively low, but the estimated treatment effects are nearly zero in other areas. To save 1 kWh of electricity, the program cost 2 cents in inland areas, 91 cents in coastal areas, and 14.8 cents for all service areas.

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Chapter 1

Do Consumers Respond to Marginal or Average Price? Evidence from Nonlinear Electricity Pricing

1.1 Introduction

Economic theory generally assumes that individuals use marginal prices to make economic decisions. This assumption plays a particularly critical role in the design of nonlinear price schedules in taxation and retail pricing. For example, taxpayers on a progressive income tax schedule pay nonlinear income tax rates that change with taxable income. In standard economic models, taxpayers are assumed to know the nonlinear tax structure, and make decisions on their labor supply with respect to the marginal tax rate they would pay for an additional hour of work. Theoretical and empirical studies of optimal taxation generally take this assumption as given when examining the welfare consequence of nonlinear taxation (e.g. Mirrlees 1971, Atkinson and Stiglitz 1976, Diamond 1998, Saez 2001). Likewise, firms use nonlinear price schedules in a wide variety of markets: electricity, natural gas, water, transportation, and cell phone networks. A common way to study the policy outcomes of such pricing strategies is to estimate demand based on the assumption that consumers are fully aware of, and therefore respond to, the marginal price of the nonlinear price schedules (e.g. Reiss and White 2005, Olmstead, Hanemann, and Stavins 2007).

Evidence from a series of recent studies, however, suggests that individuals may not respond to nonlinear pricing in a way that the standard economic model predicts. A large number of surveys show that a majority of people do not know the marginal price of their nonlinear tax, electricity, and water rates.¹ Furthermore, in laboratory experiments, many

¹Liebman (1998) and Fujii and Hawley (1988) find substantial confusion about marginal tax rates. Brown, Hoffman, and Baxter (1975) find that only 4.4% of households know their marginal price of electricity, and

individuals show cognitive difficulty in understanding nonlinear price structures, and many of them use their average price rather than actual marginal price to make economic decisions.² Finally, most studies do not find bunching of individuals around the kink points of nonlinear price schedules as first noted by Heckman (1983).³ The absence of bunching implies either that individuals respond to marginal price with nearly zero elasticity or that they respond to other perceptions of price rather than the actual marginal price they are paying.

In this paper, I explore three possible predictions about how consumers respond to nonlinear price schedules. In the standard model of nonlinear budget sets, consumers face no uncertainty about their consumption and there is no cognitive cost to process information about complex price schedules. In this case, a standard utility maximization problem leads them to respond to marginal price. Alternatively, if consumers account for uncertainty about their consumption, they use expected marginal price to maximize expected utility.⁴ Finally, consumers may make a sub-optimal choice by using the average price of their total payment as an approximation of the actual marginal price. Liebman and Zeckhauser (2004) describe this behavior as “schmeduling” and note that consumers may make this sub-optimal choice particularly because the information required to calculate average price is readily available, whereas marginal price response requires an understanding of the details of the nonlinear price structure.

I exploit a spatial discontinuity in electric utility service areas in southern California to empirically examine whether consumers respond to marginal, expected marginal, or average price when faced with nonlinear electricity price schedules. The service area border of two electric utilities lies within city boundaries in several cities. As a result, households in the same city are served by two different electric utilities. I specifically focus on households located within one mile of the utility border; their demographics, housing characteristics, and weather conditions are nearly identical. However, households in one utility service territory experience substantially different nonlinear electricity price schedules than the households in the other service territory because the two electric utilities independently set their price schedules. This is a nearly ideal research environment to investigate how individuals respond to nonlinear price schedules. Most previous studies of nonlinear tax and price schedules lack

Carter and Milon (2005) find that only 6% of households know their marginal price of water.

²For example, de Bartolome (1995) finds that many individuals in his laboratory experiment use their average tax rate as if it is their marginal tax rate when making economic decisions based on tax tables.

³Most studies of income tax records do not find bunching except for self-employed workers. For example, Saez (1999) finds no bunching across wage earners in income tax schedules in tax return data in the US. Chetty et al. (2010) find small but significant bunching for wage earners in their Danish tax recode data, although institutional factors in Denmark are likely to affect the bunching in addition to labor supply responses. In electricity, Borenstein (2009) finds no bunching in household-level electricity billing data.

⁴Saez (1999) and Borenstein (2009) suggest that individuals may use expected marginal price in the presence of uncertainty. Although MaCurdy, Green, and Paarsch (1990) do not explicitly consider expected marginal price, their application of a differentiable approximation to nonlinear tax schedules leads to a similar price schedule to a series of expected marginal price with a normally distributed error term.

clean control groups, which creates several identification problems.⁵

My empirical analysis relies on a panel data set of household-level monthly electricity billing records for nearly all households on either side of the utility border. This confidential data set is directly provided by the two electric utilities, Southern California Edison (SCE) and San Diego Gas & Electric (SDG&E). The data set includes detailed information about each customer's monthly bills from 1999 to 2008. Throughout the sample period, each utility independently changed their price schedules multiple times. As a result, this ten-year sample period enables me to exploit both cross-sectional and time-series price variation to investigate how consumers respond to nonlinear pricing.

I find strong empirical evidence that consumers respond to average price rather than marginal or expected marginal price. The evolution of consumption from 1999 to 2008 is inconsistent with the prediction that consumption is affected by marginal price. In particular, when marginal price and average price change in opposite directions, consumption moves in response to average price. In my econometric estimation, I find that when different price variables are jointly estimated, the partial effect of average price is economically and statistically significant, whereas marginal price and expected marginal price have statistically insignificant effects on electricity consumption. These results are robust when I limit the sample to households even closer to the utility border.

Why do consumers respond to average price rather than marginal price? One possible explanation is that it can be seen as bounded rational to use average price for an approximation of actual marginal price if the cognitive cost of responding to marginal price is higher than the utility gain. In fact, a small cognitive cost can lead consumers to rely on average price because the utility gain from re-optimizing consumption with marginal price is likely to be quite small given that consumers have already optimized with respect to average price. For example, even with one of the steepest nonlinear price schedules in the sample period, consumers with quasilinear utility can gain less than \$2 per month on average by re-optimizing consumption with respect to marginal price rather than average price.⁶

Even though this sub-optimal response has a minimal impact on individual welfare, it can critically alter two important welfare implications of nonlinear pricing.⁷ First, a major policy objective of California's nonlinear electricity pricing is to promote energy conservation. For the same reason, many electric, natural gas, and water utilities in the US switched from

⁵Heckman (1996), Blundell, Duncan, and Meghir (1998), Goolsbee (2000), and Saez, Slemrod, and Giertz (2009a) describe why the natural experiment approach commonly used in studies of nonlinear price schedules is likely to violate the identification assumptions.

⁶I calculate this utility gain with a price elasticity assumption of -0.5. The utility gain from the re-optimization becomes even smaller if a smaller price elasticity is assumed.

⁷An individual consumer does not lose much surplus by using her average price as an approximation of the marginal price because optimization with respect to the average price is near rational (Akerlof and Yellen 1985 and Mankiw 1985). However, the collection of such behavior has significant effects on the welfare implications of nonlinear pricing.

a flat rate schedule to a nonlinear price schedule.⁸ I show that the sub-optimal response makes nonlinear price schedules less successful in reducing total consumption. In particular, I find that California’s current five-tier electricity tariffs may result in a slight increase in total consumption compared to an alternative flat rate tariff if consumers respond to average price. Second, introducing nonlinear electricity pricing results in deadweight loss because the structure of the price schedules usually do not reflect the marginal cost of electricity. I investigate how the sub-optimal response affects the efficiency costs of nonlinear pricing. With a reasonable range of marginal costs of electricity, the sub-optimal response reduces the efficiency costs of nonlinear pricing. I show that, however, when the social marginal cost of electricity is substantially higher than the private marginal cost (e.g. because of negative environmental externalities from electricity generation), the sub-optimal response will increase the efficiency costs.

This study contributes to the literature on nonlinear pricing in two ways. First, my empirical strategy addresses the identification problems that have hampered previous studies of nonlinear tax and price schedules. A commonly used difference-in-differences (DD) approach in the literature relies on time-series price variation in nonlinear price schedules. For example, the income tax literature typically uses tax reforms as a source of identification: when the tax rates applicable at certain income levels change more substantially than the tax rates at other income levels, some taxpayers are more likely to face large changes in the applicable tax rate than others. Heckman (1996), Blundell, Duncan, and Meghir (1998), Goolsbee (2000), and Saez, Slemrod, and Giertz (2009a) note that this standard DD estimation requires a parallel trend assumption between high income earners and low income earners, which is likely to be violated. Indeed, Borenstein (2009) and Saez, Slemrod, and Giertz (2009a) apply the standard DD approach to time-series price variation in electricity prices and income tax rates, and find that estimation results are sensitive to the choice of control variables, instruments, and time periods of the price variation. My identification strategy takes a difference-in-difference-in-differences (DDD) approach by using households on the other side of the utility border as a control group. Therefore, it allows for different underlying trends between high and low electricity users, as long as the differences in the trends are not systematically different across the utility border.

The second contribution of this paper is that the estimation results provide strong empirical evidence based on field data that consumers respond to average price rather than marginal or expected marginal price when faced with nonlinear price schedules. Aside from laboratory experiments (e.g. de Bartolome 1995), evidence from field data has been limited because non-experimental data rarely provide sufficient exogenous price variation to separately identify the impact of the three prices. In a typical nonlinear price schedule, the

⁸BC Hydro (2008) conducts a survey of 61 U.S. utilities and finds that about one-third of them use increasing block pricing for residential customers.

marginal, expected marginal, and average price are highly collinear, which creates multicollinearity problems between the variables. As a result, previous studies present inconclusive results (e.g. Liebman and Zeckhauser 2004 and Borenstein (2009)).⁹ My empirical strategy exploits rich cross-sectional and time-series price variation across the utility border. In particular, consumers in one utility service area often experience an increase in marginal price but a decrease in average price relative to consumers in the other utility service area. This price variation enables me to separately identify the effects of marginal, expected marginal, and average price on consumption.

This paper also relates to several recent studies on limited attention to complex and less salient price incentives: tax rates (Chetty, Looney, and Kroft 2009), price vs. shipping fees (Hossain and Morgan 2006, Brown, Hossain, and Morgan 2010), and rebates for car purchases (Busse, Silva-Risso, and Zettelmeyer 2006). My empirical results support that, at least in the case of electricity demand, consumers facing nonlinear price schedules optimize consumption with respect to their average price rather than the actual marginal price they are paying. Although further studies are required to generalize this result to nonlinear price schedules in other contexts,¹⁰ the findings of this paper suggest that the presence of average price response can be a possible explanation for why most previous studies do not find bunching of individuals around the kink points in nonlinear tax and price schedules.

Finally, the results have important implications for US climate change legislation. In the cap-and-trade program proposed in the American Clean Energy and Security Act of 2009, about 30% of emission permits are to be given to electric utilities as a free allowance.¹¹ The proposal explicitly prohibits electric utilities from distributing the value to their customers based on a customer's electricity consumption. Instead, it recommends providing a fixed credit on electricity bills. The rationale behind the policy is to preserve a consumer's incentive to conserve electricity by not reducing the marginal price. However, if customers respond to the average price of their electricity bills, the fixed credit also discourages conservation, and therefore may increase electricity consumption.¹²

⁹Liebman and Zeckhauser (2004) use variation in average and marginal tax rates created by the introduction of child credit. They note that their results may not be conclusive because the estimates may not be global minimum in their maximum likelihood estimation. Borenstein (2009) finds that consumers are more likely to respond to their expected marginal price or average price rather than their marginal price, however, reports that is inconclusive whether consumers respond to their expected marginal price or average price. Shin (1985) finds evidence of average price response in electricity consumption, but the evidence is based on aggregate annual consumption data at the electric utility level.

¹⁰To date, there is limited number of studies that use field data to examine whether taxpayers respond to their marginal or average income tax rates. For example, Feldman and Katuscak (2006) present that their findings in the child tax credit data are more consistent with the response to average tax rates.

¹¹The bill is also known as the Waxman-Markey Bill. It was approved by the House of Representatives on June 26, 2009, and is still in consideration in the Senate.

¹²Use of allowances is described on page 901 of Congress (2009). "In general, an electricity local distribution company shall not use the value of emission allowances distributed under this subsection to provide to any ratepayer a rebate that is based solely on the quantity of electricity delivered to such ratepayer"... "it shall,

The paper proceeds as follows. Section 2 presents a conceptual framework for the analysis. Section 3 describes the research design and data. Section 4 presents the empirical framework. Section 5 presents the results, and Section 7 examines the welfare consequences of the sub-optimal response to nonlinear price schedules. Section 8 concludes and discusses future research avenues.

1.2 Conceptual Framework and Theoretical Predictions

This section describes a conceptual framework of how consumers make economic decisions when faced with nonlinear price schedules. I first present the standard model of nonlinear budget sets, where consumers face no uncertainty about their consumption, and there is no cognitive cost of processing information about complex price schedules. Second, I consider consumer behavior in the presence of uncertainty about consumption. Finally, I introduce cognitive and information costs of complex price schedules and consider a possibility of limited attention to such price schedules.

1.2.1 The Standard Model of Nonlinear Budget Sets¹³

Consider a consumer who faces a two-tier nonlinear electricity price schedule for electricity consumption x . The marginal price equals p_1 for up to k units of consumption and p_2 for any additional consumption. Suppose that the consumer has wealth W and quasilinear utility:¹⁴

$$u(x, y) = W + V(x). \tag{1.1}$$

In the standard model of nonlinear budget sets, the consumer solves the following utility maximization problem:

$$\max_x u(x) = W - (p_1 \cdot x_1 + p_2 \cdot x_2) + V(x), \tag{1.2}$$

to the maximum extent practicable, provide such rebates with regard to the fixed portion of ratepayers' bills or as a fixed credit or rebate on electricity bills." Burtraw (2009) and Burtraw, Walls, and Blonz (2010) note that distributing a fixed credit may not work in the desired way if residential customers do not pay attention to the difference between their marginal price of electricity and their electricity bill.

¹³Burtless and Hausman (1978), Hanemann (1984), Hausman (1985), and Moffitt (1990) provide detailed discussions about consumer maximization problems under nonlinear (kinked) budget constraints.

¹⁴Quasilinear utility functions assume that there is no income effect on electricity consumption. With more general forms of utility functions, such income effects affect a consumer's maximization problem through the consumer's virtual income. In the case of residential electricity demand, however, income effects are likely to be extremely small. In my sample, a median consumer pays \$60 electricity bill per month, therefore even a 50% change in average price would produce an income change of \$30 per month, about 0.4% of monthly median household income. In the literature, estimates of the income elasticity of residential electricity demand is between 0.1 to 1.0. Therefore, the income effect of this price change would result in a change in consumption between 0.04% to 0.4%.

where x_1 and x_2 are consumption in the first and second tier. The demand under the standard model can be described as:

$$x_{MP}^* = \begin{cases} x^*(p_1) & \text{if } x^*(p_1) \leq k \\ k & \text{if } x^*(p_2) \leq k \leq x^*(p_1) \\ x^*(p_2) & \text{if } x^*(p_2) \geq k, \end{cases} \quad (1.3)$$

where $x^*(p_1)$ and $x^*(p_2)$ are the demand when the consumer faces a linear price schedule of p_1 or p_2 .

The model provides two important predictions. First, if consumer preferences are convex and smoothly distributed across the kink point k , the distribution of consumption should show bunching of consumers across the kink (Heckman 1983). In other words, a disproportionately large number of indifference curves would intersect the kink of the nonlinear budget constraint. Saez (2009) shows how elasticities can be estimated by examining bunching around kinks under the assumption that individuals respond to nonlinear price schedules as the standard model predicts. Second, when consumers are on the linear part of the price schedule, they optimize their consumption with respect to the marginal price they face.

In the simplest model, consumers do not have uncertainty about their consumption. For example, monthly electricity consumption is likely to involve uncertainty because of unexpected demand shocks during the monthly billing period. Saez (1999) and Borenstein (2009) introduce models that relax this assumption. If consumers are aware of their uncertainty, their optimal choice is to react not to the ex-post marginal price but to their expected marginal price. For example, if consumers believe that they will have a stochastic error ϵ in x during the billing period, they solve

$$\max_x E[u(x)] = W - E[(p_1 \cdot x_1 + p_2 \cdot x_2)] + E[V(x)]. \quad (1.4)$$

The first order condition implies that they choose x_{EMP}^* where the expected marginal utility is equal to the expected marginal price. Note that this optimization behavior requires the same or slightly more information than the standard model. As with the standard model, consumers need to know about price structures, and also need to take into account their uncertainty about electricity consumption during the billing period.

1.2.2 A Model with Limited Attention to Complex Price Schedules

Although most previous studies use the standard model to estimate the behavioral response to nonlinear price schedules, they assume that consumers pay considerable attention to price

schedules and consumption levels. If the information cost is high, and there is another way to approximate their actual price reasonably, consumers may use a simplified price to guide their consumption.

Liebman and Zeckhauser (2004) point out a possible behavior in their alternative model called “schmeduling.” They claim that under complex nonlinear price schedules, people may make a sub-optimal choice by responding to the average price of their total payment. I consider a model with cognitive and information costs. Similar to Chetty (2009), I consider that consumers have two choices. First, they can pay a cost c to get the necessary information to respond to their marginal or expected marginal price. This cost includes the time to look up their actual price structure, understand their billing cycle, and monitor their cumulative consumption levels. Alternatively, consumers can use their average price to approximate electricity prices. In this way, consumers do not necessarily understand nonlinear price structures. Looking at their total payment and total usage tells them about their average price. Even this behavior involves some costs compared to the choice of completely ignoring electricity bills. Thus, I consider that the cost of responding to average price is normalized to zero, and therefore, c implies the relative cost of responding to marginal price as compared to average price.

If consumers use their average price, their problem is:

$$\max_x u(x) = W - AP(x) \cdot x + V(x). \quad (1.5)$$

Consumers choose x_{AP}^* that maximizes their utility. Then the resulting demand function x^{**} can be described as:

$$x(p)^{**} = \begin{cases} x_{MP}^* & \text{if } \Delta u(p) \equiv u(x_{MP}^*) - u(x_{AP}^*) \geq c \\ x_{AP}^* & \text{otherwise.} \end{cases} \quad (1.6)$$

Therefore, the key condition is $\Delta u(p) \equiv u(x_{MP}^*) - u(x_{AP}^*) \geq c$. The information cost c is unobservable, but it is possible to calculate the magnitude of $\Delta u(p)$ by assuming a functional form for the utility function. For example, suppose the utility function has the following form:

$$V(x) = \begin{cases} a_i \frac{1}{1+1/\beta} x^{1+1/\beta} & \text{if } \beta \neq -1 \\ a_i \ln(x) & \text{if } \beta = -1. \end{cases} \quad (1.7)$$

Then, the optimal demand for the standard model and the inattention model can be described as:

$$x_{MP}^*(p) = \left(\frac{MP(x_{MP}^*)}{a_i} \right)^\beta \quad (1.8)$$

$$x_{AP}^*(p) = \left(\frac{AP(x_{MP}^*)}{a_i} \right)^\beta. \quad (1.9)$$

With this quasilinear utility function, $\Delta u(p)$ simply equals the difference in consumer surplus between $x_{MP}^*(p)$ and $x_{AP}^*(p)$. As an example, I calculated $\Delta u(p)$ using Southern California Edison's price schedule in 2007. With price elasticity $\beta = -0.5$, $\Delta u(p) \approx \$2$ per month for average consumers. It means that consumers can get \$2 per month as a utility gain if they re-optimize their consumption with respect to their actual marginal price instead of their average price. The average monthly bill is around \$60, therefore, the gain is about 3% of the average consumer's electricity bill. If this utility gain is less than the information cost c , consumers are better off using their average price than the actual marginal price they are paying.¹⁵

Therefore, the different models provide at least three different predictions for how consumers react to nonlinear pricing. The standard model predicts that consumers respond to marginal price. If there is uncertainty about consumption, consumers may react to expected marginal price. Finally, the inattention model predicts that they will use average price as a proxy for actual marginal price if the cost for re-optimization c is larger than the gain from re-optimizing. In the rest of the paper, I empirically examine which model best explains consumer behavior by examining household electricity demand under nonlinear electricity pricing.

1.3 Research Design and Data

The research design of this study has three key components that constitute the research environment where nearly identical groups of households experience substantially different nonlinear price schedules. First, in six cities in my sample, households in the same city are served by two different electric utilities because the service area border of the two utilities lies within the city boundaries. Second, I focus on households located within one mile of the utility border so that demographics, housing characteristics, and weather conditions are nearly identical between households in one side of the utility border and those in the other side. Third, the two groups of households experience substantially different nonlinear price

¹⁵Chetty (2009) shows a similar simulation using income tax rate schedules. He compares the utility gain between 1) not responding to tax rate changes and 2) responding to the change in marginal tax rates. In my case, I compare the utility gain between i) responding to marginal prices and ii) responding to average prices.

schedules because the two utilities independently set their price schedule. I describe the details of the three components in the following sub-sections.

1.3.1 A Spatial Discontinuity in Electric Utility Service Areas

Southern California Edison (SCE) and San Diego Gas & Electric (SDG&E) are investor-owned electric utilities that provide electricity in southern California. Figure 1.1 presents the territory map of the two utilities. SCE provides electricity for large parts of southern California, whereas SDG&E covers a major part of San Diego County and the southern part of Orange County. This study particularly focuses on their territory border in Orange County.

Figure 1.2 shows the territory border of the two utilities and city boundaries in Orange County. In six cities, the territory border of the two utilities lies within city boundaries. SCE serves the north side and SDG&E serves the south side of the utility border. As a result, households in the same city are served by the two different electric utilities. In most parts of the US, utility borders lie along city, county, or state boundaries. In this area, by contrast, the utility border lies within the city boundaries because the utility border had been established long before the city boundaries were defined.¹⁶

This study area provides several additional advantages for examining nonlinear electricity pricing. First, the two groups of households experience substantially different pricing because the two utilities change their price schedules independently over time. Second, the utility borders lie in populated areas, which allows me to have a large number of observations even when restricting the sample to households within one mile of the utility border. Third, all households in this area are served by the same natural gas provider, Southern California Gas Company, therefore both groups of households receive separate gas and electric bills. Finally, locations of buildings solely determine which electric utility serves a given household; households cannot choose their retail service providers.

I focus on households that are located within one mile of the utility border to conduct my analysis for comparable groups of households. In addition, I exclude the two cities, Rancho Santa Margarita and Las Flores, that do not have the utility border inside the city limits. The research design is similar to a regression discontinuity design (RDD) in Black (1999). Black uses housing prices across school district boundaries to estimate how school quality affects housing prices. I examine changes in electricity consumption across the utility border to estimate how nonlinear pricing affects household electricity consumption. An important distinction between Black (1999) and this study's research design is that I use a panel data set for each group of households whereas Black uses a cross sectional data set.

¹⁶In 1940's, SCE and SDG&E connected their the transmission lines in this area and established the territory border (Crawford and Society. 1991 and Myers 1983). Most city boundaries in this area were established around 1980's.

Therefore, the spatial discontinuity in electric utility service areas allows me to control for time-variant unobservable shocks as well as time-invariant unobservable factors. The next section describes the data and summary statistics for each group of households.

1.3.2 Data and Summary Statistics

The primary data of this study consist of a panel data set of household-level monthly electricity billing records from 1999 to 2008. Under a confidentiality agreement, SCE and SDG&E provided the complete billing history of essentially all residential customers in their service areas.¹⁷ Each monthly record includes a customer’s account ID, premise ID, billing start date and end date, monthly consumption, monthly bill, tariff type, climate zone, and nine-digit zip code. The names of customers and their exact addresses are excluded in the records made available for this study.

The billing data do not include price and demographic information. I collect historical price schedules using documents published by each utility and the California Public Utility Commission. To ensure the preciseness of the price information, I verify that it is consistent with each customer’s monthly bill in the billing data. To obtain demographic information, I match each customer’s nine-digit zip code to a census block group in the 2000 US Census data.

In the focus area of this study, I use households that satisfy the following criteria. First, I focus on households that are on the standard price schedule.¹⁸ Second, I use premises that exist during my whole sample period from 1999 to 2008. This procedure results in a data set of 54,280 premises in six cities: Laguna Beach, Laguna Niguel, Aliso Viejo, Laguna Hills, Mission Viejo, and Coto de Caza. The sample includes 25,710 premises in SCE’s territory and 28,570 premises in SDG&E’s territory.

Table 1.1 summarizes demographic characteristics within one mile of the utility border. I match each household’s nine-digit zip code to a US Census block group, and then calculate the mean of each demographic variable on each side of the border. The table also includes the mean electricity consumption in 1999, in which SCE and SDG&E had nearly the same two-tier nonlinear price schedules with only slightly higher prices for SCE customers. Demographic characteristics and electricity consumption in 1999 are comparable across the utility border except that the SDG&E side includes slightly more households that fall into the top income category.

¹⁷A very small number of customers are not individually metered in this area. The data sets include only individually-metered customers.

¹⁸In both utility areas, over 85% of households are on the standard tariff schedule that is default for customers. In addition, about 15% of households are on the California Alternative Rate for Energy (CARE) program, a means-tested price schedule for low income households. The rest of custom res are on other tariffs such as time-of-use pricing. This study focuses on households that are on the standard tariff.

1.3.3 Price Variation

Households across the utility border experience substantially different nonlinear price schedules. Figure 1.3 shows an example of their cross-sectional price variation in August 2002. The marginal price of electricity is a step function of monthly consumption. The utilities allocate a “baseline” consumption level for households. The baseline depends on a household’s climate zone that is defined by the utilities. Within the climate zone, however, the baseline is the same for all households regardless of their household size or housing structure. Because households in this study area are in the same climate zones, they receive essentially the same amount of baselines.¹⁹ Their price schedules consist of five-tier electricity rates; the marginal price equals the first tier rate up to 100% of the baseline, the second tier rate up to 130%, the third tier rate up to 200%, the fourth tier rate up to 300%, and the fifth tier rate over 300% of the baseline.

In addition to the cross-sectional price variation, the five tier rates have different time-series price variation between the two utilities. Figure 1.4 displays each of the five tier rates over time. In 1999 and early 2000, SCE and SDG&E had nearly the same two-tier nonlinear price schedules with only slightly higher prices for SCE customers. The first price shock occurred during the California electricity crisis in the summer of 2000.²⁰ The rates for SDG&E customers started to increase in May in response to increases in wholesale electricity prices. In August, the first and second tier rates increased to 22.74¢ and 25.17¢. This increase translated into a 100% rate increase for SDG&E customers relative to their rates in 1999. The rates for SCE customers, in contrast, stayed at 1999 levels because their retail prices were not affected by wholesale prices. The second price shock happened in 2001, when SCE introduced five-tier price schedules in June, and SDG&E followed four months later, although their rates were different. Afterwards, the utilities changed the tier rates differently over time.

Their price schedules are regulated by the California Public Utility Commission. Each utility proposes a rate change independently to the commission, and the rate change is applied to consumers after the commission’s approval. The two utilities have different price schedules for the following reasons. First, they have different electricity generation portfolios. Therefore, changes in input costs affect their total costs of generation differently. Second,

¹⁹In summer billing months, both SCE and SDG&E customers in this area receive 10.2 kWh per day for their baseline. In winter billing month, the baseline is 10.1 kWh per day for SCE customers and 10.8 kWh per day for SDG&E customers. In the billing data, the monthly bills and price variables are calculated based on the exact baseline of each individual bill.

²⁰By August of 2000, wholesale energy prices had more than tripled from the end of 1999, which caused large-scale blackouts, price spikes in retail electricity rates, financial losses to electric utilities in California. Many cost factors and demand shocks contributed to this rise, but several studies have also found the market power of suppliers to be significant throughout this period. See Joskow (2001), Borenstein, Bushnell, and Wolak (2002), Bushnell and Mansur (2005), Puller (2007), and Reiss and White (2008).

the utilities have different sunk losses from the 2000-01 California electricity crisis that is need to be collected from ratepayers. Third, as Figure 1.2 shows, SCE and SDG&E cover very different service areas in southern California, therefore, face different total demand and costs of electricity distributions.

The price variation has three advantageous features in estimating the response to non-linear price schedules. First, the magnitude of the variation is substantial. Cross-sectionally, households on either side of the utility border always have substantially different tier rates. These tier rates, furthermore, changed frequently over time. Second, the time-series price change is non-monotonic. For example, compared to SCE, the fifth tier rate in SDG&E was higher in 2000, lower in 2001, 2002, and 2003, higher in 2004 and 2005, lower in 2006, 2007, and 2008, and again higher in 2009. Finally, the difference in marginal prices on either side of the utility border is often significantly different from the difference in average prices. Figure 1.3, for example, shows the marginal and average price in August 2002. Consider customers on the third tier. The marginal price is essentially the same across the utility border. The average price, however, is higher for SDG&E customers. Similarly, consider customers on the fourth tier. The marginal price is higher for SCE customers, whereas the average price is higher for SDG&E customers. The price variation helps identify whether households respond to marginal or average price.

1.4 Identification and Estimation

This section describes the econometric models that I use to estimate the response to nonlinear electricity prices. Most of the recent literature on nonlinear budget sets employ difference-in-differences methods that use changes in nonlinear rate schedules as the source of identification. I first discuss identification problems in the conventional methods and then introduce the present study's identification strategy.

1.4.1 A Conventional Approach Using Panel Data

Let x_{it} denote household i 's average daily electricity consumption during billing month t and $p_t(x_{it})$ be the price of electricity, which is either the marginal or average price of x_{it} . Suppose that the household has a quasi-linear utility function and responds to electricity prices with a constant elasticity β . Then, the demand function can be described as:

$$\ln x_{it} = \alpha_i + \beta \ln p_t(x_{it}) + \eta_{it}, \quad (1.10)$$

with a household fixed effect α_i and an error term η_{it} . Note the assumptions in the model. First, a quasi-linear utility function eliminates income effects from a price change. Second,

the response to price is immediate and does not have lagged effects. Third, the elasticity is constant over time and over households. I first focus on the simple model and then come back to these assumptions.

Ordinary Least Squares (OLS) produce an inconsistent estimate of β because $p_t(x_{it})$ is a function of x_{it} . Under increasing block price schedules, η_{it} is positively correlated with $p_t(x_{it})$.²¹ To overcome the simultaneity bias, previous studies use the following difference-in-differences method with changes in rate structures. Suppose that between year t_0 and t , a utility changes the tier rates of their increasing block schedule. If the tier rates applicable at certain consumption levels change more substantially than other tier rates, households with different levels of consumption tend to experience different price changes. For example, if the utility increases the top tier rate and does not change other tier rates, households with larger consumption are more likely to experience a price increase. Therefore, ex-ante consumption x_{it_0} may predict the price change that each household will face. Let $\Delta \ln x_{it} = \ln x_{it} - \ln x_{it_0}$ denote the log change in household i 's consumption between a billing period in year t_0 and the same billing period in year t , and $\Delta \ln p_t(x_{it}) = \ln p_t(x_{it}) - \ln p_{t_0}(x_{it_0})$ the log change in the price. Consider the two-stage least squares (2SLS) estimation for the equation:

$$\Delta \ln x_{it} = \alpha'_i + \beta \Delta \ln p_t(x_{it}) + \varepsilon_{it}, \quad (1.11)$$

instrumenting for $\Delta \ln p_t(x_{it})$ with $\widehat{\Delta \ln p_t(x_{it})} = \ln p_t(x_{it_0}) - \ln p_{t_0}(x_{it_0})$ where $p_t(x_{it_0})$ is the predicted price in period t with household i 's consumption in t_0 . Given that the price schedule $p_t(\cdot)$ itself is exogenous to the household, the 2SLS produces a consistent estimate of β if x_{it_0} is uncorrelated with $\varepsilon_{it} = \eta_{it} - \eta_{it_0}$.

1.4.2 Econometric Identification Problems

The condition $Cov(\varepsilon_{it}, x_{it_0}) = 0$ requires a parallel trend assumption: in the absence of price changes, households with larger x_{it_0} and those with smaller x_{it_0} would have equivalent changes in their consumption. The recent empirical literature on nonlinear budget sets points out two concerns for this identifying assumption.²²

First, instruments based on x_{it_0} create a mean reversion problem. Suppose that a household gets a positive transitory shock at t_0 . Then, the observed consumption is larger at t_0 and smaller at t_1 aside from any response to a price change. That is, in panel data of household electricity consumption, mean reversion produces a negative correlation between x_{it_0} and $\varepsilon_{it} = \eta_{it} - \eta_{it_0}$. This systematic negative correlation produces substantial bias par-

²¹For example, if a household has a positive shock in η_{it} (e.g. a friend's visit) that is not observable to researchers, the household will locate in the higher tier of its nonlinear rate schedule.

²²Saez, Slemrod, and Giertz (2009a) provides a detail discussion of similar identification problems in empirical studies of the labor supply response to income taxes.

ticularly when a price change is concentrated at lower or higher levels of consumption, which is often the case in changes in nonlinear rate schedules. One potential solution is to estimate mean reversion using multiple years of data with assumptions on its parametric functional form and its stability over time. In general, however, the functional form of mean reversion is unknown, and thus the identification of behavioral response to a rate change will entirely rely on the functional form assumption of mean reversion.²³

Second, in addition to mean reversion, one needs to control for any changes that differentially affect households with different levels of consumption. For example, economic shocks or weather shocks may have systematically different effects on households across different consumption levels. Moreover, if there is an underlying distributional change in electricity consumption between time periods, it needs to be disentangled from rate changes.

1.4.3 Identification Using Price Variation Across the Utility Border

To prevent the mean reversion problem, recent studies suggest using repeated-cross section analysis (e.g. Saez 2004, Saez, Slemrod, and Giertz 2009a). To understand the concept of this approach, suppose that there is a distribution of household electricity consumption that does not change from time t_0 to t_1 in the absence of price changes. Suppose that the utility increases the top tier rate of the nonlinear price schedule from t_0 to t_1 . Then, if consumers have negatively sloped demand curves, the upper end of the distribution should shift towards the middle. Thus, if the distribution is otherwise stable between the two periods, it is possible to estimate the price elasticity directly by looking at the changes in distribution.

Following Saez (2004), I first illustrate the case in which I use only one electric utility. Suppose that the utility changes its price schedule over time. The goal is to examine how the price change affects the distribution of consumption. As an example, consider the top 10% of the distribution in each time period. The 2SLS

$$\ln x_{it} = \beta \ln p_t(x_{it}) + \lambda + Z'_{it} \delta + \varepsilon_{it}, \quad (1.12)$$

using time dummy variables $Time_t$ as instruments consistently estimates the price elasticity α if $Cov(Time_t, \varepsilon_{it}) = 0$ for each t . This assumption is violated if there are time-specific unobservable shocks that are not captured by the control variables in Z_{it} .

To control for time-specific unobservable factors, I use two electric utilities and households located within 1 mile of the utility border. Consider the top 10% consumption in each utility for each t . I run the following 2SLS

²³For example, Gruber and Saez (2002) use tax reforms in multiple years and include flexible parametric functions of base year income to control for the mean reversion of individual income by assuming that the mean reversion does not change between different years.

$$\ln x_{it} = \beta \ln p_{ut}(x_{it}) + \gamma_u + \lambda_t + Z'_{it} \delta + \varepsilon_{it}, \quad (1.13)$$

using the interaction of time dummy variables and a utility dummy variable $Time_t \cdot Utility_i$ as instruments. γ_u is a utility fixed effect and λ_t is a time fixed effect. The identification assumption is that $Cov(Time_t \cdot Utility_i, \varepsilon_{it}) = 0$ for each t . Thus, the required assumption is the usual parallel trend assumption in difference-in-differences (DD) estimation: in the absence of price change, the top 10% of consumption evolves in the same way on either side of the utility border conditional on Z_{it} . To examine how each part of consumption distribution changes with respect to changes in prices, I run equation (1.13) for the top 10% of the distribution, the next 10%, ..., and the last 10% separately.

In this DD approach, the identification assumption holds as long as there is no systematic differences in time-specific unobservable shocks on either side of the utility border. In the samples located within 1 mile of the border, this identification assumption is probably reasonable. One way to check the plausibility of this assumption is to look at changes in consumption in the years where there is no differences in a price change between the two utilities.

In addition, the identification assumption can be weakened by running difference-in-difference-in-differences (DDD) by pooling each part of the distribution. Denote G_1 as a dummy variable for the first decile group of the consumption distribution, G_2 for the second decile group, ..., and G_{10} for the top decile group of the consumption distribution. That is, the ten dummy variables G_g are simply group dummy variables for ten deciles. Pooling all data, I run the 2SLS

$$\ln x_{it} = \beta \ln p_{ut}(x_{it}) + \gamma_{ut} + \lambda_{gt} + \theta_{gu} + Z'_{it} \delta + \varepsilon_{it}, \quad (1.14)$$

using the three-way interactions of time dummy variables, decile group variables, and utility dummy variable $Time_t \cdot G_g \cdot Utility_i$ as instruments. As in the standard DDD estimation (e.g.. Gruber (1994) and Gruber and Poterba (1994)), this model provides full nonparametric control for utility-specific time effects that are common across decile (γ_{ut}), time-varying decile effects (λ_{gt}), and utility-specific deciles effects (θ_{gu}). The identification assumption is that $Cov(Time_t \cdot G_g \cdot Utility_i, \varepsilon_{it}) = 0$ for each t and g . Thus, the required assumption is that there is no contemporaneous shock that affects the *relative* outcomes of decile groups in the same utility for the same time period.

To test how consumers respond to nonlinear pricing, I include both marginal and average prices in the model. In this case, the estimating equation is

$$\ln x_{it} = \beta_1 \ln m p_{ut}(x_{it}) + \beta_2 \ln a p_{ut}(x_{it}) + \gamma_{ut} + \lambda_{gt} + \theta_{gu} + Z'_{it} \delta + \varepsilon_{it}. \quad (1.15)$$

The standard model predicts $H_0 : \beta_2 = 0$. Once the marginal price is included in the

model, the average price does not affect consumption. The model with inattention predicts $H_0 : \beta_1 = 0$. Once the average price is included in the model, the marginal price does not affect consumption. Note that in general, it is statistically difficult to separately identify β_1 and β_2 because changes in marginal prices and average prices are typically highly correlated in nonlinear rate schedules. When marginal and average prices move in the same way, the regression has multicollinearity problems and the standard errors for β_1 and β_2 become large. I exploit rich price variation across the utility border and over time to jointly estimate the two coefficients.

The nonparametric control variables γ_{ut} , λ_{gt} , and θ_{gu} flexibly control for unobservable economic and weather shocks to household electricity consumption. In addition to these variables, I include two sets of dummy variables in Z_{it} to control for unobservable factors in further flexible ways. The first set is time-varying city level fixed effects $City_t$ that captures time-variant unobservable shocks that are specific to each city. Second, consumers have different billing cycles, therefore, weather conditions can be different among different billing cycles given a billing month. To control for different shocks to each billing cycle, I also include time-varying billing cycle level fixed effects $Cycle_t$.

1.5 Results

This section presents three empirical findings of this paper. In the first part, I show that the histograms of electricity consumption do not reveal bunching of consumers around the kink points in nonlinear electricity price schedules. The absence of bunching implies either that consumers have nearly zero price elasticity for electricity demand, or that they respond to other perceptions of price than the actual marginal price they are paying. To investigate what can explain the absence of bunching, the second part examines the difference-in-differences in price and consumption within one mile of the territory border of the two electric utilities. Using price variation during the California electricity crisis, I demonstrate that consumers indeed respond to electricity prices with non-zero price elasticities. Furthermore, exploiting price variation during the full sample period from 1999 to 2008, I show graphical evidence that consumers respond to average price rather than marginal price. The final part of the analysis employs econometric estimation to statistically examine whether consumers respond to marginal, expected marginal, or average price when faced with nonlinear price schedules.

1.5.1 Bunching Around Kink Points

The standard model of nonlinear budget sets predict that consumers choose demand based on equation (2.3). Suppose that preferences for electricity consumption are convex and smoothly distributed in the population. Then, if households respond to their marginal price,

many demand curves intersect with the kinks, therefore disproportionately more households should bunch around the kinks.

In 1999, consumers faced essentially flat rate pricing with a slight step between the first and second tier. Therefore, the distribution of consumption in 1999 can provide a baseline case where there is no steep kink point in the price schedule. Panel A of Figure 1.5 displays a histogram of consumption for SCE customers in 1999. I use monthly consumption data from all twelve months in 1999. The histogram shows that the consumption is smoothly distributed.

After 2001, SCE introduced steep five-tier price schedules. With steep steps in the price schedule, the distribution of consumption should be different from the baseline case observed in 1999. Panel B of Figure 1.5 displays a histogram of consumption for SCE customers in 2007, where SCE customers had the steepest five-tier price schedule in my sample period. The histogram shows that the shape of the distribution is as smooth as the histogram in 1999, and there is no bunching around the kink points. In particular, there is no bunching even around the second kink, where the marginal price discontinuously increases by 80%.

The absence of bunching could be explained by two possible reasons. First, no bunching may imply that consumers have nearly zero price elasticity for electricity demand. If the demand curve is vertical, there will be no bunching regardless of the type of electricity price that consumers use for their economic decisions. The second possible reason is that consumers may respond to other perceptions of price. For example, if consumers respond to average price, there will be no bunching even if the demand curve has a significant price elasticity. As Figure 1.3 shows, the average price of electricity is smoothly increasing in consumption without having any kink points. The following sections use price variation across the utility border to examine which of the two reasons can explain the absence of bunching.

1.5.2 Difference-in-Differences Across the Utility Border

Across the service area border of SCE and SDG&E, consumers experience different changes in electricity price. To investigate whether consumers change electricity consumption in response to changes in electricity price, this section examines the difference-in-differences (DD) in consumption and price across the utility border. As described in Section 3, I use households located within one mile of the utility border in Figure 1.2. For each of the following DD estimates, I first calculate the mean percent change in consumption for each of SCE and SDG&E customers. Second, I calculate the DD estimates by subtracting the mean percent change of SCE customers from the mean percent change of SDG&E customers. Therefore, the DD estimates show the relative change in consumption for SDG&E customers relative to SCE customers.

In my sample period, the largest short-run price spike occurred during the California electricity crisis in 2000. SCE and SDG&E had similar two-tier nonlinear price schedules with a very slight step between the first tier and the second tier in 1999. For example, Panel A of Figure 1.5 displays SCE’s price schedule in 1999. Consumers paid the first tier rate up to the baseline consumption level and paid the second tier rate for any additional consumption. Figure 1.4 shows that both of the first and second tier rates did not change in SCE from 1999 to 2000. The tier rates for SDG&E customers, however, significantly increased in the summer of 2000. The price increase was corresponding to an increase in wholesale electricity price because SDG&E’s retail electricity price was indexed to the wholesale price. The price for SCE customers, however, stayed at the 1999 level because SCE’s retail electricity price was not indexed to the wholesale price.²⁴ As a result, only SDG&E customers experienced a price spike with an approximately 100% increase in marginal and average electricity price during the electricity crisis.

Did consumers respond to this price change? Figure 1.6 provides evidence that consumers indeed changed consumption in response to the price change. Using households located 1 mile of the utility border, I calculate the difference-in-differences in mean consumption. For each side of the utility border, I first calculate the mean percent change in consumption from a billing month in 1999 to the same billing month in 2000. I then calculate the difference-in-differences by subtracting the mean percent change of SCE customers from the mean percent change of SDG&E customers.²⁵ In the same way, I calculate the difference-in-differences in their average price. The graph shows that there was a lag before consumers started to respond to the price spike. In the June and July billing months, SDG&E customers experienced an increase in price relative to SCE customers. Their consumption, however, did not respond to the price increase immediately. Instead, it started to change in the August billing month, in which consumption in SDG&E decreased by 14.5% compared to SCE.²⁶ Note that as long as other factors affected SCE and SDG&E customers in the same way, this difference-in-differences estimate shows the change in consumption purely driven by the change in price. For the same period, Reiss and White (2008) estimate the change in consumption for SDG&E customers. Reiss and White note that their estimate may contain not only the price effect but also other effects such as media coverages and public appeals for conservation during the electricity crisis. An advantage of the current research design is that such unobservable

²⁴The California wholesale electricity market was restructured in 1998. The retail electricity price, however, continued to be fixed for most consumers to make electric utilities to recover the sunk costs of assets due to the transitions to market based wholesale pricing. SDG&E recovered its sunk costs relatively early, therefore, ended the retail rate freeze and started to index the retail rate to the wholesale price in July 1999. On the other hand, other utilities including SCE continued the retail rate freeze during the electricity crisis in 2000.

²⁵In addition, I subtract the time-specific city level fixed effects and time-specific billing cycle fixed effects from the DD estimates to control for time-variant unobservable shocks that are specific to cities and billing cycles.

²⁶Bushnell and Mansur (2005) find similar evidence of lagged price responses during the electricity crisis.

effects are absorbed by the first difference between SCE and SDG&E customers as long as these effects were not systematically different across the utility border within one mile of the border.

To see the robustness of the result, Figure 1.7 presents the changes in consumption by distance from the utility border. The horizontal axis shows miles from the border as negative values for SCE's territory and positive values for SDG&E's territory. That is, the left hand side of the vertical line represents the distance from the border for SCE customers, and the right hand side represents the distance from the border for SDG&E customers. The dots represent the mean percent change in consumption from a billing month in 1999 to the same billing month in 2000 in a 0.25 mile bandwidth. City specific time fixed effects and billing cycle specific time fixed effects are subtracted from the estimate to control for the change in weather and other factors. Panel A shows that in July 2000, there is no systematic difference in the change in consumption between SCE customers and SDG&E customers regardless of their distance from the utility border.²⁷ In contrast, Panel B demonstrates that in August 2000, the change in consumption is significantly different between households right across the utility border.²⁸ The discrete jump in this graph confirms that the difference-in-differences in consumption presented in Figure 1.6 are driven by the difference in electric utility service territories and not by potential confounding factors among households with different distances from the utility border.

Importantly, Figure 1.6 also shows that there is no systematic "slope" in the change in consumption over the distance from the utility border. In a regression discontinuity design (RDD), one can control for potential systematic trends of a forcing variable²⁹ either by including continuous control functions of the forcing variable, or by narrowing the range of the sample sufficiently close to its discontinuity point (e.g. Angrist and Pischke 1999, Chay, McEwan, and Urquiola 2005, Imbens and Lemieux 2008). As in Black (1999), this study takes the second approach; I limit the sample to households within one mile of the utility border. The absence of systematic slope indicates that the choice of the distance from the utility border is unlikely to affect the difference-in-differences estimates as long as I limit the sample within one mile of the utility border. Indeed, in the following section, I show that the estimates of my econometric estimation do not change with the choice of the distance.

These results provide evidence that consumers indeed responded to the change in electricity price. From 1999 to 2000, however, the change in marginal price and the change in

²⁷Similarly, there is no systematic difference in the change in consumption between SCE and SDG&E customers in January, February, March, April, May, and June billing month in 2000.

²⁸The same diagrams for other months after August also show a jump in the change in consumption right across the utility border.

²⁹A "forcing variable" is the variable that determines the discrete treatment status of the variable of interest. For example, in this study, the distance from the utility border can be seen as the forcing variable that determines which of the two utilities provides electricity.

average price were virtually equivalent for most consumers, because the first tier rate and the second tier rate were changed in the same proportion in their two-tier nonlinear price schedules. This price variation, therefore, does not allow me to identify whether consumers responded to the change in marginal price or the change in average price. To examine whether consumers respond to marginal, expected marginal, or average price, I exploit price variation during the full sample period from 1999 to 2008 in the following analysis.

SCE and SDG&E introduced different five-tier nonlinear price schedules in 2001. Moreover, the two utilities changed each of the five tier rates differently over time as presented in Figure 1.4. For example, the first and second tier rates did not change much in both utilities after 2001, whereas the third to fifth tier rates had substantially different changes over time. As a result, lower electricity consumers and higher electricity consumers experienced different exogenous changes in price. In the following analysis, therefore, I examine the change in price and consumption separately for each decile of electricity consumption distributions. In this section, I use January billing months as an example to show graphical evidence. In the next section, I include all billing months to conduct econometric analyses.

Panel A of Figure 1.8 examines whether large electricity users respond to marginal price or average price when faced with nonlinear electricity price schedules. The graph presents the difference-in-differences in price and consumption for the top decile of consumption distribution. In each year, I include only the following two groups of consumers: SCE customers in the top decile of SCE's consumption distribution and SDG&E customers in the top decile of SDG&E's consumption distribution. To see how the marginal price changed for SDG&E customers relative to SCE customers, I calculate the difference-in-differences in marginal price in the following way. I first calculate the mean percent change in marginal price from 1999 for each of SCE and SDG&E customers. Second, I calculate the difference-in-differences by subtracting the mean percent change of SCE customers from the mean percent change of SDG&E customers. Therefore, it shows how SDG&E's marginal price evolved from 1999 relative to SCE. In the same way, I calculate the difference-in-differences in average price and the DD in consumption for the top decile of consumption distributions.

The top decile of consumption distributions in the two utilities experienced substantially different changes in marginal and average price after 2001. In 2000, the difference-in-differences in marginal and average prices were nearly zero, which implies that SDG&E customers had nearly the same price change as SCE customers. In 2001, SDG&E's marginal and average prices increased about 30% more than SCE's price. Importantly, the relative change in marginal price and the relative change in average price were quite different in 2002, 2003, 2007, and 2008. In these years, SDG&E's marginal price *decreased* more than SCE's marginal price, but their average price *increased* more than SCE's average price. Therefore, if consumers respond to marginal price, SDG&E's consumption should increase more than SCE's consumption in these years. Similarly, if they respond to average price, their

consumption should decrease more than SCE's consumption.

In these years, the difference-in-differences in consumption was negative, which implies that SDG&E's consumption decreased more than SCE's consumption. Therefore, unless the price elasticity of electricity demand is positive, the relative change in consumption is inconsistent with the relative change in marginal price. The graphical evidence suggests that the relative change in consumption is more consistent with the relative change in average price than marginal price, although formal econometric analyses are required to discuss the statistical inferences of the results.

Panel B of Figure 1.8 provides the same analysis for the fifth decile of consumption distributions. The fifth decile includes consumers between the 40th percentile to the 50th percentile of each consumption distribution. This graph, therefore, examines the response of consumers whose consumption is closer to the median consumption level. In 2002, 2003, and 2008, SDG&E's marginal price had nearly the same change as SCE's marginal price. Therefore, the standard economic model predicts that SDG&E's consumption should have the same change as SCE's consumption. The difference-in-differences in consumption, however, is negative, which implies that SDG&E's consumption decreased more than SCE's consumption in these years. It is inconsistent with the prediction of the standard economic model. Instead, the difference-in-differences in consumption evolves more in line with the difference-in-differences in average price.

Figure 1.8 uses the top and fifth deciles of January billing months as an example to show graphical evidence. The same graphical analyses for other deciles and other billing months provide similar evidence except that the first and second bottom deciles usually do not allow me to identify whether consumers respond to marginal or average price. As Figure 1.4 shows, in most of the sample period, the first tier rate and the second tier rate were changed by the same proportion. Therefore, the change in marginal price and the change in average price are highly collinear for very low electricity users. I provide the statistical evidence of this point in the next section.

1.5.3 Regression Results

The previous section provides graphical evidence that consumers respond to average price rather than marginal price when faced with nonlinear price schedules. In particular, Figure 1.8 uses the top and fifth deciles of consumption distributions in January billing months as an example to show that the relative change in consumption is more consistent with the relative change in average price rather than marginal price. In this section, I econometrically examine how consumers respond to nonlinear price schedules by using the full sample from January 1999 to December 2008 and also exploiting all price variation in each decile of consumption distributions.

Table 1.2 shows results of the difference-in-difference-in-differences (DDD) estimation described in equation (1.14). The unit of observation is a household-level monthly electricity bill. The dependent variable is log of daily average electricity consumption during billing months, and the data include 120 months from January 1999 to December 2008. To exploit all price variation in each decile of consumption distributions, this regression includes the full data set from all parts of consumption distributions. An implicit assumption made in this pooled regression is that the price elasticity is the same for each part of the consumption distributions. In the next section, I show that results are robust even when this assumption is relaxed.

First, I include only the marginal price of electricity as a price variable. Column 1 of Table 1.2 shows that the price elasticity estimate equals -0.087 for the marginal price model. Second, I include only the average price of electricity as a price variable. Column 2 shows that the price elasticity estimate is equal to -0.112 for the average price model. In Column 3, I include both marginal and average price. Suppose that consumers respond to the nonlinear price schedule as the standard economic model predicts. Then, once the marginal price is included in the regression, adding the average price should not change the estimated coefficients if consumers respond to their marginal price and do not respond to their average price. Column 3 shows the opposite result. Once the average price is included, adding the marginal price does not statistically change the effect of the average price. Moreover, the effect of marginal price becomes economically small and statistically insignificant. The last three columns show the same regression but use households located within 0.5 mile from the utility border. The results are robust between 1 mile from the border and 0.5 mile from the border.

In addition to marginal price, Saez (1999) and Borenstein (2009) suggest the possibility that consumers respond to *expected* marginal price if they maximize expected utility by accounting for uncertainty about their consumption. The response to expected marginal price can be a reason for the absence of bunching around kink points because expected marginal prices with considerable uncertainty will make the kink of nonlinear price schedules smoothed. Previous studies find inconclusive empirical results between average price and expected marginal price. Liebman and Zeckhauser (2004) run a maximum likelihood model to test the ratio of taxpayers that respond to their expected marginal tax rate and those who respond to their average tax rate. Liebman and Zeckhauser note that their estimation results suggest that a half of their samples respond to their average tax rate, although the estimates may not be global minimum in their maximum likelihood estimation. Similarly, in his estimation of electricity demand, Borenstein (2009) reports that is inconclusive whether consumers respond to their expected marginal price or average price.

To test whether consumers respond to expected marginal price or average price, I run the same regression as in Table 1.2 but use expected marginal price instead of marginal

price. I calculate expected marginal price by assuming that consumers have errors with a standard deviation of 20% of their consumption. Table 1.3 presents the results, which provides evidence that consumers respond to average price rather than expected marginal price. Column 3 shows that once the average price is included, adding the expected marginal price does not statistically change the effect of the average price. Furthermore, the effect of expected marginal price becomes economically small and statistically insignificant in the joint estimation. Column 4 to 6 show that these results are robust when I limit the sample to households even closer to the utility border than one mile.

The full sample DDD regression has an implicit assumption about the price elasticity. It assumes that the price elasticity is the same across the consumption distribution. To relax this assumption, I estimate the same regression as column 3 of Table 1.2 for each decile of consumption distribution separately. Table 1.4 shows that the main results do not change even when this assumption is relaxed. Except for the bottom two groups of the distribution, the regression results reveal that the average price dominates the response to the price schedule. In addition, at least in my data, the price elasticity for average price does not vary much across the consumption distribution. Note that I cannot test the response to marginal price and average price at the bottom two deciles because the average price and marginal price are likely to be similar at the bottom of the distribution. As a result, the standard errors are large for these two deciles.

These regression results provide strong evidence that consumers respond to average price rather than marginal price or expected marginal price. In the following exercises, I investigate three additional policy relevant questions: 1) heterogeneous price responses by income, 2) heterogeneous price responses by consumption, and 3) medium long run responses.

First, I examine whether the price elasticity is different between households with different income levels. To estimate the price elasticity separately for lower and higher income levels, I divide the sample into two groups by their income levels. In my sample, the median of median household income is equal to \$89,472. Therefore, the lower income groups includes households whose income is less than the median, and the higher income group includes other households. Columns 1 and 2 of table 1.5 show estimation results from the separate regressions for the two groups. The price elasticity is slightly larger for the lower income group. I also run a regression using the pooled data and the interaction term between the price variable and a dummy variable for one of the income groups to whether their price elasticity is statistically different. The difference is statistically different at the 5% significance level.

Similarly, I explore whether the price elasticity is different between households with different consumption levels. This question is particularly important for the design of nonlinear price schedules because potentially different price elasticities between different consumption groups are often used by policy makers to justify differentiating the marginal price for dif-

ferent consumption levels. To estimate the price elasticity separately for households with lower and higher consumption levels, I divide the sample into two groups by consumption levels. Column 3 and 4 show that the price elasticity estimates are not statistically different between small users and large users in my sample.

Finally, I consider that consumers may respond to a price change with a lag because they may learn about a price change gradually. One way to take into account the lag response is to aggregate data up to some longer time periods (Knittel and Sandler 2010). I aggregate each customer's monthly billing data to the annual level. I run the same regression model using the annual data. Thus, the price elasticity estimate tells us the percent change in consumption when a consumer's average price is increased by 1% for the twelve month period. The elasticity estimate is - 0.201, which is about twice as large as the original estimate that comes from monthly data. For policy analysis, both short-run and medium-long-run elasticities are important for different policy implications. Therefore, I conduct the following welfare analysis using both short-run and medium-long-run price elasticity estimates.

1.6 Welfare Analysis

The results in the previous section provide strong evidence that consumers respond to their average price of electricity when faced with nonlinear electricity price schedules. This section investigates the welfare consequences of this sub-optimal behavior. In particular, I examine how this behavior changes 1) the effect of multi-tier tariffs on energy conservation and 2) the efficiency costs of nonlinear pricing.

1.6.1 The Effect of Multi-Tier Tariffs on Energy Conservation

A major policy objective of California's nonlinear electricity pricing is to promote energy conservation. Proponents of the price schedule argue that the five-tier increasing block price structure creates a stronger incentive to save electricity than a conventional flat rate tariff. For the same reason, many electric, natural gas, and water utilities in the US switched from a flat rate tariff to a multi-tier tariff. In the following exercises, I explore whether five-tier tariffs actually reduce total electricity consumption relative to an alternative flat rate tariff.

To examine the effect of five-tier tariffs on total consumption, I calculate counterfactual consumption by making the following two assumptions. First, as in the previous section, I assume that consumers have a log-linear demand function $x_i = (p_i/a_i)^\beta$ with a price elasticity β . Second, based on the empirical findings in the previous section, I assume that consumers are currently responding to their average price on the five-tier tariffs. Figure 1.9 illustrates a consumer's demand curve $x(p)$ and observed consumption $x(ap)$. The figure also shows two counterfactual consumption levels. Suppose that consumer i responds to the actual

marginal price schedules so that consumes $x(mp)$, where the demand curve intersects with the price schedule. Now, suppose that the price schedule is switched to a conventional flat rate tariff. Then, the counterfactual consumption would be $x(flat)$. I obtain the counterfactual consumption for each consumer, and aggregate them to find total consumption for the three cases.

When consumption changes in the counterfactual scenarios, the utility's total revenue and total cost also change. To keep total consumption comparable between the observed and two counterfactual cases, I assume that the utility maintains the same profit by adjusting the tariff in the following way. First, I assume that the long-run marginal cost of quantity changes is equal to the average cost of electricity under the existing five-tier tariffs. For example, for Southern California Edison's tariff in 2007, the marginal cost based on this assumption equals 16.73¢/kWh.³⁰ Then, the alternative flat rate tariff is simply a flat rate with 16.73¢/kWh, which produces the same profit as the existing five-tier tariff. Second, when consumers respond to their marginal price, I assume that the utility adjusts each tier rate by the same proportion to keep profit neutrality. For example, for SCE's tariff in 2007, the proportional adjustment for each tier rate is 2.84% if the price elasticity equals -0.201.

Table 1.6 presents results for Southern California Edison in 2007, where consumers had one of the steepest five-tier price schedules.³¹ I include all SCE's residential customers that are on the standard five-tier tariff. The total observed consumption is 20,611 GWh. I compute counterfactual consumption using the two estimates from the previous section: the short run price elasticity estimate -0.112 in Table 1.2 and the medium long run price elasticity estimate -0.201 in Table 1.5. The table also includes asymptotic standard errors calculated by the delta method. Column 3 shows the counterfactual consumption when consumers have the flat rate tariff with 16.73¢/kWh. Contrary to the policy objective, the observed consumption under the existing five-tier tariff is 0.54% higher than the consumption under the flat rate tariff. This is because, when the utility switches from the flat rate tariff to the existing five tier tariff, more consumers experience a *decrease* in average prices because prices become lower for consumption in lower tiers. On the other hand, if consumers respond to their marginal price, the switch from the flat to five-tier tariff makes more consumers have an *increase* in marginal prices. As a result, the total consumption is 5.31% lower with the five-tier tariff compared to the flat rate tariff if consumers respond to their actual marginal

³⁰The marginal costs based on this assumption can be either lower or higher than the true long-run marginal cost. It can be too low if, for example, the expansion of electricity supply is more costly due to constraints on new transmission lines. It can be too high if, for instance, there are economies of scale in electricity supply. However, for small elasticities, adjustments of alternative tariffs are not very sensitive to the assumption of marginal costs, because the marginal cost affects only the net change in consumption. On the other hand, the calculation of the deadweight is sensitive to assumptions on marginal costs, which I show in the next section.

³¹For other years, and also for San Diego Gas & Electric, I calculate the same statistics, and the results are similar to the case for SCE in 2007.

price. This result also hold with the short-run price elasticity.

The results provide an important policy implication. The change in consumption in response to multi-tier tariffs critically depends on whether consumers respond to marginal or average price. Most previous studies examine the design of optimal pricing based on the assumption that consumers respond to marginal price. Examples include the design of optimal nonlinear income taxation (Mirrlees 1971, Atkinson and Stiglitz 1976, Diamond 1998, and Saez 2001), electricity pricing (Reiss and White 2005), and water pricing (Olmstead, Hanemann, and Stavins 2007). Under that assumption, the price elasticity is the sufficient statistic for predicting major policy outcomes. Table 1.6 suggests, however, that the policy outcome depends on both the price elasticity and what type of price perception consumers have.

1.6.2 Efficiency Costs

This section examines how the sub-optimal response that is found in the empirical results changes the efficiency costs of nonlinear pricing. In general, multi-tier electricity price schedules are not constructed to reflect the cost structures of electricity (Faruqui (2008)). Although the marginal cost of electricity is likely to depend on the timing of consumption such as on-peak and off-peak periods, multi-tier price schedules take no account of the timing of use. Furthermore, there is limited evidence that the marginal cost of electricity that each consumer imposes is a function of their monthly consumption during each of their billing cycles. Therefore, imposing multi-tier marginal prices is likely to create efficiency costs because many consumers pay marginal prices that do not reflect the marginal cost of electricity.

I again start with the assumption that the long-run marginal cost of electricity is equal to the average cost of electricity under the existing five-tier tariffs, which equals 16.73¢/kWh for SCE in 2007. This marginal cost can be higher or lower than the social marginal cost depending on the cost structures of electricity supply as well as environmental externalities. I come back to this point later by showing results with different assumptions on the marginal cost of electricity. When the marginal cost equals 16.73¢/kWh, the flat rate tariff in Figure 1.9 produces zero efficiency costs because the marginal price for each consumer is equal to the marginal cost. Suppose that the utility introduces the five-tier tariff that is shown in the figure. If a consumer has a demand curve $x(p)$ and responds to the average price, then the deadweight loss from the consumption $x(ap)$, is the area DEF in the figure. Instead, if the consumer responds to the marginal price, the deadweight loss from the consumption $x(mp)$ is the area ABF. For the consumer illustrated in the figure, the deadweight loss is larger with the marginal price response than the average price response because $x(ap)$ is closer to the social optimal level of consumption $x(flat)$. Note that the relationship between the deadweight loss of the average price response, $dwl(ap)$, and the deadweight loss of the

marginal price response, $dwl(mp)$, depends on the demand curve as well as the marginal cost.

In general, when consumers chooses a consumption $x(p^*)$, the deadweight loss is calculated as the following.

$$\begin{aligned}
 dwl(p^*) &= \int_{mc}^{p^*} x(p) dp - x(p^*) \cdot p^* && \text{if } p^* \geq mc \\
 &x(p^*) \cdot p^* - \int_{p^*}^{mc} x(p) dp && \text{if } p^* \leq mc.
 \end{aligned} \tag{1.16}$$

First, I obtain $dwl(ap)$ using the observed consumption by assuming that consumers are currently responding to their average price. Second, I calculate the conterfactual consumption $x(mp)$ for each individual bill and calculate $dwl(mp)$, which is a counterfactual deadweight loss if consumers respond to their marginal price instead of their average price. Finally, I aggregate the deadweight loss for each consumer to find the total efficiency cost for SCE in 2007.

Table 1.7 presents results with different assumptions on the price elasticity and the marginal cost of electricity. With the price elasticity of -0.201, $dwl(mp)$ equals \$71.6 million and $dwl(ap)$ equals \$23.41 million. The intuition behind the result is that when the marginal cost equals 16.73¢/kWh, the average price is closer to the marginal cost for most consumption levels, so that the average price distorts consumption less than the marginal price.

What would happen to the deadweight loss if the true social marginal cost is lower or higher than 16.73¢/kWh? To examine this point, Table 1.7 includes results with the the marginal cost of 10¢, 20¢, and 25¢ per kWh. The marginal cost of 25¢/kWh is probably closer to the upper bound of the social marginal cost that includes environmental externalities from electricity generation.³² With the marginal cost of 20¢/kWh, $dwl(mp)$ is still larger than $dwl(ap)$. However, when the marginal cost equals 25¢/kWh, the relationship is flipped.

Figure 1.10 shows the deadweight loss for continuous values of the social marginal cost with the price elasticity of -0.201. $dwl(mp)$ is larger than $dwl(ap)$ for cost values up to 21.13¢/kWh. If the social marginal cost exceeds this value (for example, if environmental externalities from electricity generation are very large), the sub-optimal response creates larger deadweight loss than the optimal response. This result comes from the fact that when the social marginal cost becomes very high, the marginal price turns out to be closer to the social marginal cost of electricity than the average price for many consumers, so that the

³²For instance, an increase in the marginal cost by five cents due to greenhouse gas emissions alone would require a price on GHGs of around \$100 per ton of CO₂ equivalent (Borenstein 2010).

excessive consumption obtained from the average price response has larger negative impacts on the social welfare compared to the marginal price response.

1.7 Conclusion and Discussion

This paper explores three different predictions about how consumers respond to nonlinear price schedules. The standard model of nonlinear budget sets predict that consumers optimize their consumption with respect to marginal price, or expected marginal price when they account for uncertainty about their consumption. An alternative prediction is that consumers may make a sub-optimal choice by responding to average price. Theoretically, consumers make this sub-optimal choice when the cognitive costs of responding to marginal price are higher than the utility gain from re-optimizing with respect to marginal price. To empirically test the three predictions, I exploit a spatial discontinuity in electric utility service areas, where nearly identical households experience substantially different nonlinear electricity pricing across the utility border.

The empirical findings strongly support that consumers respond to average price rather than marginal or expected marginal price when faced with nonlinear electricity price schedules. The evolution of consumption from 1999 to 2008 is inconsistent with the prediction that consumption is affected by marginal price. In particular, when marginal price and average price change in opposite directions, consumption moves in response to average price. In my econometric estimation, I find that when different price variables are jointly estimated, the partial effect of average price is economically and statistically significant, whereas marginal price and expected marginal price have statistically insignificant effects on electricity consumption. These results are robust when I limit the sample to households even closer to the utility border.

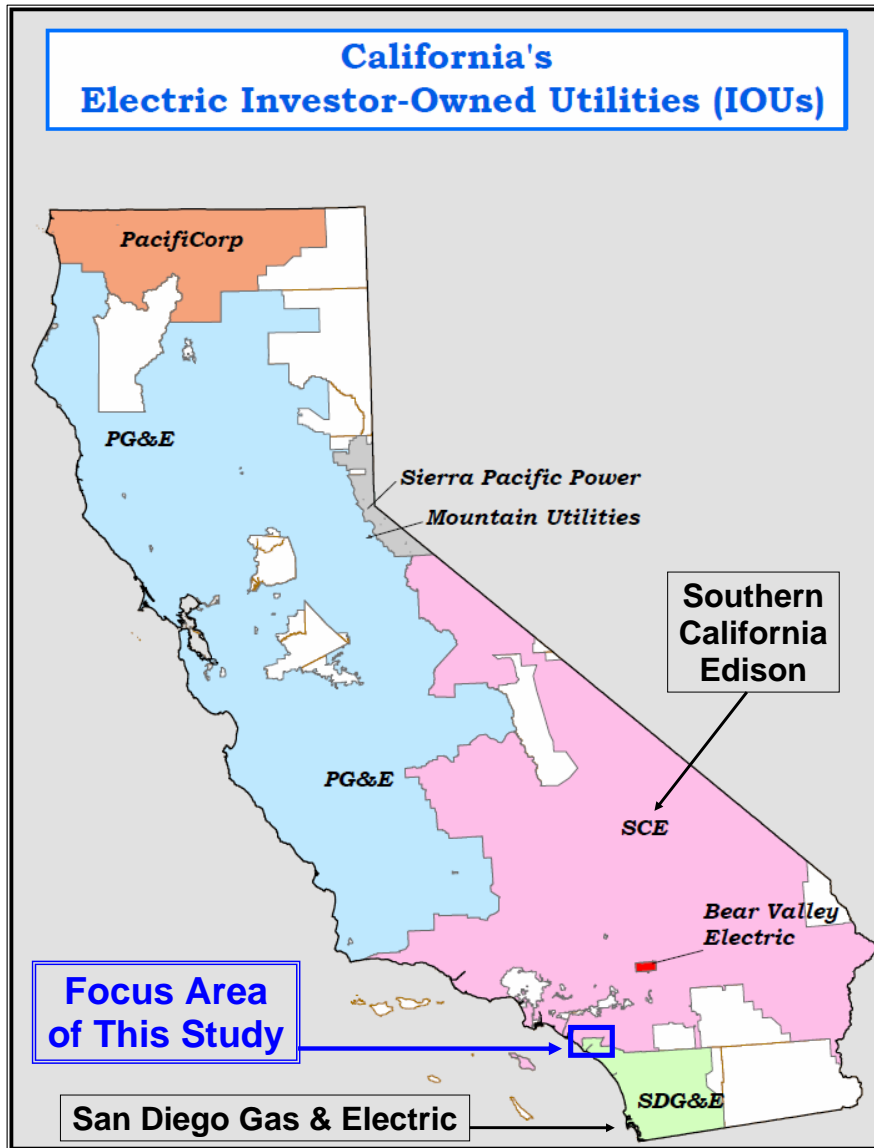
Even though this sub-optimal response has a minimal impact on individual welfare, it can critically alter two important policy implications of nonlinear pricing. First, it makes nonlinear price schedules less successful in reducing total consumption. In particular, I find that California's current five-tier electricity tariffs may result in a slight increase in total consumption compared to an alternative flat rate tariff. Second, under a reasonable range of private marginal costs of electricity, average price response reduces the efficiency costs of nonlinear pricing. However, when the social marginal cost of electricity is substantially higher than the private marginal cost, for example because of externalities from electricity generation, the response to average price increases the efficiency costs.

Why do consumers respond to their average price rather than marginal price? Given the current environment for most consumers, the information cost required to react to their marginal price is likely to be higher than the utility gain. For example, I show that even with one of the steepest nonlinear price schedules in the sample period, consumers with quasi-

linear utility can gain less than \$2 per month on average by re-optimizing consumption with respect to marginal price rather than average price. This utility gain is likely to be less than the information cost for most consumers for two reasons given their current conditions. First, it is not straightforward for most consumers to monitor cumulative electricity consumption during their billing cycle without having special home devices inside their houses. Second, the design of monthly electricity bills in most electric utilities generally makes it hard for consumers to figure out their marginal price.

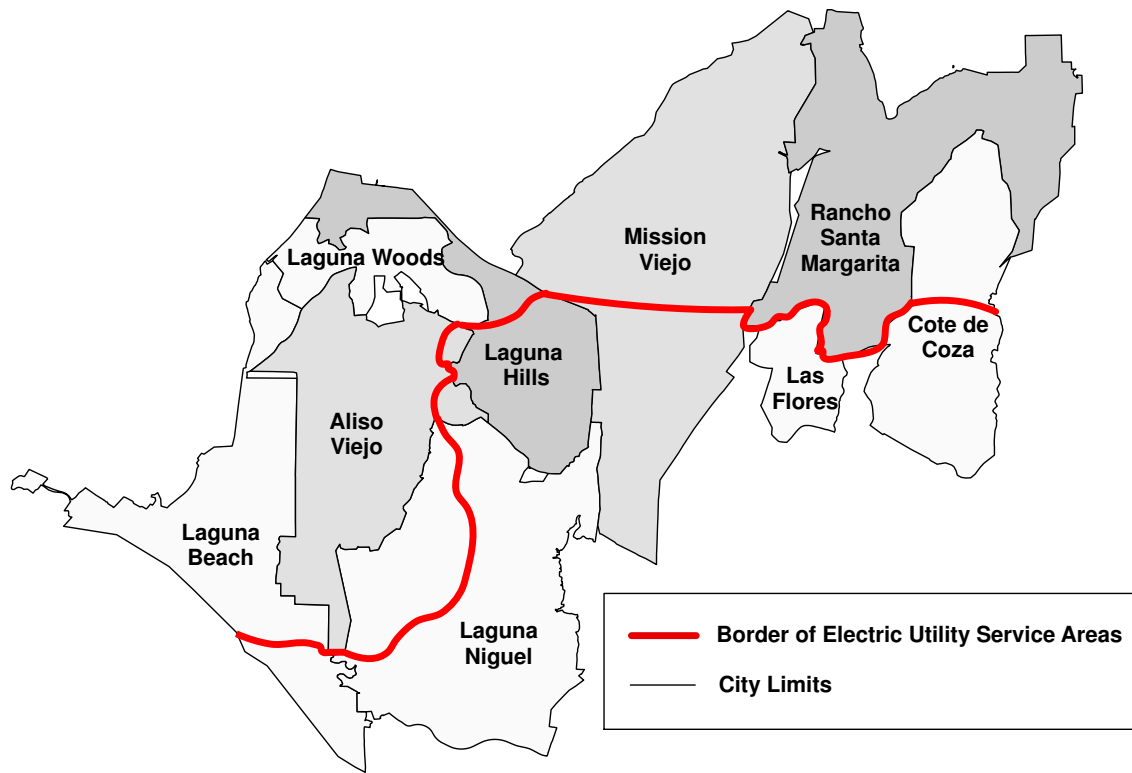
The concern about information costs motivates us to ask an important question for future research: does information provision help consumers respond to their actual marginal price? For income tax schedules, Chetty and Saez (2009) conduct a randomized controlled experiment in which a half of the taxpayers in their sample receive instructions about income tax schedules. Chetty and Saez find that the information provision indeed changes the labor supply response to marginal income tax rates. Similar research on residential electricity consumption could show how much of the sub-optimal behavior can be explained by information barriers, and could provide policy implications about how we can better inform consumers about their economic incentives.

Figure 1.1: Service Territories of California's Investor-Owned Electric Utilities



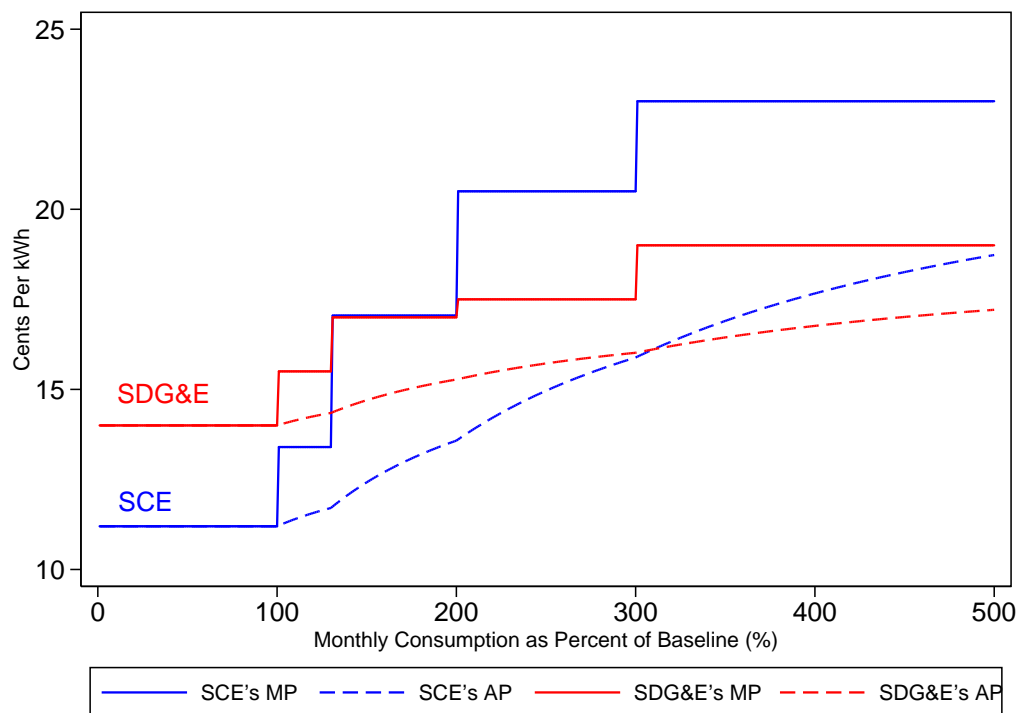
Notes: This figure shows a service territory map of California's investor-owned electric utilities. The original map is provided by the California Energy Commission. Blank areas indicate that these areas are served by electric utilities that are not investor-owned. In this study, I use two electric utilities: Southern California Edison (SCE) and San Diego Gas & Electric (SDG&E). SCE provides electricity for a large part of southern California, whereas SDG&E covers a major part of San Diego County and the southern part of Orange County. This study particularly focuses on the territory border of SCE and SDG&E in Orange County, which is shown in Figure 1.2.

Figure 1.2: A Spatial Discontinuity in Electric Utility Service Areas in Orange County, California



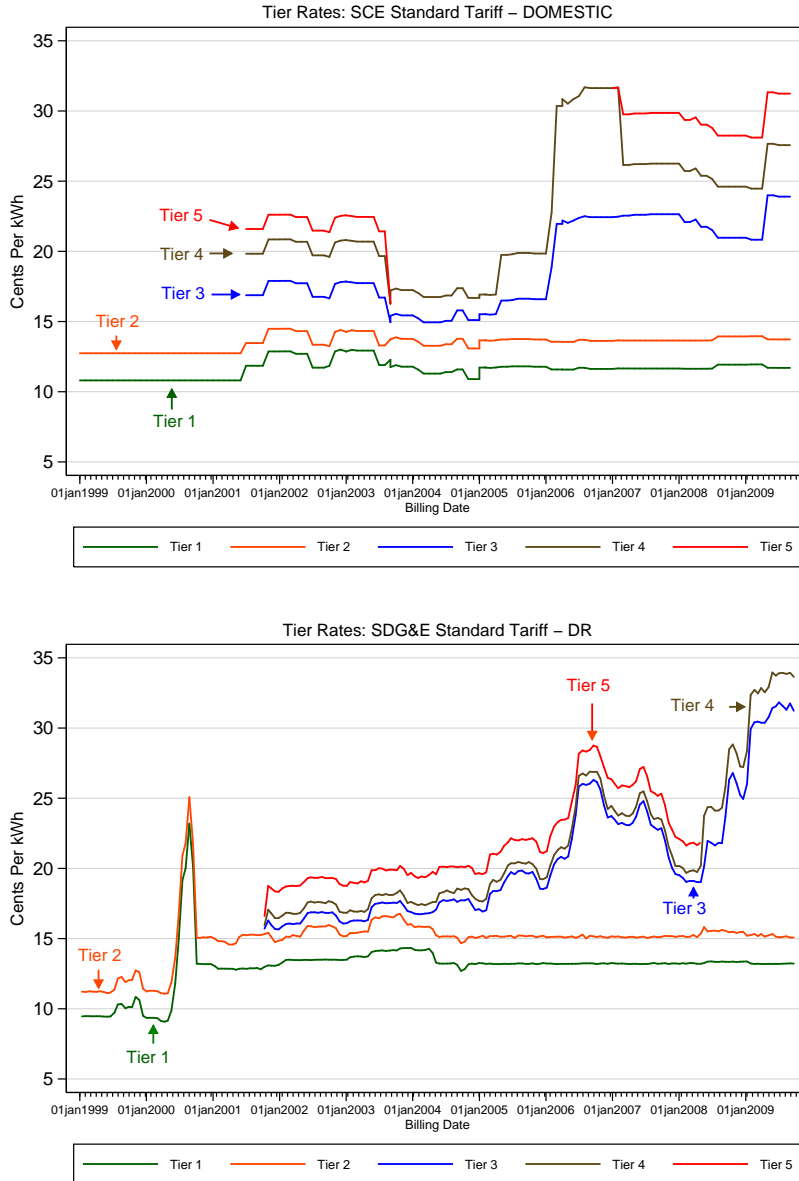
Notes: The bold line shows the service area border of Southern California Edison and San Diego Gas & Electric. SCE provides electricity for the north side of the border and SDG&E covers the south side. The map also presents city limits. The utility border exists inside the city limits in Laguna Beach, Laguna Niguel, Aliso Viejo, Laguna Hills, Mission Viejo, and Coto de Caza.

Figure 1.3: Standard Residential Electricity Price Schedules in SCE and SDG&E in 2002



Notes: The figure presents five-tier increasing block price schedules in Southern California Edison (SCE) and San Diego Gas & Electric (SDG&E). About 80% of their customers are on these standard price schedules. The price of 1 kWh is a step function of monthly consumption as a percent of the baseline that is assigned by the utilities. The marginal price equals the first tier rate up to 100% of the baseline, the second tier rate up to 130%, the third tier rate up to 200%, the fourth tier rate up to 300%, and the fifth tier rate over 300% of the baseline. The figure shows the price schedules in 2002 as an example. The utilities change the tier rates frequently as shown in Figure 1.4. The dashed lines show the average price that is defined as a customer’s monthly bill divided by monthly consumption. Therefore, it is a smooth increasing function in monthly consumption. For the same consumption level, customers have different marginal and average prices depending on their electric utility. For example, consider customers on the third tier. The marginal price is essentially the same between the utilities. The average price, however, is higher for SDG&E customers. Similarly, consider customers on the fourth tier. The marginal price is higher for SCE customers, whereas the average price is higher for SDG&E customers.

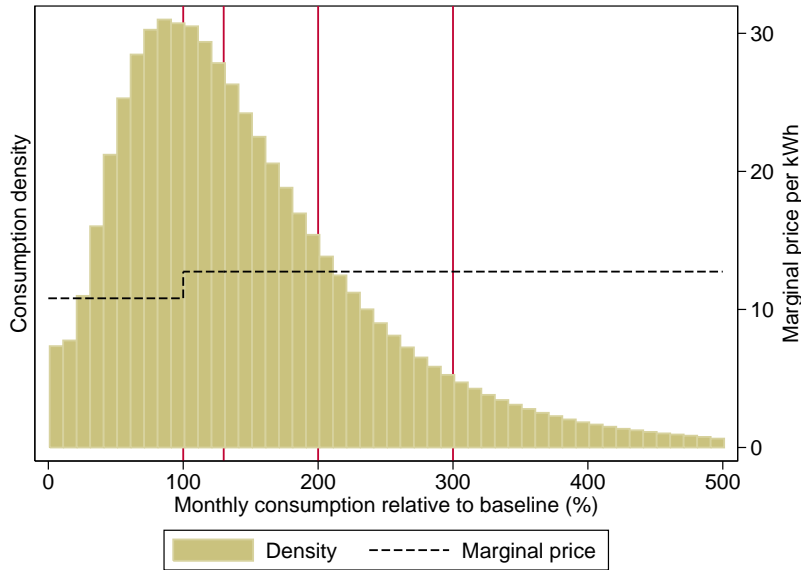
Figure 1.4: Tier Rates for Standard Price Schedules from 1999 to 2009



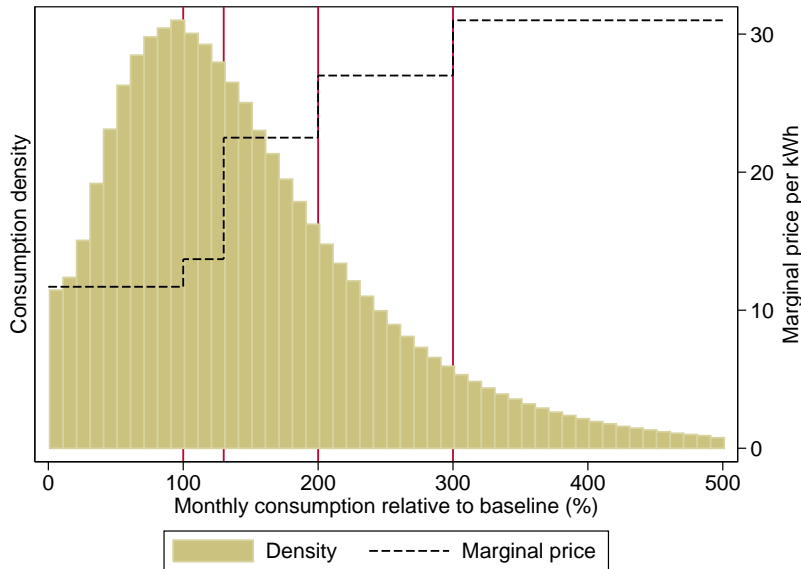
Notes: The figures display how residential electricity prices changed over time in Southern California Edison and San Diego Gas & Electric. Each of the five tier rates corresponds to the tier rates in the five-tier increasing block price schedules presented in Figure 1.3. The third, fourth, and fifth tiers did not exist before 2001. The fifth tier did not exist between 2004 and 2006 in SCE, and after 2008 in SDG&E.

Figure 1.5: Consumption Density in 1999 and 2007: Bunching Around Kink Points

Panel A. Consumption density and price schedule in 1999

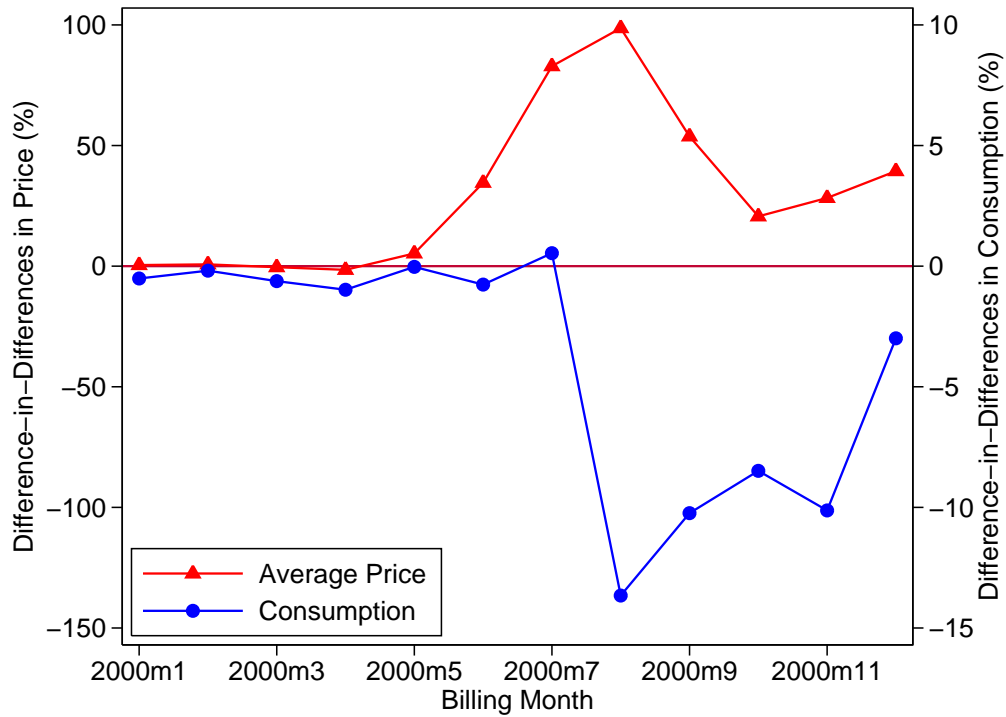


Panel B. Consumption density and price schedule in 2007



Notes: The figures display the histogram of household-level monthly electricity consumption for Southern California Edison in 1999 (Panel A) and 2007 (Panel B). The horizontal axis shows consumption relative to customers' baselines. The bin size is 10% of the baseline consumption quantity. The figures also show the marginal price. The solid lines display locations of the kinks in the five-tier increasing block rates. The distribution is smooth and does not have visible bunching of customers around the kinks.

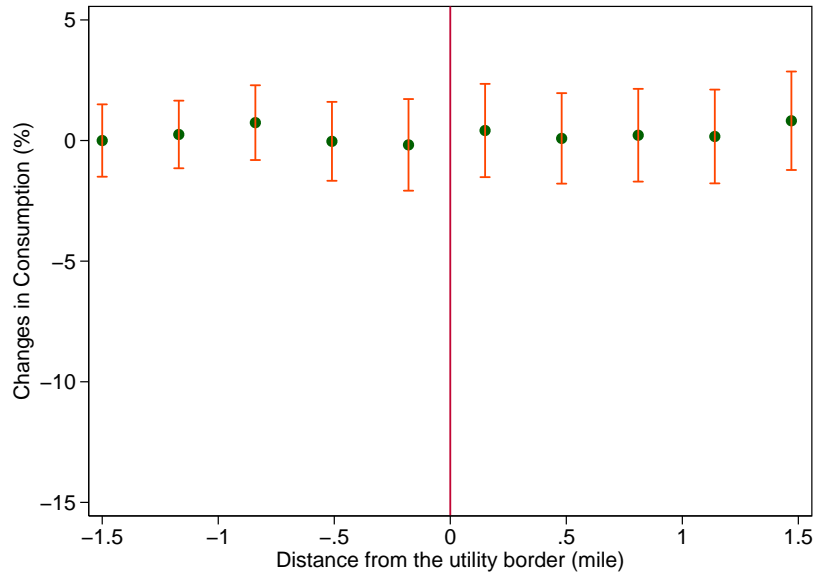
Figure 1.6: Difference-in-Differences in Price and Consumption in 2000



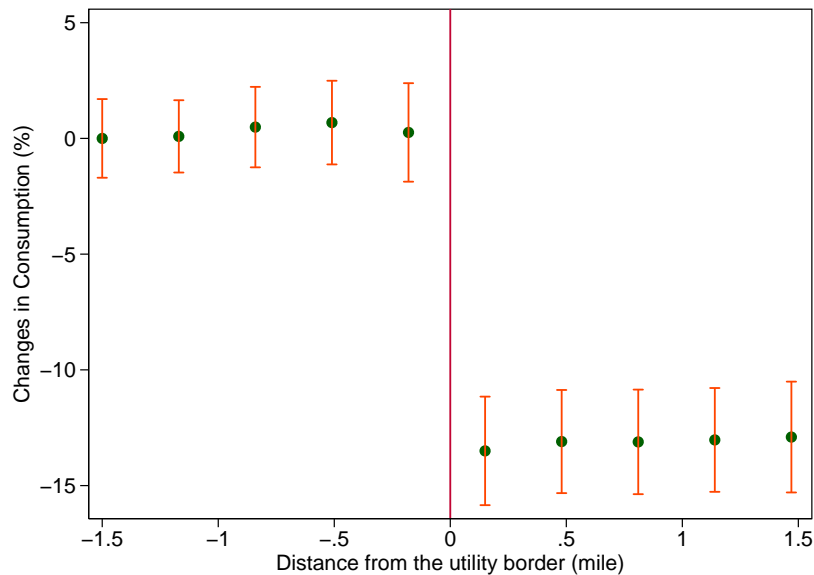
Notes: The first figure shows relative percent changes in tier rates for SDG&E customers relative to SCE customers. I first calculate changes in each tier rate from 1999 to 2000. Then, I calculate its difference-in-differences by subtracting the change in SCE's tier rates from the change in SDG&E's tier rates. Similarly, the second figure presents the relative percent change in consumption.

Figure 1.7: Changes in Consumption from 1999 to 2000 by Distance from the Utility Border

Panel A. Changes in Consumption from July 1999 to July 2000



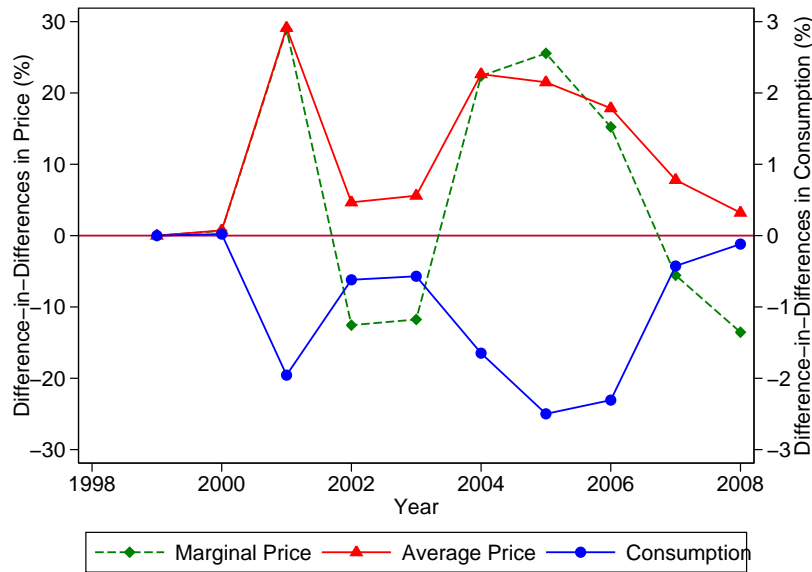
Panel B. Changes in Consumption from August 1999 to August 2000



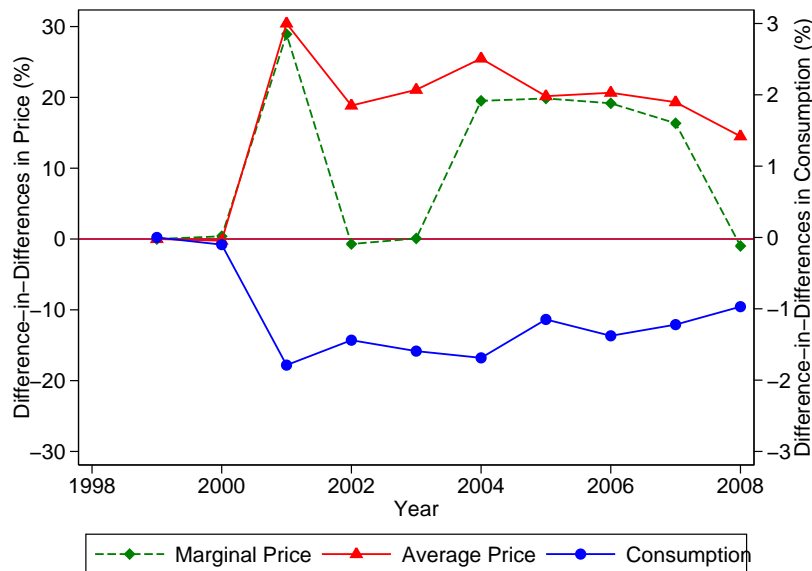
Notes: The figures show the changes in consumption from a billing month in 1999 to the same billing month in 2000 by the distance from the utility border. The horizontal axis shows miles from the border as negative values for SCE's territory and positive values for SDG&E's territory. That is, the left hand side of the vertical line represents the distance from the border for SCE customers, and the right hand side represents the distance from the border for SDG&E customers. The dots represent the mean percent change in consumption from a billing month in 1999 to the same billing month in 2000 in a 0.25 mile bandwidth. City-specific time fixed effects and billing-cycle-specific time fixed effects are subtracted from the estimate to control for the change in weather and other factors. The range bar shows the 95% confidence intervals.

Figure 1.8: Difference-in-Differences in Price and Consumption in January Billing Months

Panel A. Top Decile (90% - 100%) of Consumption Distributions

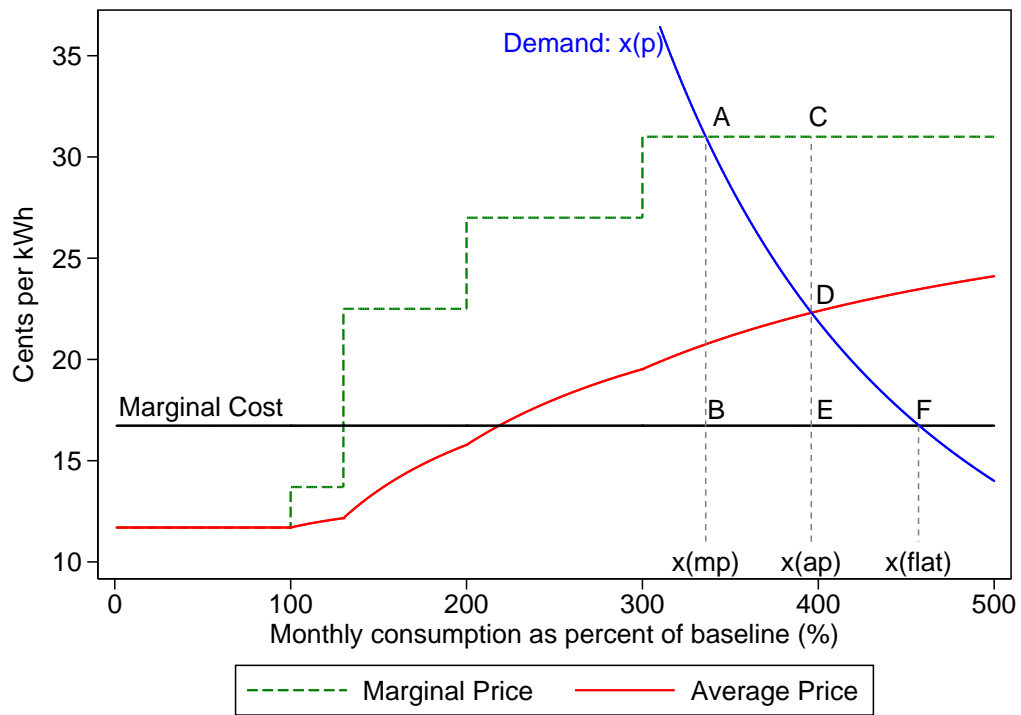


Panel B. Fifth Decile (40% - 50%) of Consumption Distributions



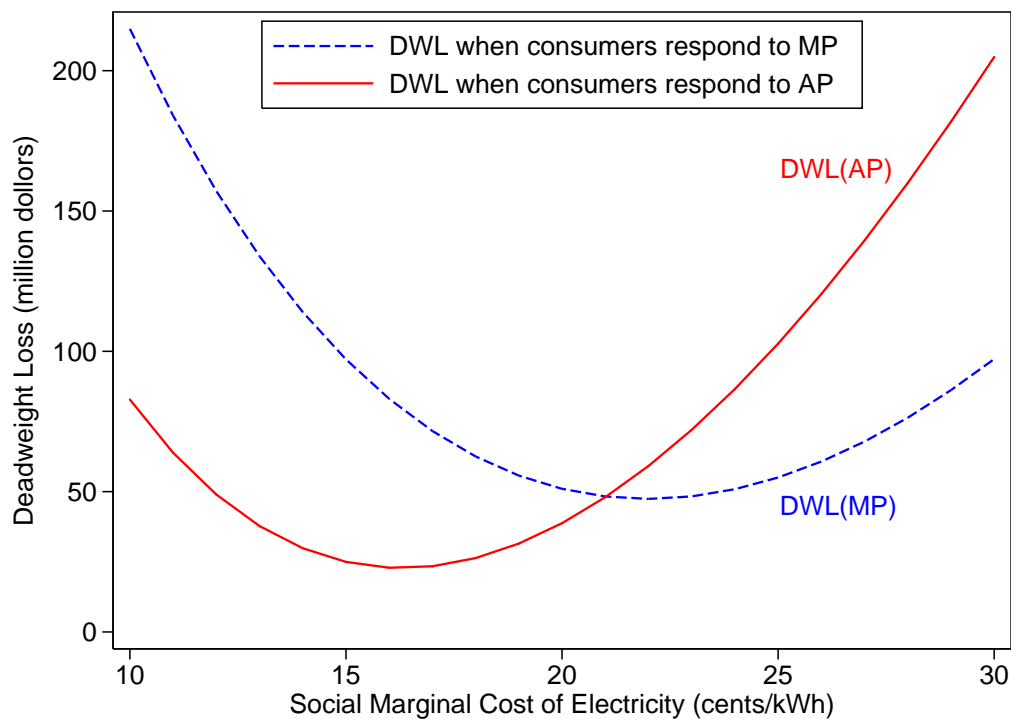
Notes: The figures show the difference-in-differences in price and consumption of January billing months relative to the initial year 1999. First, for each side of the border, I calculate the mean percent change in price and consumption from 1999. Second, I calculate difference-in-differences by subtracting the mean percent change of SCE customers from the mean percent change of SDG&E customers. Thus, the graph shows how SDG&E customers price and consumption evolved compared to SCE customers. Panel A examines the evolution of the top 10% consumption. Panel B examines the evolution of the top 60-70% consumption.

Figure 1.9: Welfare Effects of the Sub-Optimal Price Response to Nonlinear Price Schedules



Notes: This figure illustrates the welfare effect of the sub-optimal response to nonlinear pricing described in the text. The solid line shows SCE’s marginal price in 2007 and the dashed line presents the average price. The figure also includes the marginal cost that equals 16.73 cents/kWh.

Figure 1.10: Efficiency Costs of Nonlinear Pricing for Different Social Marginal Costs of Electricity



Notes: This figure presents the deadweight loss from the five-tier tariffs in Southern California Edison in 2007 for different assumptions on the social marginal cost of electricity as well as on how consumers respond to nonlinear pricing. I include all residential customers in SCE in 2007 that are on the standard five-tier tariff. The deadweight loss is calculated with the price elasticity of -0.201. The solid line shows the deadweight loss when consumers respond to their average price. The dashed line displays a counterfactual deadweight loss when consumers respond to their marginal price. The deadweight loss is larger for the marginal price response when the social marginal cost is less than 21.13¢/kWh and becomes smaller when the social marginal cost exceeds the cutoff value.

Table 1.1: Household Characteristics Across the Utility Border

	SCE side	SDG&E side	T-statistic
Household size	2.69	2.75	-0.48
Per capita income	38809	39690	-0.67
%Households with annual income below 20k	6.85	6.37	0.48
%Households with annual income 20-40k	13.37	12.65	0.84
%Households with annual income 40-60k	15.53	14.97	0.35
%Households with annual income 60-100k	29.62	28.72	0.42
%Households with annual income over 100k	34.52	37.38	-1.01
Median home value	364143	375987	-0.84
Median monthly rent	1388	1411	-0.19
Average daily electricity use (kWh) in 1999:			
January	19.54	19.96	-0.25
February	18.10	18.67	-0.32
March	17.75	17.80	-0.30
April	17.38	17.65	-0.34
May	16.40	16.90	-0.32
June	16.38	16.69	-0.15
July	20.03	19.56	0.18
August	21.88	21.89	-0.01
September	20.85	21.16	-0.12
October	20.62	20.47	-0.10
November	19.47	20.26	-0.41
December	18.64	19.49	-0.26

Notes: The first part of the table shows demographic characteristics on either side of the service area border between Southern California Edison and San Diego Gas & Electric. Each side includes households located within 1 mile from the utility border. I match nine-digit zip codes in the billing data with US Census blocks to calculate the mean of each variable from US Census 2000. T-statistics represent the t-statistic for the null that the difference in means between the two sides are equal. The t-statistics for demographic variables are adjusted for clustering at the Census block level. The second part shows the mean consumption for each billing month in 1999. Note that in 1999, SCE and SDG&E had essentially the same electricity price schedules. The t-statistics for electricity consumption are adjusted for clustering at the city by utility level.

Table 1.2: Marginal Price vs. Average Price

Distance from border	1 mile			0.5 mile		
	(1)	(2)	(3)	(4)	(5)	(6)
ln(MP)	-.087 (.007)		-.007 (.015)	-.092 (.011)		-.009 (.020)
ln(AP)		-.112 (.006)	-.108 (.013)		-.121 (.011)	-.114 (.017)
Observations	6,513,600			3,520,320		

Notes: This table presents results of the 2SLS regression in equation (1.14). The unit of observation is household-level monthly electricity bills. The dependent variables are log of daily average electricity consumption during a billing month. The data include 120 months from January 1999 to December 2008. The first three columns use premises located within 1 mile of the utility border. The last three columns use premises within 0.5 mile from the utility border. Standard errors are adjusted for clustering at the city by utility level.

Table 1.3: Expected Marginal Price vs. Average Price

Distance from border	1 mile			0.5 mile		
	(1)	(2)	(3)	(4)	(5)	(6)
ln(EMP)	-.096 (.008)		-.015 (.025)	-.103 (.013)		-.018 (.032)
ln(AP)		-.112 (.006)	-.103 (.021)		-.121 (.011)	-.107 (.029)
Observations	6,513,600			3,520,320		

Notes: This table presents results of the 2SLS regression in equation (1.14). The unit of observation is household-level monthly electricity bills. The dependent variables are log of daily average electricity consumption during a billing month. The data include 120 months from January 1999 to December 2008. The first three columns use premises located within 1 mile of the utility border. The last three columns use premises within 0.5 mile from the utility border. Standard errors are adjusted for clustering at the city by utility level.

Table 1.4: Marginal Price vs. Average Price: Separate Regressions for Each Decile

Decile	Top	9th	8th	7th	6th
ln(MP)	-.005 (.024)	-.006 (.023)	-.017 (.020)	.007 (.018)	-.016 (.018)
ln(AP)	-.102 (.038)	-.095 (.029)	-.098 (.031)	-.112 (.026)	-.107 (.024)
Observations	651360	651360	651360	651360	651360

Decile	5th	4th	3rd	2nd	Bottom
ln(MP)	.017 (.018)	.001 (.020)	-.013 (.053)	.456 (.259)	.780 (.445)
ln(AP)	-.109 (.022)	-.096 (.027)	-.114 (.064)	-.463 (.251)	-.860 (.472)
Observations	651360	651360	651360	651360	651360

Notes: This table presents results of the 2SLS regression in equation (1.13). The unit of observation is household-level monthly electricity bills. The dependent variables are log of daily average electricity consumption during a billing month. The data include 120 months from January 1999 to December 2008. Each regression includes a part of the distribution for each utility given a time period. For example, the first column includes the top 10% of household consumption in each time period for each utility. All regressions use premises located within 1 mile of the utility border. Standard errors are adjusted for clustering at the city by utility level.

Table 1.5: Heterogeneity and Medium Long Run Responses

	Heterogeneity by Income		Heterogeneity by Consumption		Medium long run responses
	Lower (1)	Higher (2)	Lower (3)	Higher (4)	
ln(AP)	-.129 (.009)	-.093 (.007)	-.114 (.018)	-.111 (.010)	-.201 (.021)
Observations	3,256,800	3,256,800	3,256,800	3,256,800	542,800

Notes: This table presents results of the 2SLS regression in equation (1.14). The unit of observation is household-level monthly electricity bills. The dependent variables are log of daily average electricity consumption during a billing month. The data include 120 months from January 1999 to December 2008. The first column includes households with income less than the median in the sample and the second column includes the other half of the sample. The third column includes the first to fifth deciles of household consumption, and the fourth column includes the other half. The last column shows results for the data that are aggregated to annual bill levels. All regressions use premises within 1 mile of the utility border. Standard errors are adjusted for clustering at the city by utility levels.

Table 1.6: The Effect of Five-Tier Tariffs on Energy Conservation

Observed Consumption (GWh)	Price Elasticity Assumption	Counterfactual Consumption (GWh)		%Change in Consumption from a Flat Rate to Five-Tier Rates	
		Flat Rate	Marginal Price of Five-Tier Rates	MP Reponse	AP Response
(1)	(2)	(3)	(4)	(5)	(6)
20611	-.201	20501	19413	-5.31% (0.88%)	0.54% (0.09%)
20611	-.112	20549	19989	-2.72% (0.43%)	0.30% (0.05%)

Notes: The table shows the total consumption for three cases using Southern California Edison's monthly billing data in 2007. I include all residential customers in SCE in 2007 that are on the standard five-tier tariff. Column 1 presents observed consumption in the data sets. I calculate two types of counterfactual consumption. Column 3 is counterfactual consumption when consumers have an alternative flat rate tariff of 16.73¢/kWh. Column 4 shows counterfactual consumption when consumers are still on the existing five-tier tariff but respond to their actual marginal price instead of their average price. Column 5 presents % changes from column 3 to 4, whereas column 6 shows % changes from column 1 to 3. Asymptotic standard errors are calculated by the delta method.

Table 1.7: Efficiency Costs of Nonlinear Pricing

	DWL (\$M)		Difference (\$M)
	MP Response	AP Response	
	(1)	(2)	(3)
A. Elasticity = - 0.201			
MC = 10.00¢/kWh	214.90	82.81	132.09
MC = 16.73¢/kWh	71.60	23.41	48.19
MC = 20.00¢/kWh	51.01	38.77	12.24
MC = 25.00¢/kWh	55.04	102.73	-47.69
B. Elasticity = - 0.112			
MC = 10.00¢/kWh	124.34	45.45	78.90
MC = 16.73¢/kWh	42.23	13.12	29.11
MC = 20.00¢/kWh	29.75	21.98	7.77
MC = 25.00¢/kWh	30.85	58.65	-27.80

Notes: The table shows the deadweight loss from the five-tier tariffs in Southern California Edison in 2007 for different assumptions on 1) the price elasticity, 2) the marginal cost of electricity, and 3) whether consumers respond to marginal or average price. I include all residential customers in SCE in 2007 that are on the standard five-tier tariff. Figure 1.10 also presents the deadweight loss for different continuous values of the marginal cost assumptions.

Chapter 2

How Do Consumers Respond to Nonlinear Pricing ? Evidence from Household Water Demand

2.1 Introduction

How do consumers respond to nonlinear pricing? Answers to this question play a central role in many areas of economics. For example, taxpayers in many countries make decisions about their labor supply, savings, interest payments, and retirement under nonlinear income tax schedules. Likewise, consumers in many markets including cell phone networks, electricity, natural gas, and water, choose their consumption under nonlinear price schedules. In each case, the policy implications of nonlinear pricing critically depend on how people respond to nonlinear pricing.

Empirical studies face two major challenges in answering this question. First, it is often difficult to find a counterfactual group that experiences a different price schedule than the group of interest. For example, in non-experimental income tax data, all comparable taxpayers are on the same tax schedule. The lack of clean control groups creates several identification problems as pointed out in recent studies by Heckman (1996), Blundell, Duncan, and Meghir (1998), Goolsbee (2000), and Saez, Slemrod, and Giertz (2009a). Second, economic theory and evidence from laboratory experiments provide different implications about whether or not consumers respond to marginal price. The standard model of nonlinear budget sets predict that consumers respond to marginal price. However, laboratory experiments often find that people have limited understanding of nonlinear price structures and tend to respond to average price.¹ Liebman and Zeckhauser (2004) provide an alternative

¹Fujii and Hawley (1988) find that many taxpayers do not know their marginal tax rate. de Bartolome (1995) finds that many subjects in his lab experiment use the average tax rate as if it is the marginal rate.

theory, “schmeduling”, where consumers under a complex price schedule make a sub-optimal choice by responding to average price. Nevertheless, most empirical studies estimate demand based on the assumption that consumers are fully aware of, and therefore respond to, the marginal price of the nonlinear price schedules (e.g. Reiss and White 2005, Olmstead, Hanemann, and Stavins 2007).

This paper exploits price variation in a residential water market in Southern California to investigate whether consumers respond to marginal price or alternative price signals when faced with nonlinear price schedules. Residential water consumers in Irvine Ranch Water District (IRWD) pay steep increasing block prices where the marginal price increases by 100% when their consumption exceeds a cutoff level. In addition to this price variation, IRWD’s policy change provides a nearly ideal research environment to study the response to nonlinear price schedules.

I conduct three empirical analyses. First, I follow the methods in Saez (1999), Saez (2009), and Chetty et al. (2010) to explore whether I find bunching of consumers in the five-tier nonlinear water price schedules. An important implication from the standard theory of nonlinear budget constraints is that a disproportionately large number of indifference curves would intersect the kink points of the nonlinear budget constraint. As a result, if consumers respond to marginal price, the distribution of consumption should show bunching of consumers at the kink points of nonlinear price schedules.

Second, I apply a regression discontinuity design to estimate the price elasticity with respect to marginal price. The change in IRWD’s nonlinear price schedule between the winter and summer month produces a discontinuous change in marginal price around the kink points of the nonlinear price schedule. Consumers who had nearly the same amount of consumption one month experience a substantially different change in their marginal price the next month. I use a regression discontinuity design, which is similar to Saez (2003)’s bracket creep study for the elasticity of taxable income, to explore whether consumers respond to marginal price.

Finally, I exploit the policy change in one of IRWD’s service areas to examine whether consumers respond to marginal price, expected marginal price, or average price when faced with nonlinear price schedules. In 2005, the price schedule in the service area was transformed from a flat marginal price schedule to IRWD’s standard five-tier increasing block price schedule. Importantly, this policy change produces an increase in marginal price and a decrease in average price for many consumers in the area. This price variation *between* the marginal price and average price enables me to separately identify the partial effect of each price variable. Furthermore, the surrounding service areas did not have the same price change as the treatment area in 2005. I focus on the samples within one mile of the service area border to examine how the consumption in the treatment area changed in response to the policy change relative to the control area.

My empirical analysis relies on a panel data set of household-level monthly water billing records for nearly all households in the area of this study. This confidential data set was directly provided by IRWD. The data set includes detailed information about each customer's monthly bills from 1994 to 2008. I particularly focus on the years around the policy change in 2005 to employ the third empirical analysis. The data in 2006, 2007, and 2008 allow me to examine how the policy change in 2005 affected long-run water consumption behavior.

Results from the three empirical analyses provide strong evidence that consumers respond to average price rather than marginal or expected marginal price when faced with nonlinear price schedules for water. First, I find that the consumption density does not reveal bunching of consumers in any of the kink points in the nonlinear water price schedule. There is no evidence of bunching even in the price schedules that have quite steep discontinuous increases in marginal price. Second, the regression discontinuity estimation provides no evidence of the response to marginal price. The price elasticity estimates with respect to marginal price are close to zero with tight standard errors. Finally, the analysis based on the policy reform in 2005 provides evidence that consumers respond to average price. In particular, when I include both marginal price and average price in the price elasticity estimation, the marginal price has nearly zero effect on consumption, while the average price has a statistically and economically significant effect on consumption. Likewise, when I include both expected marginal price and average price in the price elasticity estimation, the expected marginal price has nearly zero effect on consumption, while the average price has a statistically and economically significant effect on consumption.

Estimates from the price elasticity estimation also provide several notable findings regarding the magnitude of the price elasticity. First, I find slightly larger price elasticity estimates for the summer months. The short-run price elasticity with respect to average price is $-.127$ for the summer months and $-.097$ for the winter months. Second, I also find larger price elasticity estimates for the long-run response to the policy reform in 2005. The estimated long-run price elasticity is $-.203$ for the summer months and $-.154$ for the winter months.

All of these estimates have tighter standard errors than previous studies in residential water demand because the price variation in my research design is substantially larger than the price variation in most previous studies. In addition to allowing for narrower standard errors, this substantial price variation also allows me to obtain reliable estimates in the presence of frictions that consumers may face in responding to a price change. Chetty (2009) shows that when agents have such frictions, bounds on elasticity estimates shrink at a quadratic rate with log price. As a result, pooling several small price changes, although useful in improving statistical precision, yields less information about the structural elasticity than studying a few large price changes.

Both my short-run and long-run price elasticity estimates are lower than most estimates

in the literature on residential water demand. Espey, Espey, and Shaw (1997) provide a meta analysis of residential water demand and show that the mean price elasticity is 0.51. In recent studies, Hewitt and Hanemann (1995) and Olmstead, Hanemann, and Stavins (2007) use a discrete continuous choice model to estimate price elasticity. Hewitt and Hanemann (1995) find a price elasticity estimate of -1.6 and Olmstead, Hanemann, and Stavins (2007) finds an estimate of -.64 for consumers that have increasing block price schedules.

The paper proceeds as follows. Section 2 presents an institutional background and describes the data. Section 3 presents the empirical framework and results. Section 4 concludes and discusses future research avenues.

2.2 Institutional Background and Data

This section provides institutional background and a description of the data. The first part describes the background of Irvine Ranch Water District (IRWD). The second part explains the water utility's residential water price schedule and its price variation. Finally, the last part presents a description of the data.

2.2.1 Irvine Ranch Water District

Irvine Ranch Water District (IRWD), originally formed in 1961 under the provisions of the state of California Water Code, is an independent special district² serving Central Orange County, California. The district provides potable water, waste-water collection and treatment, recycled water programs, and urban runoff treatment to a population of 331,500 in 2011. The district serves residential, commercial, industrial, public authority, landscape irrigation, and agricultural customers. As an independent public agency, the district is governed by a five-member, publicly elected Board of Directors.

Figure 2.1 and 2.2 present IRWD's service areas, which are approximately 181 square miles from the Pacific coast to the foothills. The District serves the City of Irvine and portions of the Cities of Costa Mesa, Lake Forest, Newport Beach, Tustin, Santa Ana, Orange and unincorporated Orange County.

One of the important recent historical events in IRWD is its consolidations with several other water districts. From 1997 to 2008, IRWD has consolidated with five water districts. In most cases, the objective of the consolidations is to reduce overhead and administrative costs and lower rates and charges to customers of the consolidated district. One of these

²Special districts are one of the forms of local government. Special districts may be dependent (part of a city or county government) or independent (governed by its own publicly elected board of directors). Special districts are further divided into enterprise special districts (fees are billed or assessed, with the amount linked to what each customer uses) and non enterprise special districts (dependent on tax dollars). IRWD is an independent, enterprise special district.

consolidations is closely related to my research design in this study. In 1997, the shareholders of the Santa Ana Heights Water Company elected to merge with IRWD due to rising costs of imported water and lack of potable ground water supplies. As a result, approximately 10,000 residents in the former area of the Santa Ana Heights Water Company have been served by IRWD starting in 1997. The important fact about this consolidation is that from 1997 to 2004, households in this consolidated area were on the flat marginal price schedule that had been used by the former water provider. In 2004, IRWD announced that the price schedule in Santa Ana Heights service area was going to be transformed to the standard block price schedule that was used for most customers in the district.

2.2.2 Five-Tier Increasing Block Price Schedule in IRWD

Most residential customers in IRWD pay five-tier increasing block prices for their water consumption. The solid line in Figure 2.3 shows the five-tier increasing block price schedule in August 2002. In every month, IRWD allocates a “baseline allocation” to each customer. The baseline allocation depends on seasons (summer and winter months) and customer types. In 2002, for example, the allocation for single-family households in a typical 30 day billing cycle was 18 CCF³ in the summer months (May to November) and 14 CCF in the winter months (December to April). Condominium customers and apartment customers have different baseline allocations, although this study focuses on single-family customers. In the five-tier increasing block price schedule, consumers pay five different marginal prices for their monthly consumption relative to the baseline allocation. The marginal price equals the first tier rate for up to 40% of the baseline, the second tier rate for up to 100%, the third tier rate for up to 150%, the fourth tier rate for up to 200%, and the fifth tier rate for over 200% of the baseline. Mean consumption usually falls on the third tier and a fair number of consumers fall on the fifth tier.

The five-tier increasing block price in IRWD is very steep compared to similar price schedules in other water districts, electricity prices, and tax rates. The third tier rate is set to be twice as large as the second tier rate, the fourth tier rate is twice as large as the third tier rate, and the fifth tier rate is twice as large as the fourth tier rate. Therefore, consumers face a 100% increase in their marginal price when their consumption exceeds the kink points of these tiers. In terms of a percentage increase in marginal rate, this 100% increase is substantially larger than a price increase in other multi-tier nonlinear price schedules. For example, the five-tier increasing block electricity price schedule in California is one of the most steepest nonlinear price schedules in residential electricity pricing, but the price differences between the tiers are usually between 30% and 60%.

Panel A of Figure 2.4 presents the time-series price variation of each of the five tier

³1 CCF is 100 cubic feet, which is equal to 748 gallons.

rates for most consumers in IRWD. From 2000 to 2011, the five tier rates had continuous increases. In 2011, the marginal price for the fifth tier is about \$9.48, which is approximately \$5 larger than the fourth tier rate. Because of the consolidations, consumers in different service areas had different price schedules. Panel B presents the price schedule for Santa Ana Heights customers. After their service area was consolidated in 1997, they were on the flat marginal price schedule until 2004. Starting in 2005, their price schedule was changed to the standard five-tier block price that is shown in Panel A. Figure 2.5 presents the price schedules for Lake Forest, another service area that experienced a price change because of its consolidation. This area was consolidated in 2001, and had a flat marginal price schedule until 2008. IRWD changed their schedule to a five-tier block price schedule that is slightly different from the one for most service areas in 2008.

IRWD changes the price schedules for a couple of reasons. In most cases, the reason is related to changes in costs of providing service such as costs of chemicals, energy costs to operate wells, pumping stations and the water reclamation plants. The other reason is related to consolidations. After a consolidation, IRWD usually waits some years to change the former company's price schedule to IRWD's block price schedule. In one of the sections in this study, I use the price variation from the consolidation of Santa Ana Heights service area. Using this price variation associated with the consolidation may lead to a concern that there were other changes at the time of the consolidation that might affect water consumption. IRWD, however, did not change the price schedule immediately. They introduced their block price schedule to these consumers in 2005, which was 8 years after the consolidation. Furthermore, the panel data set in this study allows me to eliminate time-invariant confounding factors. However, there is still a concern that Santa Ana Heights area and other areas may have different time-variant unobservables that may confound my analysis. To address this concern, the final empirical analysis section focuses only on households within one mile of the service area border between Santa Ana Heights service area and Irvine service area.

2.2.3 Data

The primary data set for this study consists of panel data of household-level monthly water billing records from January 1994 to 2008.⁴ I obtained the data set directly from IRWD with a confidentiality agreement. The records include all residential customers served by IRWD. Each monthly record includes a customer's address, billing start date and end date, monthly consumption, service area code, and residential types (single-family, condominium, or apartment). The records also include the square footage of a customer's unit for some customers. The billing data do not include price information. I collect historical price schedules from

⁴I thank Amy McNulty and Fiona Sanchez for their help and support and for providing the data set for this study.

documents published by IRWD. To ensure the preciseness of the price information, I verified the numbers with staff at IRWD.

For the first and second parts of the following empirical analyses, I use all of the single-family households that are on IRWD's standard five-tier increasing block price schedule. The total number of observation is 64,601 single-family households. The last part of the analysis uses single-family households that are within one mile of the service area border between Santa Ana Heights service area and Irvine service area. The total number of observations for this border sample is 5,985 households.

Table 2.1 summarizes the descriptive statistics. The first column shows the statistics for the full sample. Mean consumption is particularly high in June, July, August, and September, and low in January, February, and March. Columns 3 and 4 present the statistics for the border sample. Mean square footage is higher around the border of Santa Ana Heights service area than the full sample. Mean consumption is also slightly larger in this area. However, both of mean square footage and monthly water consumption are quite similar between the two groups within one mile of the border. The final column presents t-statistics for the difference in the means. The differences of these statistics are not statistically different from zero.

2.3 Empirical Analysis

This section provide three empirical analyses to examine how consumers respond to nonlinear water price schedules. The first method uses price variation across the kink points of a nonlinear price schedule to estimate the response to marginal price. If consumers respond to their marginal price of water, the non-linearity of price schedules would create bunching of consumers around the kink points. The second identification strategy uses a regression discontinuity design that exploits a discontinuous change in marginal price. I use that fact that consumers with nearly the same consumption level experienced substantially different changes in marginal price between November and December, and between April and May. Results from these two analyses provide evidence that consumers do not respond to marginal price. The final section, therefore, explores whether consumers respond to expected marginal price or average price by using price variation across service areas.

2.3.1 Bunching Around Kink Points

2.3.1.1 A Standard Model of Nonlinear Budget Sets and Bunching of Consumers

The standard model of nonlinear budget sets provides an important implication about demand under nonlinear price schedules. Consider a consumer who has a two-tier nonlinear

water price schedule for water consumption x . The marginal price equals p_1 for up to k units of consumption and p_2 for any additional consumption. Suppose that the consumer has wealth W and quasilinear utility:

$$u(x, y) = W + V(x). \quad (2.1)$$

In the standard model of nonlinear budget sets, the consumer solves the following utility maximization problem:

$$\max_x u(x) = W - (p_1 \cdot x_1 + p_2 \cdot x_2) + V(x), \quad (2.2)$$

where x_1 and x_2 are consumption in the first and second tier. The demand under the standard model can be described as:

$$x_{MP}^* = \begin{cases} x^*(p_1) & \text{if } x^*(p_1) \leq k \\ k & \text{if } x^*(p_2) \leq k \leq x^*(p_1) \\ x^*(p_2) & \text{if } x^*(p_2) \geq k, \end{cases} \quad (2.3)$$

where $x^*(p_1)$ and $x^*(p_2)$ are the demand when the consumer faces a linear price schedule of p_1 or p_2 .

Figure 2.6 illustrates the demand curves derived in equation (2.3). An important implication from this equation is that if consumer preferences are convex and smoothly distributed across the kink point k , many demand curves intersect the vertical part of the price schedule as illustrated in the figure. In other words, a disproportionately large number of indifference curves would intersect the kink of the nonlinear budget constraint. As a result, the distribution of consumption should show bunching of consumers across the kink points (Heckman 1983). Saez (2009) shows how elasticities can be estimated by examining bunching around kinks under the assumption that individuals respond to nonlinear price schedules as the standard model predicts.

In the income tax literature, several studies including Saez (1999), Saez (2009), and Chetty et al. (2010) use this method to estimate the elasticity of taxable income with respect to nonlinear income tax rates. Most studies that use the US income tax records do not find bunching of taxpayers except for self-employed workers. For example, Saez (2009) finds no bunching across wage earners in income tax schedules in tax return data in the US. Chetty et al. (2010) find small but significant bunching for wage earners in their Danish tax recode data, although institutional factors in Denmark are likely to affect the bunching in addition to labor supply responses. In residential electricity data, Borenstein (2009) and Ito (2010) also find no evidence of bunching of consumers in five-tier increasing block price schedules

in California.

2.3.1.2 Results

Using a large data set of household-level consumption, I look for evidence of bunching of consumers along the nonlinear price schedule in IRWD. Figure 2.4 shows the histogram of household-level monthly water consumption for the Irvine service area in Irvine Ranch Water District in 1994 (Panel A) and 2008 (Panel B). The horizontal axis shows consumption relative to customers' baseline allocation. The figures also show the marginal price (\$) of water per CCF (100 cubic feet = 748 gallons). The solid lines display the locations of the kink points in the five-tier increasing block rates.

The histograms show no evidence of bunching around the kink points in either year. In 1994, the consumption distribution is smooth and does not have visible bunching of customers around kink points. In particular, it is striking to find no bunching around the second, third, and fourth kink points, because consumers face a 100% increase in marginal price when their consumption exceeds these kink points. In terms of a percentage increase in marginal rate, this 100% increase is substantially larger than the price increase in other multi-tier nonlinear price schedules. For example, the five-tier increasing block electricity price schedule in California is one of the most steepest nonlinear price schedules in residential electricity pricing, but the price differences between the tiers are usually between 30% and 60%. In contrast, water consumers in IRWD face a 100% increase when they cross each of the second, third, and fourth kink points. No bunching of consumers provides evidence that consumers may not respond to the marginal price of water. The next section examines how consumers change their consumption when some of them experience a large increase in marginal price but others do not have a price change.

2.3.2 A RD Design to Estimate the Response to Marginal Price

This section presents the second way to estimate price elasticity with respect to marginal price. My empirical strategy is similar to a regression discontinuity design used by Saez (2002). Saez uses a bracket creep that is created by inflation to estimate the elasticity of taxable income with respect to marginal income tax rates. From 1979 to 1981, the US income tax schedule was fixed in nominal terms while inflation was high (around 10%). This high inflation produced a real change in tax rate schedules. As a result, taxpayers near the top-end of a tax bracket were more likely to creep to a higher bracket and thus experience a rise in marginal rates the following year than the other taxpayers.

An important point about the price variation in Saez's study is that the price variation does not come from changes in marginal income tax rates. In this period, the income tax schedule itself did not change. However, the bracket creep moves taxpayers near the top-end

of a bracket to the next bracket, while a similar taxpayer near the middle of the bracket is likely to remain in the same bracket. This quasi-experiment provides him with treatment and control groups for changes in the marginal income tax rate.

2.3.2.1 A RD Design Using a Discontinuous Change in Marginal Water Rates

I introduce a similar regression discontinuity design for the five-tier nonlinear price schedule in IRWD. A key component of the price schedule is a consumer’s baseline allocation. For example, consumers pay the first tier rate for up to 40% of their baseline allocation and the second tier rate for between 40% and 100% of their baseline allocation. I use the fact that the baseline allocation is different between the summer months (May to November) and winter months (December to April), which leads to a substantial horizontal shift in the whose price schedule between April and May, and between November and December.

Figure 2.8 illustrates the horizontal shift in the price schedule between November and December. Because the baseline allocation is 18 CCF for the summer months and 14 CCF for the winter months, the price schedule shifts left from November to December. As a result, consumers near the top-end of a tier in November are likely to experience an increase in their marginal price, while consumers near the bottom-end of a tier in November are unlikely to experience a change in their marginal price. For example, consider consumers that are in the fourth tier in November. A consumer that is in S_4 in November is likely to be in the next tier and experience a marginal price increase in December, while a consumer in the bottom part of the fourth tier is likely to remain in the fourth tier and therefore face the same marginal price.

2.3.2.2 Identification Strategy

Let x_{it} denote consumer i ’s average daily water consumption during billing month t and $mp_t(x_{it})$ be the marginal price of water. Suppose that the consumer has a quasi-linear utility function and responds to a water price with a constant elasticity β . Then, the demand function can be described as:

$$\ln x_{it} = \alpha_i + \beta \ln mp_t(x_{it}) + \eta_{it}, \quad (2.4)$$

with an individual fixed effect α_i and an error term η_{it} . There are some assumptions behind the model. First, the assumption of a quasi-linear utility function eliminates income effects from a price change. Second, this estimation assumes that the response to price is immediate and does not have lagged effects. Third, the elasticity is constant over time and over households.

Ordinary Least Squares (OLS) produces an inconsistent estimate of β because $mp_t(x_{it})$

is a function of x_{it} . Under increasing block price schedules, η_{it} is positively correlated with $mp_t(x_{it})$.⁵ This simultaneity bias is exactly the same problem as the identification problem in the income tax literature, which usually involves estimation under a progressive income tax schedule.

To address the simultaneity bias, I consider the following two-stage least squares (2SLS) estimation. Suppose that between billing month t_0 and t , a water utility, IRWD changes the baseline allocation as illustrated in Figure 2.8. Let $\Delta \ln x_{it} = \ln x_{it} - \ln x_{it_0}$ denote the log change in consumer i 's consumption between billing month t_0 and billing month t , and $\Delta \ln mp_t(x_{it}) = \ln mp_t(x_{it}) - \ln mp_{t_0}(x_{it_0})$ the log change in the price. Finally, for the endogenous price variable $\Delta \ln mp_t(x_{it})$, I define a set of instrumental variables:

$$S_{it}^j = \begin{cases} 1 & \text{if } x_{it_0} \in \text{treatment in tier } j=1, \dots, 4 \text{ at } t_0 \\ 0 & \text{otherwise.} \end{cases} \quad (2.5)$$

That is, $S_{it}^j = 1$ if consumer i is the top-end of tier j in t_0 . For example, consider a consumer that is in the top-end of the fourth tier. For this consumer, $S_{it}^4 = 1$ and $S_{it}^1 = S_{it}^2 = S_{it}^3 = 0$. Intuitively, the dummy variable S_{it}^j works as an instrumental variable because it is a good predictor of a price change that is produced by the change in the baseline allocation between the two billing months.

Obviously, the instruments S_{it}^j are a function of x_{it_0} . Saez, Slemrod, and Giertz (2009b) and Ito (2010) point out that when $\Delta \ln x_{it} = \ln x_{it} - \ln x_{it_0}$ is used as a left hand side variable, the error term and x_{it_0} are likely to be highly correlated because of mean reversion in consumption. Suppose that a consumer experiences a positive transitory shock at t_0 . This positive transitory shock makes the consumer's consumption at t_0 larger than the consumption at t_1 , aside from any behavioral response to a price change. That is, in panel analyses, mean reversion produces a negative correlation between the error term and x_{it_0} .

An advantage of these instruments, S_{it}^j , is that the bias from mean reversion can be controlled for by including $f(x_{it_0})$, a flexible smooth control function of x_{it_0} in a regression. In the same way as a typical regression discontinuity design, including a flexible smooth function $f(x_{it_0})$ does not destroy identification because of the discontinuous nature of S_{it}^j .

I estimate the following 2SLS equation:

$$\Delta \ln x_{it} = \gamma_t + \beta \Delta \ln mp_t(x_{it}) + f(x_{it_0}) + \varepsilon_{it}, \quad (2.6)$$

instrumenting for $\Delta \ln mp_t(x_{it})$ with a set of the four indicator variables S_{it}^j where $j = 1, \dots, 4$. As a flexible smooth function $f(x_{it_0})$, I include the first, second, and third order of polynomials of x_{it_0} .

⁵For example, if a household has a positive shock in η_{it} (e.g. a friend's visit) that is not observable to researchers, the household will locate in the higher tier of its nonlinear rate schedule.

2.3.2.3 Results

Figure 2.8 illustrates the instrumental variables that I use in the 2SLS estimation. The solid line shows the five-tier increasing block price schedule in November. The dashed line shows the price schedule in December. From November to December, the baseline allocation changes from 18 CCF to 14 CCF. As a result of this change, households whose November consumption is near the top-end of a tier are more likely to experience an increase in marginal price in December compared to households whose November consumption is near the bottom part of a tier.

How does this change in the price schedule affect a consumer's marginal price from November to December? I use consumption data in November and December in 1996 as an example to show how a consumer's marginal price was affected by the change in the price schedule. Panel A of Figure 2.9 plots the mean percent change in marginal price and predicted marginal price over November consumption levels. First, for each level of November consumption, I calculate the mean of the percentage change in "predicted" marginal price, $[mp_t(x_{it_0}) - mp_{t_0}(x_{it_0})]/m_{t_0}(x_{it_0})$ to show where the price variation comes from. This predicted marginal price tells us the price change a consumer would experience if the consumer did not change consumption from November to December. The change in predicted marginal price corresponds to Figure 2.8, which shows that consumers near the top-end of a tier experience a price increase. For example, consumers in the top-end of the second, third, or fourth tier would have a 100% increase in marginal price. This is because the tier rate in the next tier is exactly double. Second, I calculate the mean of the percentage change in "actual" marginal price, $[mp_t(x_{it}) - mp_{t_0}(x_{it_0})]/m_{t_0}(x_{it_0})$. Consumers in the top-end of each tier experienced large increases in marginal price, whereas consumers whose November consumption was slightly above the kink points had very small changes.

Another interpretation of Panel A of Figure 2.9 is that the figure shows the first stage relationship between the actual price change and the instruments. The four instrumental variables, S_{it}^j where $j = 1, \dots, 4$, strongly predict the change in marginal price. I can also use the predicted change in marginal price $[mp_t(x_{it_0}) - mp_{t_0}(x_{it_0})]/m_{t_0}(x_{it_0})$ as an instrument. Conceptually, these two different instruments exploit essentially the same exogenous price variation. In fact, the estimation results that follow do not change by using either of the two types of instruments.

Because consumers on the right and left sides of the kink points experience substantially different price changes as shown in Panel A, there should be a discontinuous difference in their changes in consumption if they actually respond to marginal price. Panel B shows that there is no evidence of such behavior found in the data. I calculate the mean percent changes in consumption as $(x_{it} - x_{it_0})/x_{it_0}$. The change in consumption shows strong mean reversion; consumers that consume less in November are likely to increase their consumption

in December whereas consumers that consume a lot in November are likely to decrease their consumption in December. However, the change in consumption is smooth across the discontinuities of the price change, which suggests that consumers do not respond to the change in marginal price.

Figure 2.9 essentially illustrates what the 2SLS in equation (2.6) estimates. In the 2SLS estimation, I regress the change in consumption on the change in marginal price by using the instruments S_{it}^j . I also include the control function $f(x_{it_0})$ to deal with mean reversion in x_{it_0} . The identification assumption is that the instruments S_{it}^j are uncorrelated with the error term in the second stage regression ε_{it} given the control function for mean reversion in consumption.

Table 2.2 presents regression discontinuity estimates of the price elasticity with respect to marginal price. I use data from 1996 for this table. Results, however, do not change when I use other years. The price elasticity estimates are nearly zero with tight standard errors. The first two columns use November and December consumption data. I first include the full sample. To control for mean reversion in consumption, I include the first, second, and third order of polynomials of x_{it_0} . Adding higher order polynomials does not change the estimate of the price elasticity. The estimation may have bias if the polynomial function of x_{it_0} does not sufficiently control for mean reversion. For a robustness check, I follow Angrist and Lavy (1999) and estimate the same equation using the samples close to the kink (discontinuity) points. The second column shows that the price elasticity estimate does not change. Finally, the last two columns include the same regression using the price change from April to May, in which the allocation baseline changes from 14 CCF to 18 CCF. The price elasticity estimates are close to zero, which suggests that consumers do not respond to the marginal price of water.

2.3.3 Using Price Variation Across Service Areas to Estimate Demand

The results from the previous two sections suggest evidence that consumers do not respond to the marginal price of water. There are two possible reasons for these results. The first possible reason is that the demand for residential water consumption has truly zero price elasticity. If the demand is fully inelastic, then the demand curves become vertical in Figure 2.6 and will produce no bunching of consumers around the kink points. Therefore, zero price elasticity will be consistent with the finding of no bunching.

Another possibility is that consumers may make their decision with respect to other price signals than marginal price. For example, suppose that consumers respond to the average price or expected marginal price of nonlinear water prices. Then, the histogram of consumption will show no bunching even if the demand has a significant price elasticity. This

is because the average price and expected marginal price of a nonlinear price schedule do not have discontinuous kink points in contrast to the discontinuous shape of its marginal price curve. For the same reason, the response to the average or expected marginal would still be consistent with the findings in the RD estimation in the previous section. The RD design exploits the discontinuous shape of the marginal price schedule, but at the same time, the RD design essentially eliminates the price variation of the average and expected marginal prices so that I can not estimate the price elasticity with respect to these two alternative perceptions of price.

2.3.3.1 Price Variation Across Service Areas

This section uses a similar empirical strategy to Ito (2010) to examine whether consumers have nearly zero price elasticity for water or if they respond to an alternative perception of price rather than marginal price. Ito (2010). Ito (2010) estimates residential electricity demand by exploiting price variation across a spatial discontinuity in electric utility service areas. The territory border of two electric utilities lies within several city boundaries in southern California. As a result, nearly identical households experience substantially different nonlinear electricity price schedules.

In this study, I exploit price variation across different service areas in IRWD. Figure 2.10 shows two different price schedules in 2002. Most consumers in IRWD paid the five-tier increasing block prices. Consumers in Santa Ana Heights service area, however, paid a flat marginal price schedule that does not change with consumption levels. The figure shows that the marginal price is higher in the flat price schedule than the block price schedule up to 100% of the baseline allocation. However, the marginal price is the same in the third tier (100% to 150% of the baseline allocation) and lower in the flat price schedule above 150% of the baseline allocation.

This substantial difference in marginal price creates notable price variation in marginal price and average price. Figure 2.10 includes the average price curve for the block price schedule. The average price for the flat price schedule is higher than the block price schedule for up to 200% of the baseline allocation and lower than the block price schedule for consumption above 200% of the baseline allocation.

Consumers in Santa Ana Heights paid the flat price until 2004. Their price schedule, however, was changed into the block price schedule in 2005. As a result, the first and second tier had decreases in both marginal and average prices. The third tier had no change in marginal price but a decrease in average price. The fourth tier had an increase in marginal price but a decrease in average price. Finally, the fifth tier had increases in both marginal and average prices.

This policy change in 2005 provides several advantages for my price elasticity estimation. First, the policy change created nearly ideal price variation *between* the change in marginal

price and the change in average price depending on their consumption levels. Consumers experienced substantially different changes in their marginal and average prices. In particular, consumers in the third tier experienced no change in marginal price but a decrease in average price. Consumers in the fourth tier experienced an increase in marginal price and a decrease in average price. Having different price variation *between* marginal price and average price is key to examining whether consumers respond to marginal or average price.

Second, this policy change provided a group that can be potentially used as a control group for the policy change. The policy change only affected consumers in Santa Ana Heights service area. Therefore, consumers in the surrounding areas, which already had the block price schedule since 1990's, can be potentially used as a control group. To use the surrounding areas as a control group, I need the parallel trend assumption in water consumption between the treatment and control group; in the absence of a price change, the water consumption in the treatment and control groups would have the same change before and after the policy change. My analysis focuses on households within one mile of the service area border. I examine the validity of this parallel trend assumption in these border samples.

Third, this policy change provides a useful research environment to explore the long-run price elasticity of water demand. In general, a rate change in water prices, electricity prices, or tax rates, occurs successively over time. When a rate change occurs frequently, it is difficult to see the long-run effects of a rate change. In this research environment, a substantial rate change happened in 2005 to Santa Ana Heights consumers, which did not happen in surrounding areas, and these two groups of consumers had exactly the same price schedule after 2005. That is, the difference between the *relative* price between the two groups had a substantial change in 2005, but no change after 2005. I exploit this environment to explore the long run effects of a rate change on water consumption.

2.3.3.2 Identification Strategy

I estimate the price elasticity for water demand using the following identification strategy that is used in Ito (2010). Let x_{it} denote household i 's average daily water consumption during billing month t and $p_t(x_{it})$ be the price of water, which is either the marginal, expected marginal, or average price of x_{it} . Suppose that the household has a quasi-linear utility function and responds to electricity prices with a constant elasticity β . Then, the demand function can be described as:

$$\ln x_{it} = \alpha_i + \beta \ln p_t(x_{it}) + \eta_{it}. \quad (2.7)$$

Ordinary Least Squares (OLS) produces an inconsistent estimate of β because $p_t(x_{it})$ is a function of x_{it} . Under increasing block price schedules, η_{it} is positively correlated with $p_t(x_{it})$. Most previous studies of nonlinear price schedules use consumer i 's previous consumption

levels (e.g. the last year’s consumption) to construct instruments. However, recent studies (e.g. Saez 2004, Saez, Slemrod, and Giertz 2009a) point out the identification problems of these instruments and suggest using repeated-cross section analysis. My identification strategy also uses repeated-cross section analysis that examine how the *distribution* of consumption changes in response to the change in price.

For both the treatment and control groups, I divide the consumption data into deciles in each time period. Denote G_1 as a dummy variable for the first decile group of the consumption distribution, G_2 for the second decile group, ..., and G_{10} for the top decile group of the consumption distribution. That is, the ten dummy variables G_g are simply group dummy variables for ten deciles. I include the data from January 2002 to December 2008. Therefore, the data set includes 84 year-month time periods. I run the 2SLS

$$\ln x_{it} = \beta \ln p_{ut}(x_{it}) + \gamma_{ut} + \lambda_{gt} + \theta_{gu} + Z'_{it} \delta + \varepsilon_{it}, \quad (2.8)$$

using the three-way interactions of time dummy variables, decile group variables, and utility dummy variable $Time_t \cdot G_g \cdot SA_i$ as instruments. SA_i is a dummy variable for Santa Ana Heights households. As in the standard DDD estimation (e.g.. Gruber (1994) and Gruber and Poterba (1994)), this model provides full nonparametric control for service-area-specific time effects that are common across decile (γ_{ut}), time-varying decile effects (λ_{gt}), and service-area-specific decile effects (θ_{gu}). The identification assumption is that $Cov(Time_t \cdot G_g \cdot SA_i, \varepsilon_{it}) = 0$ for each t and g . Thus, the required assumption is that there is no contemporaneous shock that affects the *relative* outcomes of decile groups in the same service area for the same time period.

To test whether consumers respond to marginal price or average price, I also include both prices in the model. In this case, the estimating equation is

$$\ln x_{it} = \beta_1 \ln mp_{ut}(x_{it}) + \beta_2 \ln ap_{ut}(x_{it}) + \gamma_{ut} + \lambda_{gt} + \theta_{gu} + Z'_{it} \delta + \varepsilon_{it}. \quad (2.9)$$

I also run the model that includes both expected marginal price and average price.

$$\ln x_{it} = \beta_1 \ln emp_{ut}(x_{it}) + \beta_2 \ln ap_{ut}(x_{it}) + \gamma_{ut} + \lambda_{gt} + \theta_{gu} + Z'_{it} \delta + \varepsilon_{it}. \quad (2.10)$$

The nonparametric control variables γ_{ut} , λ_{gt} , and θ_{gu} flexibly control for unobservable economic and weather shocks to household water consumption. Consumers have different billing cycles, therefore, weather conditions can be different among different billing cycles in a given billing month. To control for different shocks to each billing cycle, I also include time-varying billing cycle level fixed effects $Cycle_t$.

2.3.3.3 Results

As illustrated in Figure 2.10, consumers in Santa Ana Heights experienced different changes in marginal and average prices depending on their consumption levels. The marginal price had a decrease in the first and second tier, no change in the third tier, and an increase in the fourth and fifth tiers. The average price had a decrease in the first, second, third, and fourth tiers, and an increase in the fifth tier. Therefore, if consumers respond to their marginal price, I should observe the following distributional changes in consumption: 1) the consumption in the bottom of the consumption distribution should *fall* relative to the control group, 2) the consumption between 100% and 150% of the baseline allocation should have *no change* relative to the control group, and 3) the consumption above 150% of the baseline allocation should *rise* relative to the control group.

Figure 2.11 shows five percentiles (percentile 10, 25, 50, 75, and 90) of consumption for the treatment group (SA) and control group (IR). The vertical axis is the monthly consumption relative to the baseline allocation (%) so that I can relate this graph with the relative price change that happened to the two groups. First, I examine the validity of the control group by looking whether the parallel trend assumption holds before the policy change in 2004. In this border sample, the figure shows evidence that each percentile of the two groups moves in a parallel way before 2004.

Second, I explore the effect of the policy reform in 2005 on the consumption distribution. Relative to the control group, the treatment group's consumption increases in percentile 10, 25, 50, and 75. In contrast, the treatment group's consumption in percentile 90 falls relative to the control group. These findings contradict the prediction for the response to marginal price. Rather, these findings are more consistent with the response to average price. From 2004 to 2005, most parts of the consumption distribution experienced a decrease in average price relative to the control group. Only consumers whose consumption level is larger than 200% of the baseline allocation experienced an increase in average price. Therefore, the relative rise in consumption in percentile 10, 25, 50, and 75 are consistent with the response to average price. Furthermore, from 2004 to 2005, the treatment group's consumption in percentile 90 has a decrease relative to the control group. This finding is also consistent with the average price response because consumption levels above 200% of the baseline allocation experienced an increase in average price.

Finally, the path of the change in consumption is suggestive of the long-run response to the price change. The relative price between the treatment and control groups had a large change in 2004, but no change after that. The relative consumption, however, seems to have a gradual change over time. I estimate the short-run and long-run elasticity in the following section. A concern about the gradual change in consumption is a potential time trend that is different between the treatment and control groups. The figure provides some evidence

that this is unlikely to be a concern in this case. In 2002, 2003, and 2004, there is no clear evidence of different time trends between the two groups in each percentile. Moreover, the relative consumption starts to change at the exactly the same timing of the policy change.

To statistically estimate the price elasticity of demand, I run equation (2.8) for each of the three price definitions: marginal price, expected marginal price, and average price. I calculate expected marginal price by assuming that consumers have errors with a standard deviation of 20% of their consumption. I also estimate equation (2.9) and equation (2.10) to test whether consumers respond to marginal price, expected marginal price, or average price. First, I estimate these equations using contemporaneous price variables to obtain short-run price elasticity estimates. Second, for each price variable, I calculate the average of the twelve-month lag prices and use these price variables to estimate long-run price elasticity estimates. The intuition behind this estimation is that the twelve-month average would capture the price response to lagged prices.

Table 2.3 shows estimates for the short-run price elasticity in the summer months (May to November). The price elasticity estimate is $-.094$ for the marginal price, $-.081$ for the expected marginal price, and $-.127$ for the average price. In Column 4, I include both marginal and average price. Suppose that consumers respond to the nonlinear price schedule as the standard economic model predicts. Then, once the marginal price is included in the regression, adding the average price should not change the estimated coefficients. Column 4 shows evidence of the opposite. Once the average price is included, adding the marginal price does not statistically change the effect of the average price. Moreover, the effect of marginal price becomes economically small and statistically insignificant. Table 2.4 provides estimates for the short-run elasticity for the winter months (December to April). The magnitude of the elasticity estimates is slightly smaller than the summer months. The regressions including both marginal and average prices or expected marginal and average prices show similar results to those for the summer months.

Table 2.5 and 2.6 present the long-run price elasticity estimates for the summer and winter months. Each price variable is the twelve-month average of the variable instead of the contemporaneous price. These price elasticity estimates are significantly larger than the short-run estimates. For example, in the summer months, the price elasticity estimates are $-.171$ for the marginal price, $-.152$ for the expected marginal price, and $-.203$ for the average price. The regressions including both marginal and average prices or expected marginal and average prices show similar to the short-run price elasticity estimation. Therefore, the results provide evidence that consumers respond to average price rather than marginal or expected marginal price both in the short-run and long-run.

2.4 Conclusion and Future Work

This paper explores whether consumers respond to marginal price, expected marginal price, or average price when faced with nonlinear water price schedules. The standard model of nonlinear budget sets predicts that consumers optimize their consumption with respect to marginal price, or expected marginal price when they account for uncertainty about their consumption. An alternative prediction is that consumers may make a sub-optimal choice by responding to average price. Theoretically, consumers make this sub-optimal choice when the cognitive costs of responding to marginal price are higher than the utility gain from re-optimizing with respect to marginal price. To empirically test the three predictions, I exploit price variation in a residential water market in Southern California and conduct three empirical analyses using a panel data set of household-level monthly water billing records.

Results from the three empirical analyses provide strong evidence that consumers respond to average price rather than marginal or expected marginal price when faced with nonlinear price schedules for water. First, I find that the consumption density does not reveal bunching of consumers in any of the kink points in the nonlinear water price schedule. There is no evidence of bunching even in the price schedules that have quite steep discontinuous increases in marginal price. Second, the regression discontinuity estimation provides no evidence of the response to marginal price. The price elasticity estimates with respect to marginal price are close to zero with tight standard errors. Finally, the analysis based on the policy reform in 2005 provides evidence that consumers respond to average price. In particular, when I include both marginal price and average price in the price elasticity estimation, the marginal price has nearly zero effect on consumption, while the average price has a statistically and economically significant effect on consumption. I find the same result with the expected marginal price; when I include both expected marginal price and average price in the price elasticity estimation, the expected marginal price has nearly zero effect on consumption, while the average price has a statistically and economically significant effect on consumption.

Estimates from the price elasticity estimation also provide several notable findings regarding the magnitude of the price elasticity for water. First, I find slightly larger price elasticity estimates for the summer months. The short-run price elasticity with respect to average price is $-.127$ for the summer months and $-.097$ for the winter months. Second, I also find larger price elasticity estimates for the long-run response to the policy reform in 2005. The estimated long-run price elasticity is $-.203$ for the summer months and $-.154$ for the winter months.

This paper leaves three additional questions for my future work. First, this study focuses on the water consumption of single-family households, but the water billing data set also includes condominium households and apartment residents. It would be valuable to examine

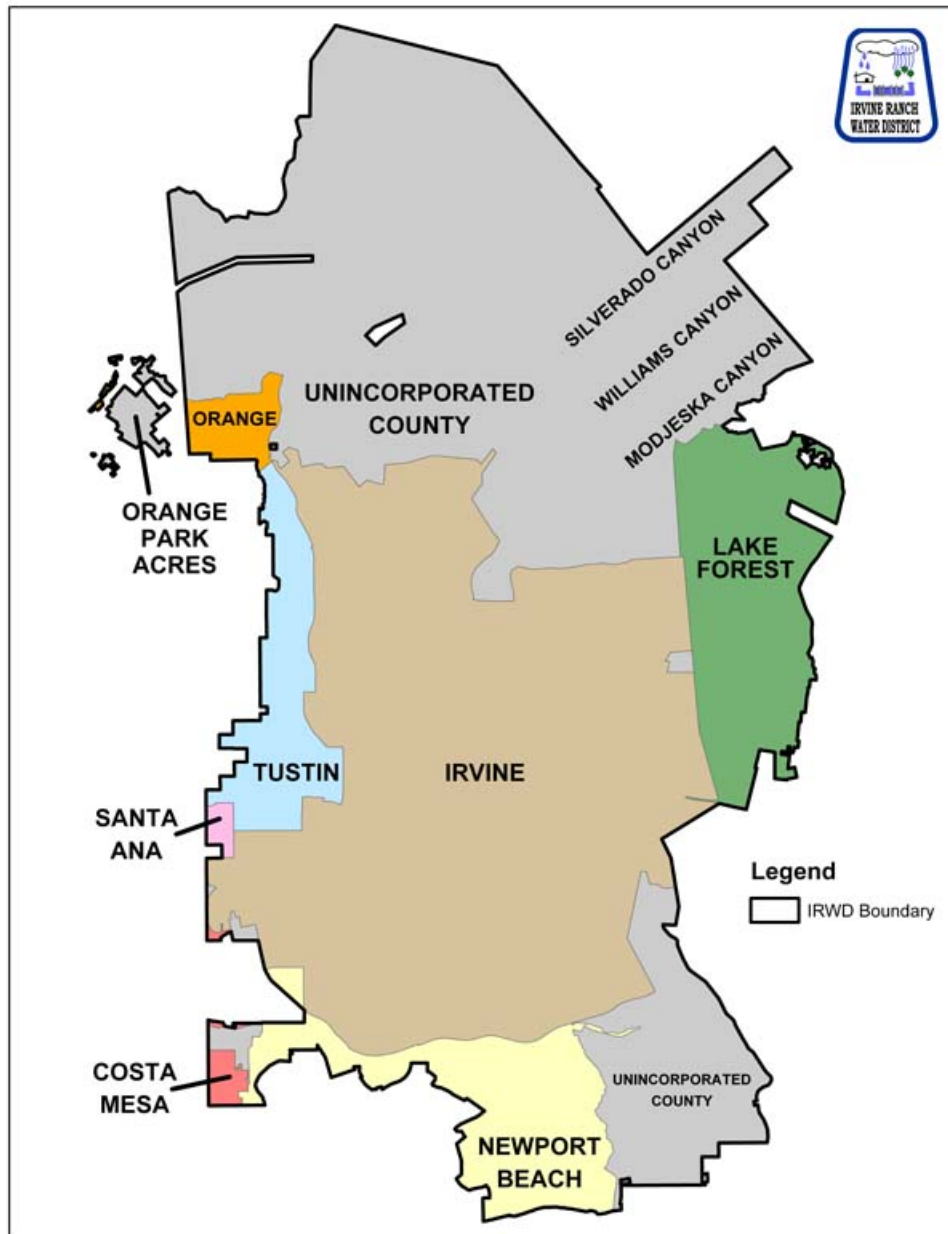
how consumers in a condominium or apartment respond to a price change because their outside water use is presumably lower than single-family households. Second, Lake Forest service area, one of other service areas in IRWD, also had a large price increase in 2008. A potential advantage of this price change is that Lake Forest service area includes a large number of households so that it may be possible to do a more detailed analysis of how different types of consumers respond to price changes differently. Finally, tax assessor's data can also be useful for exploring potential heterogeneous responses to a price change. Because the billing data set includes a consumer's address information, it would be possible to match the water consumption data with detailed housing data on swimming pools, number of bedrooms, and square footage of indoor and outdoor areas of each housing unit, if tax assessor's data were available.

Figure 2.1: Orange County and Irvine Ranch Water District (IRWD)



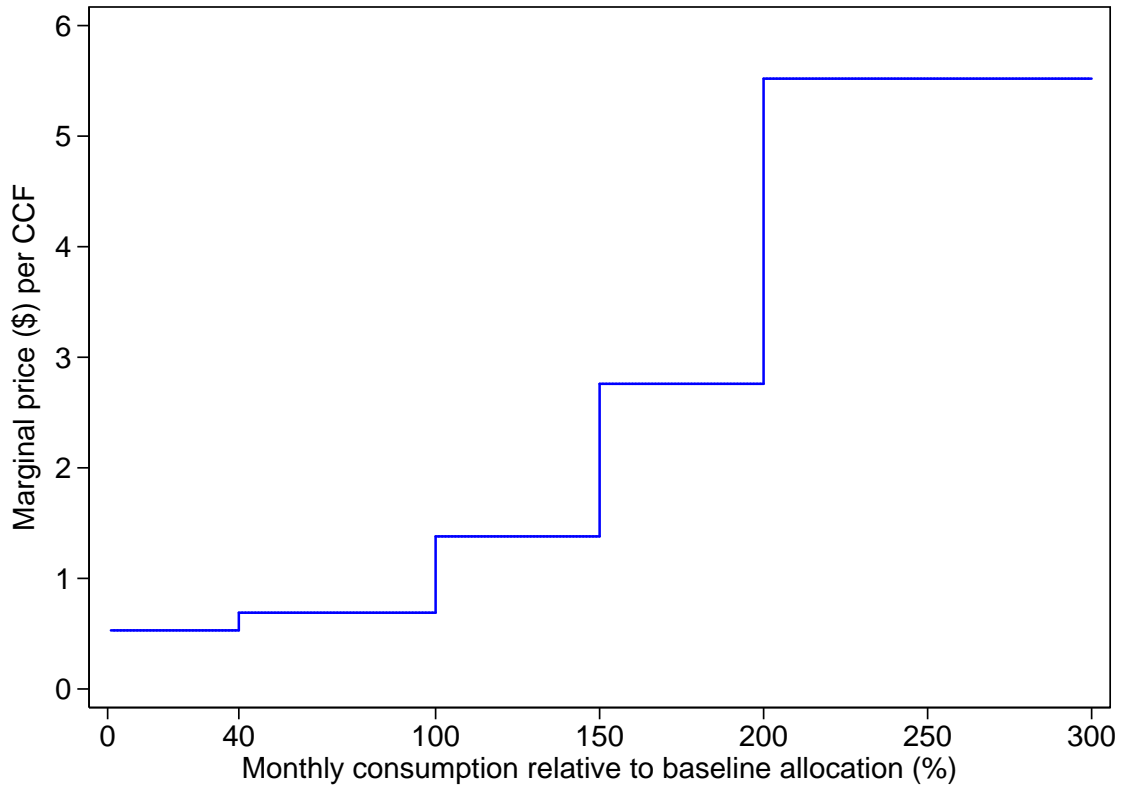
Notes: This figure shows a service territory map of Irvine Ranch Water District (IRWD). The service area approximately 181 square miles from the Pacific coast to the foothills in Orange County, California. The original map is provided by IRWD.

Figure 2.2: Service Areas of Irvine Ranch Water District (IRWD)



Notes: This figure shows service areas in Irvine Ranch Water District (IRWD). The District serves the City of Irvine and portions of the Cities of Costa Mesa, Lake Forest, Newport Beach, Tustin, Santa Ana, Orange and unincorporated Orange County. Santa Ana Heights service area was consolidated in 1997 and Lake Forest service area was consolidated in 2001. The original map is provided by IRWD.

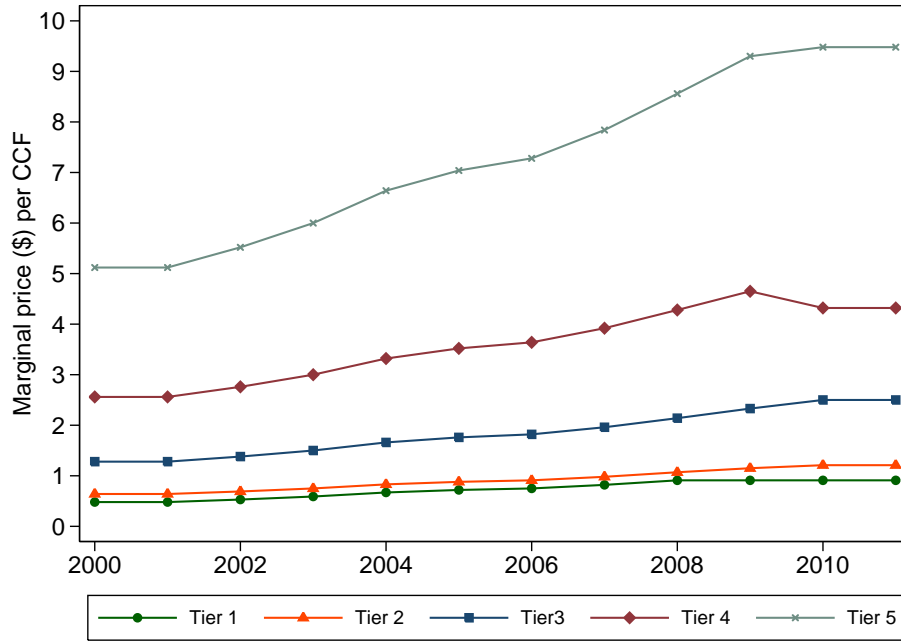
Figure 2.3: Five-Tier Increasing Block Price Schedule in IRWD in August 2002



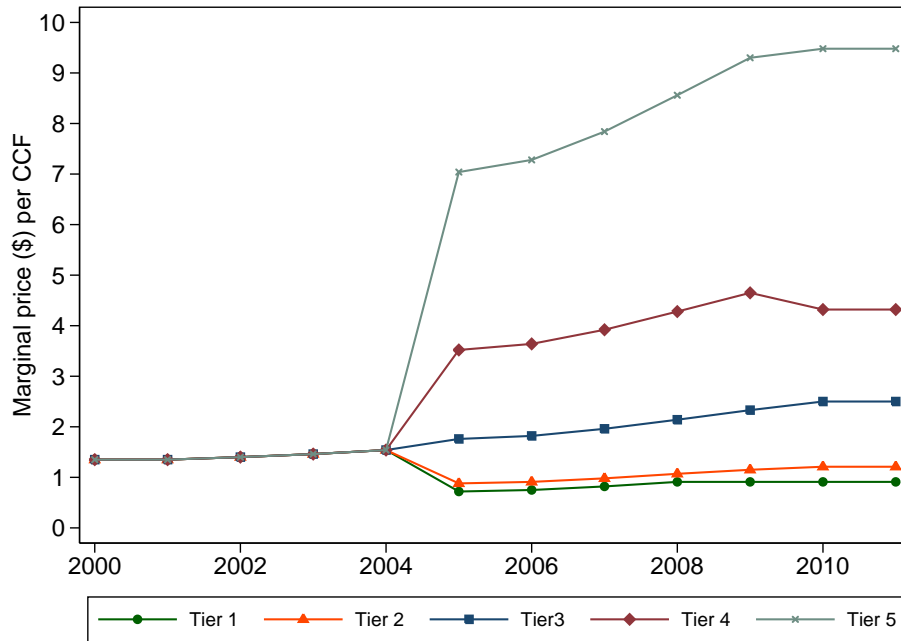
Notes: This figure shows the five-tier increasing block price schedule in IRWD in August 2002. IRWD allocates a “baseline allocation” to each customer, and the customer’s marginal price depends on consumption relative to the baseline allocation. The marginal price equals the first tier rate for up to 40% of the baseline, the second tier rate for up to 100%, the third tier rate for up to 150%, the fourth tier rate for up to 200%, and the fifth tier rate for over 200% of the baseline.

Figure 2.4: Tier Rates from 2000 to 2011

Panel A. IRWD's standard five-tier block price schedule

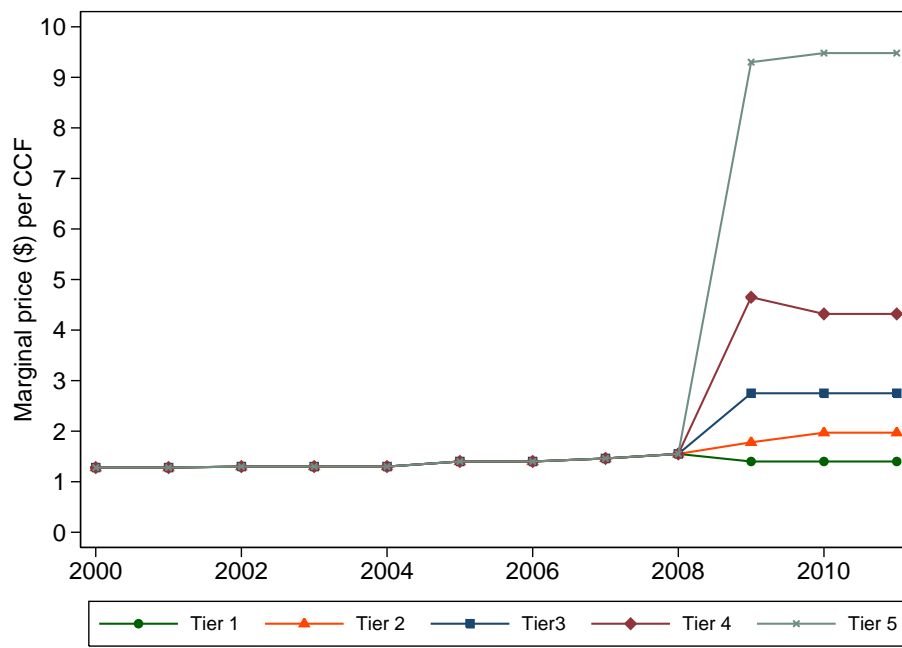


Panel B. Price Schedule in Santa Ana Heights Service Area



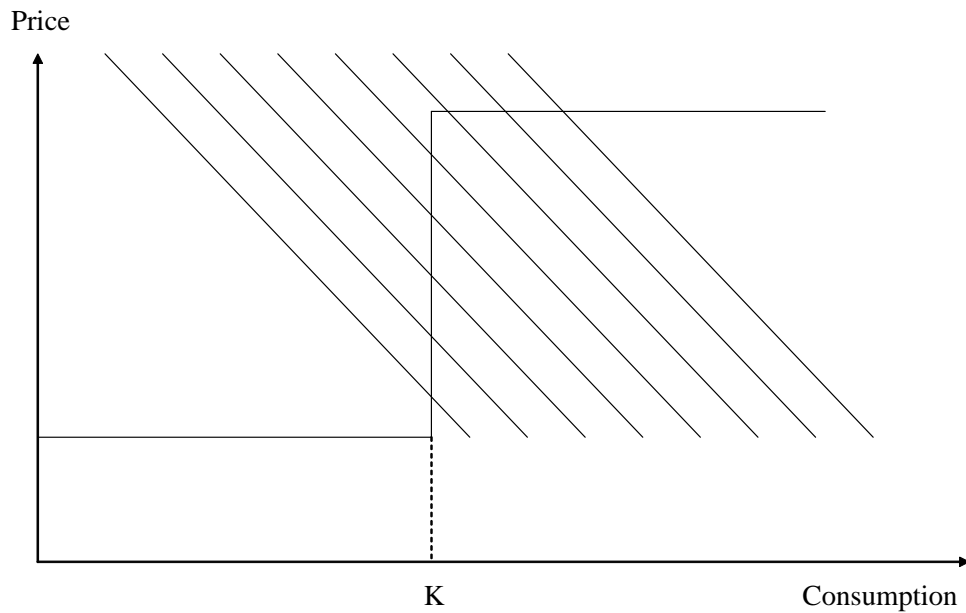
Notes: Panel A shows the time-series price variation of each of the five tier rates in IRWD's standard price schedule. Panel B shows the time-series price variation of the price schedule in Santa Ana Heights service area, which had a flat marginal price schedule until 2004 and then was transformed to IRWD's standard rate in 2005.

Figure 2.5: Tier Rates from 2000 to 2011 (Lake Forest Service Area)



Notes: This figure shows the time-series price variation of the price schedule in Lake Forest service area, which had a flat marginal price schedule until 2008 and was changed to a five-tier increasing block price schedule in 2009.

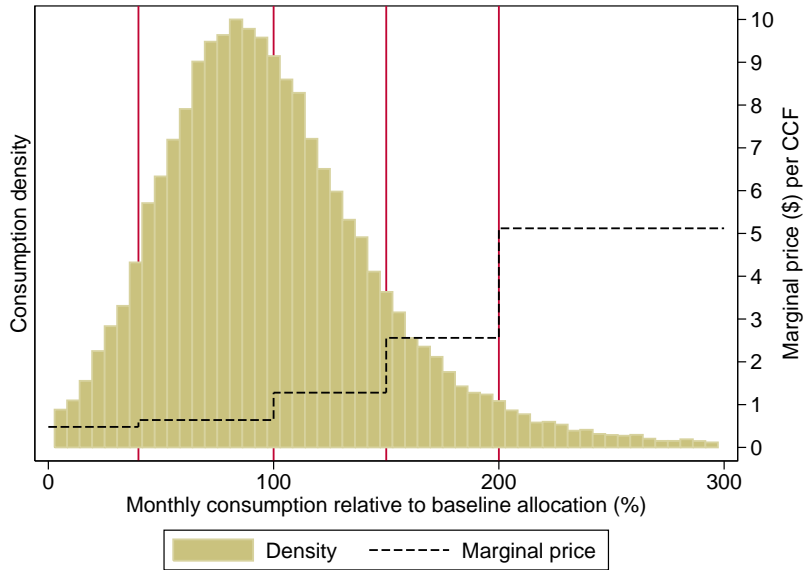
Figure 2.6: A nonlinear Price Schedule and Demand Curves



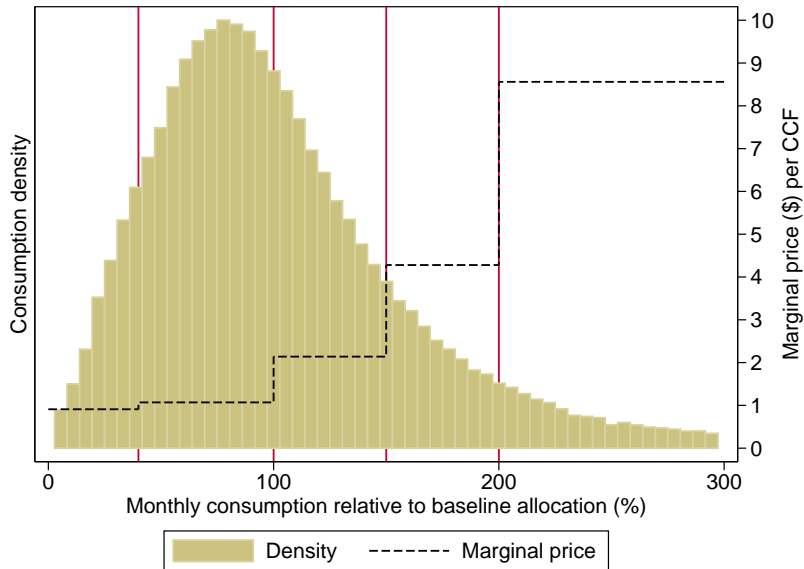
Notes: This figure shows an example of nonlinear price schedules along with demand curves. If consumer preferences are convex and smoothly distributed across the kink point k , many demand curves intersect the vertical part of the price schedule as illustrated in the figure. In other words, a disproportionately large number of indifference curves would intersect the kink of the nonlinear budget constraint. As a result, the distribution of consumption should show bunching of consumers across the kink points (Heckman (1983)) if consumers respond to the marginal price of water.

Figure 2.7: Consumption Density in 1994 and 2008: Bunching Around Kink Points

Panel A. Consumption density and price schedule in 1994

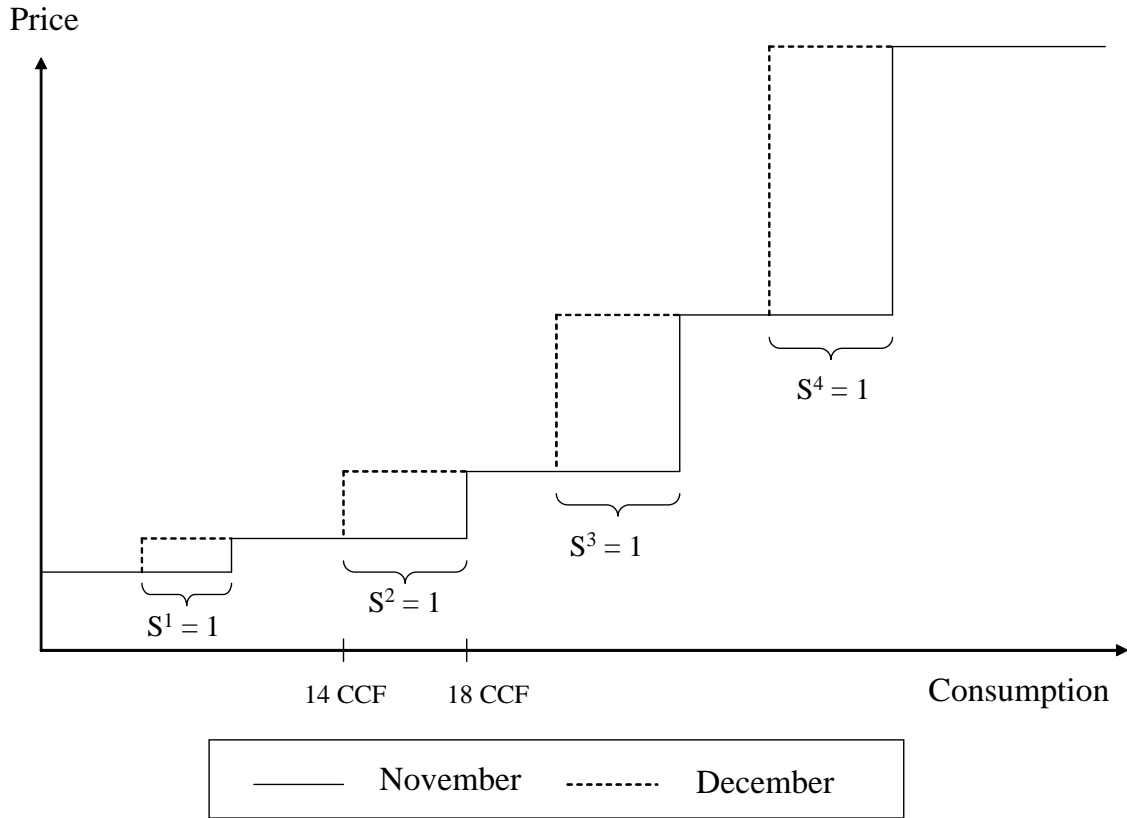


Panel B. Consumption density and price schedule in 2008



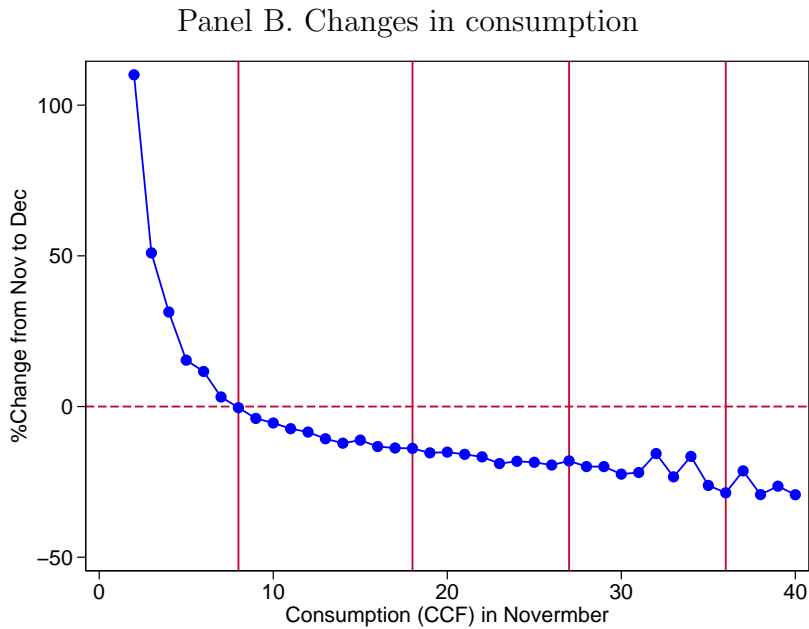
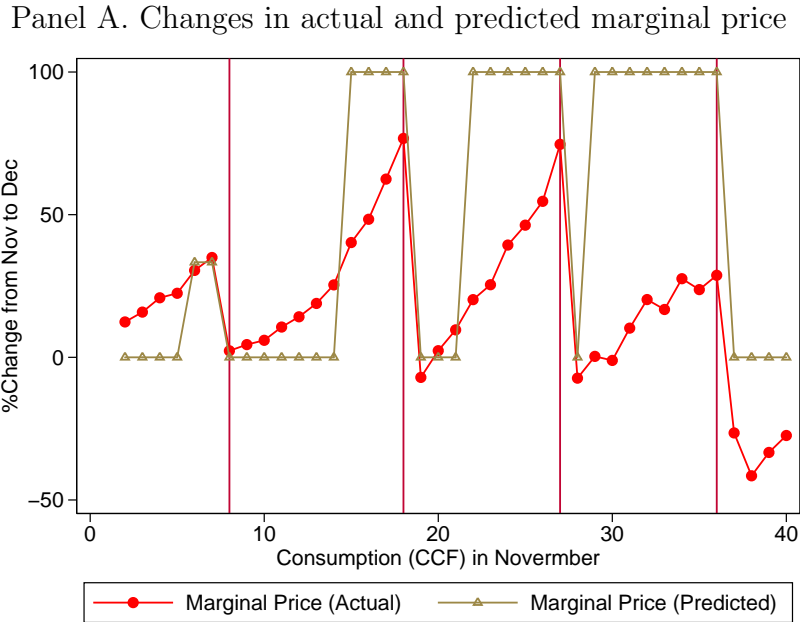
Notes: The figures display the histogram of household-level monthly water consumption for Irvine Ranch Water District in 1994 (Panel A) and 2008 (Panel B). The horizontal axis shows consumption relative to the baseline allocation. The bin size is 5% of the baseline consumption quantity. The figures also show the marginal price. The solid lines represent the locations of the kinks in the five-tier increasing block price schedules. The distribution is smooth and does not have visible bunching of customers around the kink points.

Figure 2.8: Instrumental Variables for the RD design to estimate the response to marginal price



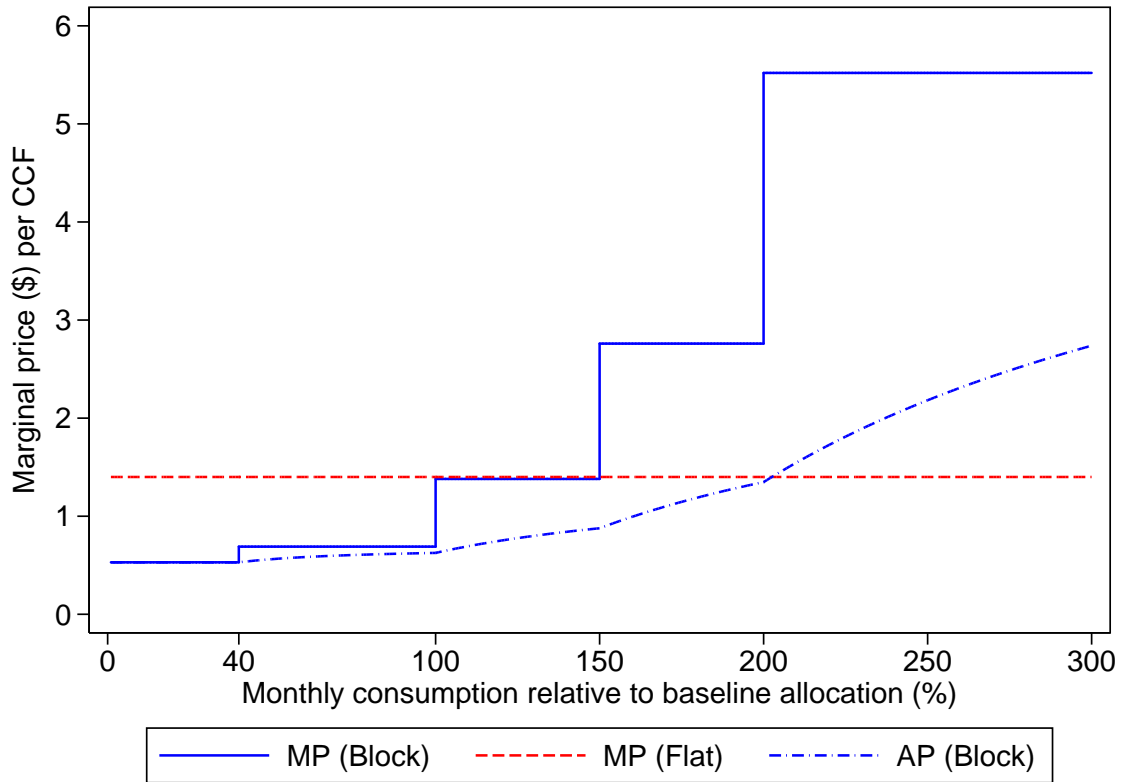
Notes: This figure illustrates the instrumental variables that I use for my regression discontinuity estimation in equation (2.6). The solid line shows the five-tier increasing block price schedule in November. The dashed line shows the price schedule in December. From November to December, the baseline allocation changes from 18 CCF to 14 CCF. As a result of this change, households whose November consumption is near the top-end of a tier are more likely to experience an increase in marginal price in December compared to households whose November consumption is near the bottom part of a tier. Each of the four instruments equal one if a consumer's November consumption falls in its range and zero otherwise.

Figure 2.9: Changes in Marginal Price and Consumption from November to December 1996



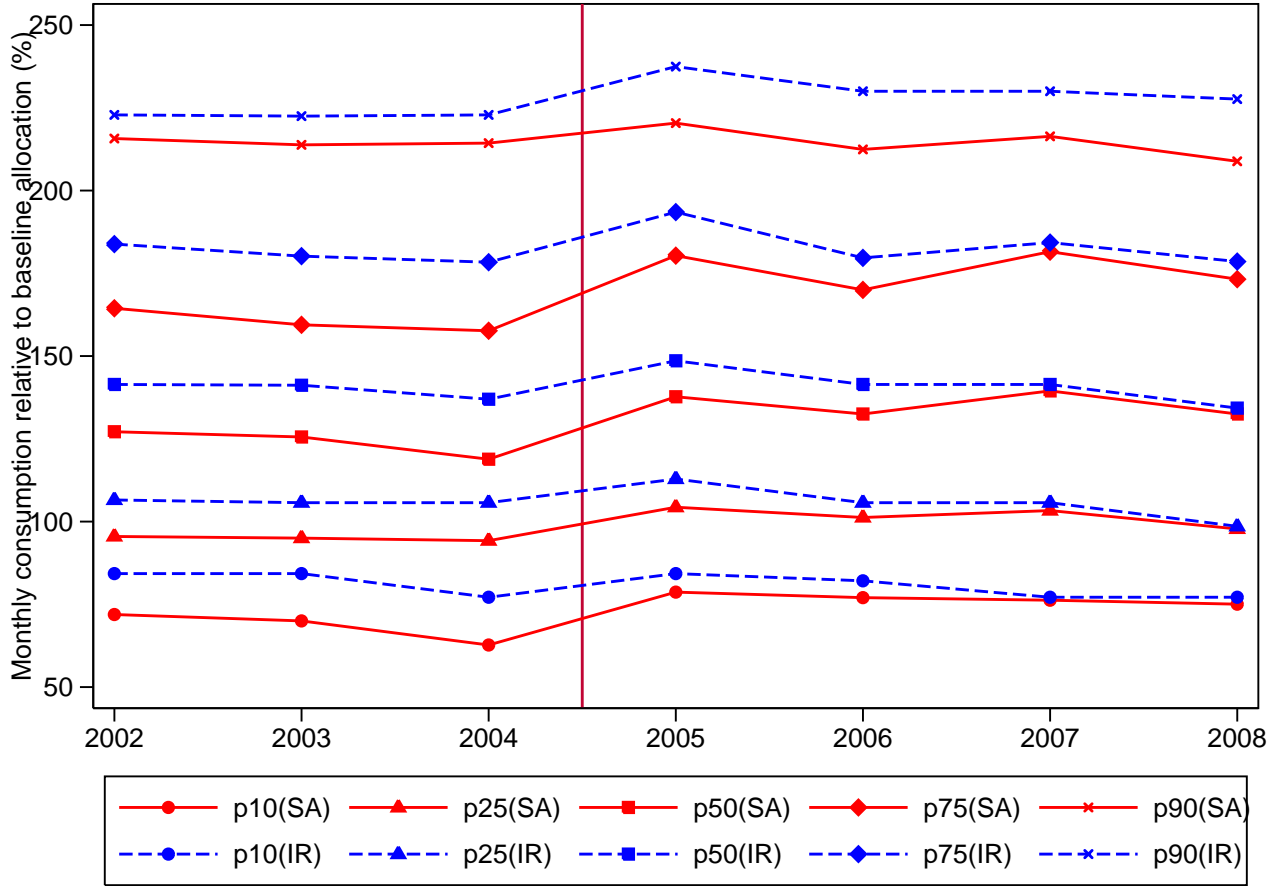
Notes: Panel A shows the mean percent change in marginal price and predicted marginal price from November to December in 1996 over November consumption levels. I calculate the mean of the percentage change in predicted marginal price, $[mp_t(x_{it_0}) - mp_{t_0}(x_{it_0})]/m_{t_0}(x_{it_0})$ and the mean of the percentage change in actual marginal price, $[mp_t(x_{it}) - mp_{t_0}(x_{it_0})]/m_{t_0}(x_{it_0})$. Panel B shows the percent change in consumption, $(x_{it} - x_{it_0})/x_{it_0}$, over November consumption levels.

Figure 2.10: Five-Tier Block Price Schedule and Flat Marginal Price Schedule in August 2002



Notes: This figure shows the five-tier increasing block price schedule in IRWD in August 2002. The figure also shows the flat marginal price schedule in Santa Ana Heights service area. Finally, the figure includes the average price of water for the five-tier increasing block price schedule. Consumers in Santa Ana Heights service area had the flat marginal price schedule until 2004 when their price schedule was switched to the five-tier increasing block price schedule.

Figure 2.11: Changes in the Consumption Distributions in the Border Samples



Notes: This figure shows five percentiles (percentile 10, 25, 50, 75, and 90) of consumption for the households within one mile of the service area border between Santa Ana Heights service area (SA) and Irvine service area (IR). The vertical axis is the monthly consumption relative to the baseline allocation (%).

Table 2.1: Descriptive Statistics

	Full samples	Households within 1 mile of the border of Santa Ana Heights service area		
		Santa Ana Heights' Side	Irvine's side	T-stat
Number of customers in 2008	64601	2750	3235	
Mean Square Footage	3609.55	4977.14	5039.72	-0.24
Mean water use (CCF) in 2008:				
January	12.79	13.93	14.15	-0.33
February	11.00	11.63	12.35	-1.28
March	12.42	13.53	14.87	-1.50
April	14.99	17.95	18.13	-0.12
May	16.65	21.13	20.96	0.08
June	17.48	22.52	21.35	0.52
July	18.89	25.11	23.14	0.73
August	18.20	23.45	22.84	0.26
September	18.61	23.18	22.95	0.09
October	17.49	20.74	22.02	-0.60
November	16.33	20.03	19.36	0.34
December	13.98	16.32	15.28	0.78

Notes: The first column shows the statistics for the full sample, and the second and third columns present the statistics for households within one mile of the border between the Santa Ana Heights service area and Irvine service area. The last column presents t-statistics for the difference in the means between the two groups in the border sample.

Table 2.2: Regression Discontinuity Estimates of Price Elasticity with Respect to Marginal Price

	November - December		April - May	
	Full sample (1)	± 3 CCF of kinks (2)	Full sample (4)	± 3 CCF of kinks (5)
$\Delta \ln(\text{MP})$	0.008 (0.014)	0.007 (0.012)	0.001 (0.011)	-0.0021 (0.012)
x_{t_0}	-14.431 (1.032)	-12.406 (3.878)	-10.046 (0.838)	-9.354 (3.946)
$x_{t_0}^2$	0.933 (0.093)	0.809 (0.318)	0.633 (0.073)	0.608 (0.321)
$x_{t_0}^3$	-0.027 (0.003)	-0.023 (0.011)	-0.018 (0.003)	-0.018 (0.011)
Constant	69.260 (3.901)	57.809 (15.581)	44.272 (3.255)	39.915 (15.958)
Observations	40150	13032	39780	12190

Notes: This table presents results of the 2SLS regression in equation (2.6). The unit of observation is household-level monthly water bills. The dependent variable is the log change in daily average water consumption during a billing month. The regression uses data from 1996, but results do not change when data from other year are used. The first two columns use November and December consumption data. The first and third columns include the full sample. The second and fourth columns include samples whose November (April for the fourth column) consumption falls between plus or minus 3 CCF from the kink points of the nonlinear price schedule. To control for the mean reversion in consumption, I include the first, second, and third order of polynomials of x_{it_0} . Adding higher orders of polynomials does not change the estimate of the price elasticity. Standard errors are adjusted for clustering at the zip code level.

Table 2.3: Price Elasticity Estimation (Summer, Short-run)

	(1)	(2)	(3)	(4)	(5)
ln(MP)	-.094 (.034)			-.010 (.022)	
ln(EMP)		-.081 (.019)			-.012 (.020)
ln(AP)			-.127 (.016)	-.120 (.022)	-.121 (.018)
Observations	251,370				

Notes: This table presents results of the 2SLS regressions in equation (2.8), (2.9), and (2.10). The unit of observation is a household-level monthly water bill. The dependent variable is log of daily average water consumption during a billing month. The data include the summer billing months (May to October) from 2002 to 2008. Standard errors are adjusted for clustering at the zip code by decile level.

Table 2.4: Price Elasticity Estimation (Winter, Short-run)

	(1)	(2)	(3)	(4)	(5)
ln(MP)	-.042 (.007)			.003 (.012)	
ln(EMP)		-.027 (.014)			-.009 (.013)
ln(AP)			-.097 (.012)	-.098 (.014)	-.100 (.013)
Observations	251,370				

Notes: This table presents results of the 2SLS regressions in equation (2.8), (2.9), and (2.10). The unit of observation is a household-level monthly water bill. The dependent variable is log of daily average water consumption during a billing month. The data include the winter billing months (November to April) from 2002 to 2008. Standard errors are adjusted for clustering at the zip code by decile level.

Table 2.5: Price Elasticity Estimation (Summer, Long-run)

	(1)	(2)	(3)	(4)	(5)
ln(MP)	-.171 (.019)			.003 (.012)	
ln(EMP)		-.152 (.023)			-.040 (.020)
ln(AP)			-.203 (.015)	-.177 (.022)	-.184 (.018)
Observations			251,370		

Notes: This table presents results of the 2SLS regressions in equation (2.8), (2.9), and (2.10). The unit of observation is a household-level monthly water bill. The dependent variable is log of daily average water consumption during a billing month. The data include the summer billing months (May to October) from 2002 to 2008. In these regressions, the price variables are the mean of the twelve-month lagged variable. Standard errors are adjusted for clustering at the zip code by decile level.

Table 2.6: Price Elasticity Estimation (Winter, Long-run)

	(1)	(2)	(3)	(4)	(5)
ln(MP)	-.068 (.015)			.005 (.012)	
ln(EMP)		-.042 (.019)			.013 (.014)
ln(AP)			-.154 (.012)	-.157 (.014)	-.158 (.013)
Observations			251,370		

Notes: This table presents results of the 2SLS regressions in equation (2.8), (2.9), and (2.10). The unit of observation is a household-level monthly water bill. The dependent variable is log of daily average water consumption during a billing month. The data include the winter billing months (November to April) from 2002 to 2008. In these regressions, the price variables are the mean of the twelve-month lagged variable. Standard errors are adjusted for clustering at the zip code by decile level.

Chapter 3

The Effect of Cash Rewards on Energy Conservation: Evidence from a Regression Discontinuity Design

3.1 Introduction

Engineering studies often suggest that improving residential energy efficiency is the least expensive way to abate global greenhouse gas emissions.¹ However, policy makers, however, generally believe that it is difficult to find a policy that can effectively change households' electricity consumption behavior. The price elasticity of residential electricity demand is relatively inelastic, and it is often politically infeasible to introduce an electricity price that is high enough to achieve a substantial consumption reduction.

A potential solution to this problem is to provide explicit financial incentives to save electricity. As an explicit financial incentive, many electric utilities offer rebate programs. Consumers receive a rebate for purchasing efficient appliances, or weatherizing homes. Also, electric utilities often offer “conservation rebate programs” that provide a rebate for rewarding a reduction in consumption achieved during a certain time period. For example, the California state government offered “California 20/20 electricity rebate program”, which provided a 20% discount on electricity bills as a financial reward for reducing electricity consumption by 20% relative to the previous year. Such conservation rebate programs allow consumers to choose how they will reduce consumption and is therefore more flexible than other rebate programs that require a purchase of specific appliances. The cost-effectiveness of these

¹For example the abatement cost curve of greenhouse gas emissions by Naucler and Enkvist (2009) indicates that the abatement cost in the residential electricity sector can be negative in the sense that improving energy efficiency at home would reduce greenhouse gas emissions and household expenditure for electricity.

programs, however, remains controversial. There is little evidence that consumers save electricity in response to the economic incentives created by these rebate programs. Another concern is that households may receive rebates simply because of the natural year-to-year fluctuation in their electricity consumption rather than concerted efforts to conserve.

This study aims to measure the treatment effect and cost-effectiveness of such conservation price-rebate programs by applying a regression discontinuity design to the California 20/20 rebate program in 2005. In the summer of 2005, most California households could receive a 20% discount on their electricity bills if they reduced their electricity consumption by 20% relative to their consumption in the summer of 2004. Nearly all California residents were enrolled in the program. However, those who started their electricity service after a certain cutoff date in 2004 were ineligible to participate. The electric utilities that offered this program strictly enforced this eligibility rule, and therefore, excluded non-eligible households from the program. Importantly, it was impossible for households to anticipate the program in advance and thus they could not strategically choose their account open date for the rebate program. Consequently, the eligibility rule excluded self-selection, and generated essentially random assignment of the program among households who opened their account near the cutoff date. I apply a regression discontinuity design to this discontinuous eligibility cutoff date to estimate the treatment effect and cost-effectiveness of the rebate program on electricity conservation.

My empirical analysis relies on a panel data set of household-level monthly electricity billing records for nearly all households in the three largest investor-owned electric utilities in California. This confidential data set was directly provided by the three electric utilities, Pacific Gas & Electric, Southern California Edison (SCE), and San Diego Gas & Electric (SDG&E). The data set includes detailed information about each customer's monthly bills in 2004 and 2005. Importantly, the data set allows me to identify the exact start and close dates of each household's electricity service so that I can conduct regression discontinuity estimation based on these dates. I combine this billing data set with weather information from the National Oceanic and Atmospheric Administration's (NOAA's) National Climate Data Center (NCDC) and demographic information from the US Census 2000 to further explore how weather conditions and income levels affect the treatment effect of the program.

Using these three sets of data, I find the following results for the effect of the 2005 California 20/20 rebate program on residential electricity consumption. First, estimates from the regression discontinuity estimation provide evidence that the rebate incentive reduced electricity consumption by 5% to 10% in the areas where the summer temperature is persistently high and the income level is relatively low. In contrast, the treatment effects are nearly zero in the areas where the summer temperature is moderate and the income level is relatively high. Second, to explore the cause of this heterogeneous treatment effect, I estimate interaction effects between the treatment variable and climate conditions, and be-

tween the treatment variable and income levels. Results from these regressions suggest that the treatment effect increases by .15 percent as average temperatures increase by 1 °F and decreases by .027 percent as income levels increase by 1%. Finally, using the estimates of the program's treatment effects, I calculate the cost and benefit of the program. Results from this exercise suggest that the program cost 91 cents to save 1 kWh of electricity in the coastal areas and 2 cents to save 1 kWh of electricity in the inland areas. In the state level, the cost per kWh reduction was 14.8 cents.

The estimated cost of reducing consumption, 14.8 cents per kWh, is larger than previous estimates reported by the electric utilities. This is partly because estimates from the electric utilities usually attribute all of the reduction in consumption by rebated customers to the presence of the rebate program. In previous studies, Reiss and White (2003) estimate the cost and benefit of the 2001 rebate program find that the average cost from June to September for San Diego Gas & Electric was 18 cents per kWh. Wirtshafter Associates (2006) uses survey results to estimate the cost and benefit of the 2005 rebate program. Their estimate ranges from 29 cents per kWh to \$1 per kWh. An important finding in my study is that I find that the cost-effectiveness is substantially different between the coastal and inland areas in California.

The results from this study provide several policy implications for the California 20/20 electricity rebate program. First, under the current rebating scheme, the expense of natural year-to-year fluctuations in electricity consumption is substantial. As a result, providing a rebate for reductions that would have happened in the absence of the program can be very costly unless the treatment effect is sufficiently large. Second, the estimation results suggest that it is important to account for heterogeneous treatment effects particularly based on different weather conditions and income levels among households. For example, my cost-effectiveness estimates for the coastal areas are by far larger than previous estimates while my estimates for the inland areas are far lower than previous estimates. Finally, the heterogeneous treatment effect suggests that the program's performance could be improved if the program focused on certain types of households to minimize rebate expenses for reductions that would have occurred in the absence of the program.

The paper proceeds as follows. Section 2 presents the background and research design. Section 3 describes the data. Section 4 presents the empirical framework. Section 5 presents the results, and Section 6 provides conclusions and future research avenues.

3.2 Background and Research Design

This section provides the institutional background and the research design of this study. First, I describe a brief history of the California 20/20 electricity rebate program. Second, I discuss the evidence and challenges of existing studies. Finally, I present this study's

regression discontinuity design.

3.2.1 California 20/20 Electricity Rebate Programs

The California 20/20 electricity rebate program originates from the initial rebate program ordered by California Governor Gray Davis in 2001 during the California electricity crisis.² The California Public Utility Commission (CPUC) expected that a continuous electricity shortage was likely to cause rolling blackouts. To prevent rolling blackouts in the summer of 2001, the CPUC ordered the three largest California investor-owned electric utilities, Pacific Gas and Electric (PG&E), Southern California Edison (SCE) and San Diego Gas & Electric, to provide their customers financial incentives to reduce electricity consumption. In the summer of 2001 and 2002, customers of the three California investor-owned electric utilities received a 20% discount for their June, July, August, and September bill if their monthly consumption was at least 20% lower than the same billing month in 2000. The CPUC ordered the same program in 2005 with a slight change in the scheme. In 2005, the original monthly-based rule was replaced by the whole summer-based rule in 2005 where customers received a 20% discount for their bills over the entire four-month period if they reduced their entire summer consumption by at least 20% relative to 2004.

This conservation rebate program was the largest in scale compared to similar rebate programs that pay households for reducing their consumption. Table 3.1 shows the scale of the 2005 rebate program for PG&E, SCE, and SDG&E. In 2005, 8% to 9% of customers received a rebate and the total rebate expense for residential customers in these electric utilities was about \$25 million. More customers received at least one rebate during the 2001 and 2002 programs because it was not based on consumption over the entire summer but on each billing month. Reiss and White (2003) report that about 39% of monthly residential bills in SDG&E qualified for a rebate in June, July, August, and September, 2001. For the same 2001 rebate program, Goldman, Barbose, and Eto (2002) note that in the three investor-owned electric utilities, about 33% of their residential customers received a rebate.

Although the CPUC aimed for a substantial reduction in electricity consumption,³ the effectiveness of the program was highly controversial. The proponents of the program argued that the simplicity of the program makes it straightforward for customers to understand the incentive and will likely encourage energy conservation. The rebate program was also more

²By August of 2000, wholesale energy prices had more than tripled from the end of 1999, which caused price spikes in retail electricity rates, and financial losses to electric utilities in California. Many cost factors and demand shocks contributed to this rise, but several studies have also found the market power of suppliers to be significant throughout this period. See Joskow (2001), Borenstein, Bushnell, and Wolak (2002), Bushnell and Mansur (2005), Puller (2007), and Reiss and White (2008).

³For example, in the executive order, CPUC (2001) estimated that the program would help reduce energy consumption by up to 3,500 gigawatt hours in total and up to 2,200 megawatt hours during critical summer peak consumption periods.

politically appealing than alternative pricing policies such as an increase in electricity price or an introduction of real-time pricing. In contrast to these alternative policies, the rebate program does not make customers feel a large economic burden even though the program's expenditure will be paid by ratepayers as an increase in electricity price.

The opponents, on the other hand, often questioned the fairness and effectiveness of the program. For example, Faruqui and George (2006) note that the program is politically popular but is likely to be inefficient for energy conservation. The first concern is that the program does not account for weather differences between the base year and target year. Therefore, if the target year turns to be cooler than the base year, many households may receive a rebate simply because of the weather difference. The second concern is that even if there turns out to be no significant weather difference between the two years, many customers will receive a rebate because of random fluctuations in their electricity consumption. For example, customers that had a friend visit in the base year or customers that traveled in the target year can reduce their target year's consumption by 20% compared to their base year without conservation efforts.

Table 3.2 shows some evidence for the two concerns by the opponents of the program. I use household-level electricity consumption data to calculate what fraction of households reduce their summer electricity consumption more than 20% when there was no rebate programs. I calculate each household's change in consumption from 2003 to 2004 and from 1999 to 2000 in Southern California Edison. Note that the rebate programs were not in effect in any of the four years. From 2003 to 2004, the median household reduced consumption by 1.7% because the summer of 2004 was cooler than 2003. More importantly, 14.3% of households reduced their consumption more than 20%. This statistic suggests that 14.3% of households would have received a rebate without a conservation effort if a rebate program were in effect in 2004. In contrast, the summer of 2000 was warmer than 1999. As a result, the median household increased consumption by 7.7%. However, even in this case, 6.8% of households reduced consumption by 20% or more. Thus, random fluctuations in household electricity consumption creates necessary costs for this rebate program. This issue sometimes leads to a concern for fairness because the program could induce a simple income transfer from one household to others unrelated to their conservation efforts. Moreover, if the rebate expense for these random fluctuations exceeds the program's actual benefit, the cost-effectiveness of the program can be lower than previous estimates.

3.2.2 Challenges to Estimating the Treatment Effect

To examine the cost-effectiveness of the program, we need a reliable estimate of the treatment effect that is produced solely by the program incentive. The estimation of this treatment effect is, however, generally challenging with non-experimental data. Obviously, it is mis-

leading to make a conclusion simply by looking at the total consumption reduction achieved by the customers that received a rebate. Some of the rebated customers received a rebate not because of their conservation effort. On the other hand, some un-rebated customers may have responded to the program incentive but failed to reach the 20% reduction cutoff to receive a rebate. Therefore, comparing rebated and un-rebated customers does not provide much information about the program's treatment effect. The second challenge is how to control for potential differences between the base and target years that are unrelated to the program but affected electricity consumption. For instance, differences in weather and economic conditions likely affect electricity consumption in the two years. Therefore, changes in electricity consumption between the two years include the program's treatment effect and other confounding factors that are unrelated to the program, and these two effects must be disentangled by researchers to find the treatment effect.

Previous studies acknowledge that it is difficult to estimate the actual treatment effect of the program. Goldman, Barbose, and Eto (2002) is the first study that examines the impact of the original California 20/20 rebate program in 2001. The study uses a survey of 400 residential customers. Based on the survey, the study finds that 70% of surveyed customers took some active steps to save electricity in 2001, 40% of surveyed customers knew about the program, and 57% of those who took active steps to conserve electricity knew about the program. Based on these numbers, the study concludes that the cost of purchasing savings through the 20/20 program was about 9 cents per kWh given the assumption that the load reductions based on their calculation are solely attributable to the 20/20 program. As Goldman, Barbose, and Eto (2002) note in the study, it is hard to quantify how much of the load reductions was actually because of the 20/20 rebate program by looking at the aggregated electricity load data and a survey of 400 residential customers.

For the same 2001 rebate program, Reiss and White (2008) estimate the treatment effect by using household-level billing data for 70,000 households in SDG&E. The study explores how household-level electricity consumption changes from the years before the California electricity crisis in 2001 to the years after the crisis. Based on the average within-household consumption changes relative to the same month during pre-crisis years, they conclude that the rebate program lowers consumption by approximately 4% to 6%. However, they also note that it is difficult to claim that this estimate solely reflects the program's treatment effect because there were other conservation programs and public appeals in effect during this period.

Finally, to my knowledge, Wirtshafter Associates (2006) is only the previous study that explores the effect of the 2005 California 20/20 program. The study uses some billing data from the electric utilities and also conduct a survey of 1,177 customers. The study uses the survey results to make two adjustments for estimation: subtract the reduction achieved by the rebated customers that was not due to their conservation efforts; and add the consumption

reduction achieved by the non-rebated customers who tried but failed to reach the 20% cutoff. The study concludes that the cost per kWh savings range from 29 cents to \$1 per kWh because a substantial level of load reductions may or may not be attributable to the program in their estimation.

A fundamental challenge in the previous studies is that researchers usually do not observe counterfactual groups. Therefore, the previous studies compare consumption between the base and target years of the program and make adjustments for weather differences between the two years. Adjusting for weather differences is difficult without knowing a correct functional form for the effect of weather on household electricity consumption and having detailed weather data. Moreover, as noted by Reiss and White (2008) and Goldman, Barbose, and Eto (2002), it is probably even more challenging to adjust for the effect of other policies such as changes in electricity price, other conservation programs, and public appeals. The next section describes how the current study overcomes these challenges by using a regression discontinuity design for the 2005 rebate program.

3.2.3 A Regression Discontinuity Design for the 2005 Rebate Program

This paper exploits a discontinuous eligibility rule in the 2005 California 20/20 rebate program to estimate how the rebate program changed household electricity consumption. To be eligible for the 2005 rebate program, customers had to start their electricity service by a certain cutoff date in 2004. Figure 3.1 illustrates how the eligibility rules were applied to customers. In SCE, for example, the cutoff date was June 5, 2004. Therefore, customers that started their electricity service on or before June 5, 2004 received a notice letter in the spring of 2005 for the 2005 rebate program, whereas customers that started their service after the cutoff date (e.g. June 6, 2004) were not eligible for the program in 2005.

The rule includes two additional key components. First, it was impossible for customers to anticipate the 2005 rebate program when they started their electricity service in 2004 because the program was announced in the spring of 2005. Therefore, it was not possible for customers to strategically choose their start date across the cutoff date of the program. Second, as long as a customer was eligible for the program, the customer automatically participated in the program without having to apply. This automatic participation rule excludes self-selection for the program. The three electric utilities strictly enforced these rules without exception.

This quasi-experimental environment provides the following advantages in estimating the program's treatment effect. The discontinuous eligibility rule generated essentially random assignment of the program among households who started their account near the cutoff date. For example, customers that started their electricity service right before the cutoff

date and right after the cutoff date are likely to have similar underlying properties for their electricity consumption, but they were assigned into different groups in terms of the treatment assignment of the rebate program. Even if there is a concern that the underlying properties might be correlated with their service start date, a regression discontinuity design (RDD) can eliminate the bias as long as the correlation between unobservable factors of electricity consumption and service start dates is continuous around the cutoff date for the rebate program.

A potential concern is whether this research design can provide enough observations to have sufficient statistical power to quantify the program treatment effect. In California, about 10,000 customers open an electric account per day. Therefore, there is a large number of observations even if I limit the samples to households that opened an account close to the cutoff date. In addition, because new accounts are generally opened in a wide range of geographical areas in California, the geographical variation allows estimating potential heterogeneous treatment effects in different regions in California. The next section explains the data sets that I use for the analysis.

3.3 Data

The primary data for this study consist of a panel data set of household-level monthly electricity billing records from 2004 to 2005 in the three largest investor-owned electric utilities in California. Under a confidentiality agreement, Pacific Gas & Electric (PG&E), Southern California Edison (SCE) and San Diego Gas & Electric (SDG&E) provided the complete billing history of essentially all residential customers in their service areas.⁴ Each monthly record includes a customer's account ID, premise ID, billing start date and end date, monthly consumption, monthly bill, tariff type, climate zone, and nine-digit zip code. The names of customers and their exact addresses are excluded in the records made available for this study. The billing record also includes each customer's tariff information. In the following analysis, I focus on customers that are on a standard tariff schedule.⁵

Figure 3.2 shows the service areas of California's electric utilities. PG&E provides gas and electric service for northern California, SCE serves electric customers in most of the southern California areas, and SDG&E provides gas and electric service around the greater San Diego metropolitan area. The 2005 rebate program was applied to customers served by all three electric utilities.

⁴A very small number of customers are not individually metered in this area. The data sets include only individually-metered customers.

⁵About 80% to 85% of customers in each utility are on the utility's standard tariff schedule. The majority of the rest of the customers are on the California Alternative Rates for Electricity (CARE) program, which is a means-tested rate discount program for low income households.

The key variable for the regression discontinuity design of this study is each customer’s account open date. The billing records include the exact open and close dates for each customer. Each day in California, about 10,000 customers open an electric account. For my main estimation, I use customers that open their electricity account within 90 days before and 90 days after the cutoff date. The number of households that are on the standard tariff and started their electricity service during these 180 days is 703,903 households for PG&E, 578,362 households for SCE, and 239,168 households for SDG&E.

The billing data do not include customers’ exact address or demographic information. To obtain demographic information, I match each customer’s nine-digit zip code to a census block group in the 2000 US Census data. The demographic information at the census block group level include median household income, the number of households, and housing characteristics.

Finally, I use daily weather data from the Cooperative Station Dataset published by the National Oceanic and Atmospheric Administration’s (NOAA’s) National Climate Data Center (NCDC).⁶ The data set includes daily minimum and maximum temperature for 370 weather stations in California. First, I match a household’s zip code with the nearest weather station by following the matching mechanism in Aroonruengsawat and Auffhammer (2009). Second, for each billing cycle, I calculate the cooling degree days (CDD), which is defined as $\sum_{t=S}^E \text{Max}\{\text{Average Temperature}(t) - 65, 0\}$ where S and E are the start and end date of the billing cycle. Figure 3.3 shows the CDD in one of the August billing cycles in 2005. The coastal areas have small numbers of CDD whereas the inland areas in PG&E and SCE service areas have large numbers of CDD since the summer temperatures are persistently high.

3.4 Identification and Estimation

This section describes the econometric models that I use to estimate the treatment effect of the California 20/20 rebate program on electricity consumption. Let y_{it} denote household i ’s average daily electricity consumption during billing month t , and $\Delta \ln y_{it} = \ln y_{it} - \ln y_{i,t-12}$ the change in log of household’s consumption between a billing period and the same billing period twelve months earlier. This twelve-month differencing removes monthly specific time-invariant unobservables for each household.

Suppose that the program enrollment is randomly assigned among households. Then, the ordinary least squares (OLS) estimation of,

$$\Delta \ln y_{it} = \alpha + \beta \cdot \text{Treat}_i + \varepsilon_{it}, \tag{3.1}$$

⁶I thank Anin Aroonruengsawat and Maximilian Auffhammer for sharing the data.

produces a consistent estimate of the average treatment effect (ATE) of the rebate incentive because a random assignment assures that the error term ε_{it} is uncorrelated with the treatment dummy variable, $Treat_i$. In the California 20/20 program, however, the treatment was not randomly assigned. Instead, the treatment was determined by the following rule.

$$Treat_i = 1 \{X_i \leq c\} \text{ where } \begin{cases} X_i = \text{account open date} \\ c = \text{cutoff date} \end{cases} \quad (3.2)$$

Because the treatment assignment is a function of X_i , the OLS estimate of equation (3.1) is biased if $E[\varepsilon_{it}|X_i] \neq 0$. For example, for the first few months after move-in, households gradually increase their electricity consumption. This tendency is found in the billing data at any time period. As a result, $\Delta \ln y_{it}$ always has a slight positive trend in X_i , which is unrelated to the rebate program. Therefore, if this trend is ignored, the condition, $E[\varepsilon_{it}|X_i] \neq 0$ will be violated. This trend in $\Delta \ln y_{it}$ is quantitatively small and it disappears in a few month after the customer's move-in. A failure to control for this trend, however, would produce an upward bias in estimates of β , because the positive trend of $\Delta \ln y_{it}$ in X_i means that customers without the treatment are likely to have systematically higher $\Delta \ln y_{it}$ compared to customers with the treatment.

The main idea of regression discontinuity designs is that a potential bias from this trend can be eliminated as long as the relationship between the confounding trend and the error term ε_{it} is smooth and continuous in X_i . Given the condition, it is possible to consistently estimate the local average treatment effect (LATE) by including flexible parametric or nonparametric controls for X_i . Including a smooth function of X_i does not destroy the identification because the treatment variable, $Treat_i$ is a discontinuous function of X_i .

Imbens and Lemieux (2008) describe two approaches to specifying a smooth control function of X_i . The first approach is to include a flexible parametric function of X_i where the slope coefficients are allowed to be different on the left and right of the cutoff date:

$$\Delta \ln y_{it} = \alpha + \beta \cdot Treat_i + \sum_{s=1}^S (\gamma^s \cdot X_i^s + \theta^s \cdot Treat_i \cdot X_i^s) + \delta_{zip} + \delta_{cycle} + \varepsilon_{i,t}, \quad (3.3)$$

The equation includes a polynomial function of s order that is allowed to have different slopes across the cutoff point. Each of X_i^s is allowed to have different coefficients for the left and right side of the cutoff date. To control for other factors that influence electricity consumption (e.g. weather differences), I also include dummy variables at the zip code level, δ_{zip} and dummy variables at the billing cycle level, δ_{cycle} . These variables control for an unobservable shock between the two years at the zip code and billing cycle levels. Imbens and Lemieux (2008) note that this parametric approach could have a disadvantage in its

parametric assumptions on the function of X_i . This concern motivates them to suggest the second approach that uses non-parametric controls for X_i by employing a local linear regression:

$$\Delta \ln y_{it} = K\left(\frac{X_i - c}{h}\right) \cdot (\alpha + \beta \cdot Treat_i + \gamma \cdot X_i + \theta \cdot Treat_i \cdot X_i + \delta_{zip} + \delta_{cycle} + \varepsilon_{i,t}). \quad (3.4)$$

The local linear regression is equivalent to a simple OLS regression but with higher weights on samples that are closer to the cutoff date. $K(\cdot)$ is a kernel function for weights and h is a bandwidth. Similar to the previous equation, this regression also allows different slope coefficients on the left and right side of the cutoff date. Previous studies suggest that a triangular kernel is the most robust for discontinuous data points (Hahn, Todd, and der Klaauw 2001, Imbens and Lemieux 2008). There is, however, no rule of thumb for choosing a right bandwidth for local linear regressions. Therefore, I provide estimation results with different bandwidth choices for robustness checks.

The parametric and non-parametric approaches have advantages and disadvantages and there is still no convincing evidence for which approach works better in regression discontinuity estimation. Therefore, I estimate both equation (3.3) and (3.4) to explore how estimates will be affected by the choice between the parametric and non-parametric approaches.

3.5 Results

3.5.1 Main Results

This section provides estimation results of the regression discontinuity estimation described in equation (3.3) and (3.4). The estimates of β can be interpreted as the program's local average treatment effect. Because the treatment effect can be different between households in different climate conditions, I present results by climate zones. The 2005 rebate program started in June and ended in September. To receive a rebate at the end of the summer, customers needed to reduce their overall electricity consumption in the four months by at least 20%. To examine whether the treatment effect is quantitatively different among the four months, I present results for each billing month separately. The results in this section suggest evidence of heterogeneous treatment effects between different climate zones. In the next section, I pool the data sets from different climate zones and estimate interaction effects of the treatment effect with other variables to examine what might explain the heterogeneous treatment effects.

In regression discontinuity estimation, graphical analyses are an important part of quantifying the magnitudes of treatment effects as well as checking the validity of identification

strategy. The nature of regression discontinuity designs suggests that the effect of the treatment of interest can be measured by the value of the discontinuity in the expected value of the outcome at a particular point (Imbens and Lemieux 2008). Therefore, inspecting the estimated version of this conditional expectation is a simple yet powerful way to visualize the identification strategy.

Figure 3.4 shows regression discontinuity estimates for the September billing month in SCE by its climate zones. The horizontal axis is a household's account open date relative to the cutoff date for the program's eligibility, $X_i^c = X_i - c$.⁷ Households on the left side of the cutoff date are the treatment group and households on the right side of the cutoff are the control group. I include only households that started their electricity service between 90 days before or 90 days after the cutoff date in 2004. In other words, the bandwidth is 90 days for each side of the cutoff date. The vertical axis shows $\widetilde{\Delta \ln y_{it}} = \Delta \ln y_{it} - \hat{\delta}_{zip} - \hat{\delta}_{cycle}$, the log change in average daily electricity consumption from the September billing month in 2004 to the September billing month in 2005. To control for weather and economic shocks, I subtract the zip code level mean and billing cycle level mean from the log change.

If the rebate program has a significant treatment effect on electricity consumption, the change in consumption from 2004 to 2005 should be lower for the treatment group relative to the control group. In that case, the conditional expectation of the outcome variable $\widetilde{\Delta \ln y_{it}}$ conditional on the running variable X_i should have a discontinuous jump across the cutoff date c . To see whether the expected value of the outcome variable has the discontinuous jump, I plot the local average value of $\widetilde{\Delta \ln y_{it}}$ over X_i^c . Each dot in Figure 3.4 shows the local average value of $\widetilde{\Delta \ln y_{it}}$ using fifteen days bandwidth of X_i^c . For the eight bins in each side of the cutoff, I take a simple local average for each bin, and plot them on the diagrams. The local averages are the estimated counterparts to the conditional mean of the outcome $E[\Delta \ln y_{it} | X_i^c, \delta_{zip}, \delta_{cycle}]$.

The top two figures show results for climate zone 10 and 17 in SCE. These climate zones include coastal areas, which have a relatively moderate summer climate condition relative to inland areas. For example, the cities of Santa Barbara, Long Beach, and Irvine are included in these climate zones. The figures suggest evidence that the program did not significantly change electricity consumption for the treatment group in these climate zones. The change in electricity consumption has a moderate positive trend in the account open date as discussed in the previous section, but it does not have a discontinuous jump at the cutoff date.

In contrast, the bottom two figures indicate evidence that the rebate program had a significant effect on electricity consumption in climate zones 15 and 16. These climate zones are located in inland areas of southern California, where the summer temperature is persistently high and households typically use an air conditioner throughout the summer. The

⁷For example, if customer i in SCE started electricity service on June 25 in 2004, then $X_i^c = 20$, because SCE's cutoff date was June 5, 2004.

next section explores in more detail how higher temperature affects the treatment effect.

To statistically estimate the magnitude of the treatment effects, I estimate the parametric regression in equation (3.3) using quadratic functions and the nonparametric local linear regression in equation (3.4) using a triangular kernel function for the sample weight. The dashed lines show fitted value for the parametric regression and the solid lines show the fitted lines for the nonparametric local linear regression. Essentially, both econometric equations estimate β as the magnitude of the jump in the outcome variable at the cutoff date by fitting parametric or nonparametric functions of X_i^c . As it is visually clear in Figure 3.4, the estimates are not statistically different between the two estimation methods. Following Imbens and Lemieux (2008), I focus on the estimates from the nonparametric local linear regression in the following, but none of the estimates are sensitive to the selection of the two estimation methods.

Each diagram in Figure 3.4 includes the point estimate from the local linear regression and the robust standard errors in the parentheses. In climate zone 10 and 17, the point estimates are close to zero and they are statistically insignificant from zero. In climate zone 15 and 16, the point estimates are -.093 and -.101 with standard errors .04 and .032, respectively. That is, households with the rebate incentive reduced their consumption by about 9% in climate zone 15 and 16 relative to households without the rebate incentive.

I find similar results in other utility territories. For example, Figure 3.5 shows the regression discontinuity estimates for the September billing cycle in the two most populated coastal areas in SDG&E. The graphical evidence suggest that, similar to coastal climate zones in SCE, the rebate program did not significantly change electricity consumption for the two areas in SDG&E. Table 3.3 summarizes the results for all billing months and all of the three utilities. The table indicates two findings that are consistent among the three electric utilities. First, in the coastal areas, the treatment effects are not statistically different from zero in all of the four summer months. However, in the inland areas, the rebate incentive lowered household consumption by 5 to 9%. Second, in the inland areas, the treatment effect is largest in the last month and is monotonically increasing from the first month. There are two possible reasons for this differences in treatment effects between the months. The first potential reason is that some households may have gradually become aware of the program when they looked at the information about the rebate program on their monthly bills. The second possible reason is that the program's design may have created a larger incentive for customers to reduce consumption at the end of the four-month period than at the beginning. Once customers have already achieved a certain amount of reduction in the first couple of months, the possibility of receiving a rebate in return for their efforts is more certain in the later months.

3.5.2 Interaction with Weather and Income

The previous section finds that the estimated treatment effects are larger in inland areas compared to coastal areas. This section explores what drives the heterogeneous treatment effect of the 2005 rebate program. In particular, I examine whether climate conditions or income differences can explain the heterogeneous treatment effects.

One of the significant differences between inland and coastal California is the summer climate conditions. For example, Figure 3.3 illustrates cooling degree days (CDD) in California in August 2005 by five-digit zip code areas. Generally, summer temperature is persistently high in the inland areas but quite moderate in the coastal areas. As a result, inland households typically use air conditioners throughout the summer while coastal households either use air conditioners very little or do not own them at all. For households that do not use an air conditioner, a 20% reduction in summer electricity consumption is challenging for typical residential electricity consumers. In contrast, for households that constantly use an air conditioner during the summer season, a 20% consumption reduction can be achieved by slightly changing the temperature settings or the length of usage.

Another significant difference between inland and coastal California is their demographic characteristics. For instance, income levels tend to be higher in coastal areas than inland areas. In previous studies on residential electricity demand, many studies find slightly larger price elasticity estimates for low income households (e.g. Reiss and White 2005 and Ito 2010). Because the 20/20 rebate program is essentially a price-discount rebate program, households with lower income may be more likely to respond to the incentive if their price elasticity is larger than households with higher income.

To examine how climate conditions and income levels affect the program's treatment effects, I focus on the September billing month from all climate zones and conduct two statistical tests. First, I focus on households in SCE's climate zone 10 and explore whether within-climate-zone variation can provide any evidence of heterogeneous treatment effects. I split households in this climate zone by the quartiles of cooling degree days and the quartiles of household income. Then, for each of the quartile, I estimate the local linear regression in equation (3.5). Table 3.4 shows the evidence that even in this coastal climate zone I find evidence that households with a large numbers of high temperature days show an economically small but statistically significant treatment effect. Similarly, the treatment effect is statistically significant for households with lower income.

As a second approach, I pool data from all climate zones and include interaction terms between the treatment variable and average temperature in each customer's billing cycle, and the treatment variable and household income to equation (3.4). This model estimates the differences in the treatment effect for different temperature values and income levels assuming that the interaction terms linearly affect the treatment effect. Column 1 of Table

3.5 shows estimation results with the interaction term between the treatment and average temperature. It indicates that the treatment effect increases by .15 percentage point when the average temperature increases 1 degree Fahrenheit. Column 2 includes the treatment effect and the interaction variable between the treatment effect and log of income. The estimates suggest that the treatment effect increases by .027 percent with an 1% increase in household income. These two interaction effects remain the same when both terms are included in the regression as Column 3 of the table shows. Therefore, results from the two estimation methods indicate that both climate conditions and income levels have a statistically significant effect on the magnitude of the program’s treatment effect.

3.5.3 Cost-Benefit Analysis

The cost-effectiveness of the program is a central policy question for the California 20/20 electricity rebate program because it has been controversial. The proponents of the program claim that the simplicity of the program can generate a substantial amount of consumption reduction with a relatively small cost, whereas many people often argue that the the program produces only a small amount of consumption reduction and therefore, is not cost effective. When a reduction in electricity consumption is required for some policy objectives, policy makers usually have several options to achieve the objective. Based on the estimates of the program’s treatment effect in the previous section, this section provides estimates of the overall cost and benefit of the 2005 rebate program. I focus on Southern California Edison’s territory in this section, but the result for other electric utilities are similar to the results presented in this section.

In Table 3.6, I calculate total electricity consumption in the summer of 2004 and 2005, the amount of rebate expenses in 2005, and the estimated consumption reduction that is produced by the program’s incentive. Column 1 shows the number of households who maintained their electricity account in the summer of 2004 and 2005. Column 2 presents the total electricity consumption of these households during the four summer months in 2005 and column 3 shows how much money was spent to pay rebates to households that reduced their consumption at least by 20% relative to 2004.

To obtain an estimate of how much of electricity consumption was saved by the rebate program, I calculate an estimated kWh reduction K_j for each climate zone j based on the estimated treatment effect $\hat{\beta}_m^j$ in Table 3.3,

$$K_j = \sum_{m=6}^9 \left(\frac{\hat{\beta}_m^j}{1 - \hat{\beta}_m^j} \cdot C_m^j \right), \quad (3.5)$$

where m is a billing month and C_m^j is aggregate consumption.⁸ Then, I calculate the cost-benefit ratio of the program as the total rebates divided by K_j . An important assumption here is that the estimated treatment effect $\hat{\beta}_m^j$, which is estimated from the regression discontinuity design, can be applied to all households in the climate zone regardless of their service start date.

Column 4 shows the estimated reduction K_j and column 5 presents the aggregate rebate expense divided by K_j . In the coastal areas, the program cost 90.7 cents to save 1 kWh electricity. On the other hand, in the inland areas, the program spent 2 cents to save 1 kWh consumption. The average cost per kWh reduction is 14.8 cents.

Note that this average estimate of the cost and benefit does not necessarily give a fully accurate evaluation of the program's cost and benefit. Ideally, we want to know how much of the reduction happened in the on-peak and off-peak periods of the electricity load. For example, if most of the reduction occurred in the on-peak load, in which the marginal cost of electricity is relatively high, the benefit of the consumption reduction is large. However, because the monthly consumption data do not give the exact timing of consumption reductions, I discuss the costs and benefits of the program based on this average number.

The estimated cost, 14.8 cents per kWh consumption reduction, is larger than the numbers that were given by the electric utilities because the utilities usually attribute all of the consumption reductions by the rebated customers to the presence of the rebate program. In previous studies, Reiss and White (2003) estimate the 2001 rebate program's costs and benefits and find that the overall cost (June to September in 2001) for SDG&E was 18 cents per kWh.

A potential reference point for discussing the program's cost is the average cost of electricity production, which was 13.37 cents per kWh in 2005 in SCE. Compared to this number, the average cost estimate, 14.8 cents per kWh, is still higher than the average cost of supplying electricity.

An important finding in the current study is that the cost-effectiveness is substantially different between the coastal and inland areas in California. Previous studies provide only aggregate cost-benefit estimates for all of California. Results in Table 3.3 suggest that the 2005 20/20 rebate program was fairly cost-effective in the inland areas but quite cost-ineffective in the coastal areas. This is because in the coastal areas, a large number of households received a rebate, but the treatment effect in these areas were nearly zero. Finally, note that these cost estimates do not include the administrative costs and advertisement fees that were associated with the rebate program. Therefore, the actual cost is likely to be higher than the cost estimates in this section when we account for these additional program

⁸Let A_m^j denote the aggregate consumption in absence of the treatment. Then, $(1 - \hat{\beta}_m^j)A_m^j = C_m^j$. Hence, $A_m^j = \frac{C_m^j}{1 - \hat{\beta}_m^j}$ and $K_m^j = \frac{\hat{\beta}_m^j}{1 - \hat{\beta}_m^j} \cdot C_m^j$.

expenses.

3.6 Conclusion and Future Work

This paper examines the treatment effect and cost-effectiveness of conservation rebate programs that are often used by electric, natural gas, and water utilities. To deal with identification problems, I apply a regression discontinuity design to the 2005 California 20/20 electricity rebate program. The discontinuous eligibility rule of the program enables me to estimate the treatment effect by controlling for confounding factors such as weather and economic conditions.

This study provides several empirical findings based on a panel data set of household-level monthly electricity billing records from the three largest electric utilities in California. First, the regression discontinuity estimates provide evidence that the rebate incentive made consumers reduce their electricity consumption by 5% to 10% in the areas where the summer temperature is persistently high and the income level is relatively low. In contrast, the treatment effects are nearly zero in the areas where the summer temperature is moderate and the income level is relatively high. Second, to explore which variables explain this heterogeneous treatment effect, I estimate interaction effects between the treatment variable and climate conditions, and between the treatment variable and income levels. Results from these regressions suggest that the treatment effect increases by .15 percent as average temperatures increase by 1 °F and decreases by .027 percent as income levels increase by 1%. Finally, using the estimates of the treatment effect, I calculate the cost-effectiveness of the program. The results from this exercise show that the program cost 90.7 cents in the coastal areas and 2 cents in the inland areas to save 1 kWh of electricity consumption. The overall cost per kWh reduction was 14.8 cents per kWh.

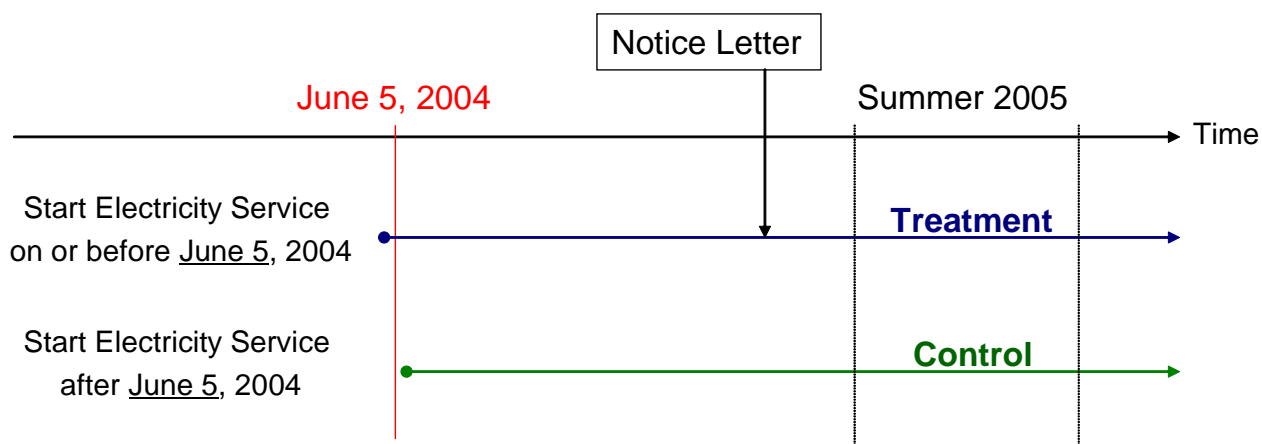
The results from this study provide several policy implications for the California 20/20 electricity rebate program. First, under the current rebating scheme, the expense of natural year-to-year fluctuations in electricity consumption is substantial. As a result, providing a rebate for reductions that would have happened in the absence of the program can be very costly unless the treatment effect is sufficiently large. Second, the estimation results suggest that it is important to account for heterogeneous treatment effects particularly based on different weather conditions and income levels among households. For example, my cost-effectiveness estimates for the coastal areas are by far larger than previous estimates while my estimates for the inland areas are far lower than previous estimates. Finally, the heterogeneous treatment effect suggests that the program's performance could be improved if the program focused on certain types of households to minimize rebate expenses for reductions that would have occurred in the absence of the program.

The paper leaves at least two important research questions for future work. First, be-

cause the rebate program required households to reduce their overall electricity consumption by 20% over the four summer billing months in 2005, there could be a dynamic response to their incentive throughout the four month period. For example, households that achieved a large reduction in the first three months do not have to reduce much of their last month's consumption to reach an overall 20% reduction. On the other hand, households that consumed too much in the first three months have no way to get a rebate regardless of their effort in the last month. Second, in this paper, I do not fully specify a consumer's electricity demand model with their rebate incentive. Instead, I estimate the average treatment effect of the program. If I model a consumer's decision more precisely in a demand model, consumers could get two different incentives from the rebate program. This is because the rebate program may affect consumption in two different ways. In one hand, the program provides an incentive to reduce consumption because households can receive a rebate only if they reduce their consumption by 20%. On the other hand, once a household receives a rebate, the rebate works as a price discount for total consumption. The household, therefore, may increase consumption in response to the price discount. For example, in an extreme case where a household is sure to use much less electricity in 2005 relative to 2004, the household has almost no incentive to reduce consumption and is likely to increase consumption in response to the expected discount for electricity price. My future work would incorporate this behavior to provide more comprehensive understanding of the program's effect on electricity demand.

Figure 3.1: Program Eligibility Rule for the 2005 California 20/20 Electricity Rebate Program

	Cutoff Date
PG&E	June 1, 2004
SCE	June 5, 2004
SDG&E	June 30, 2004



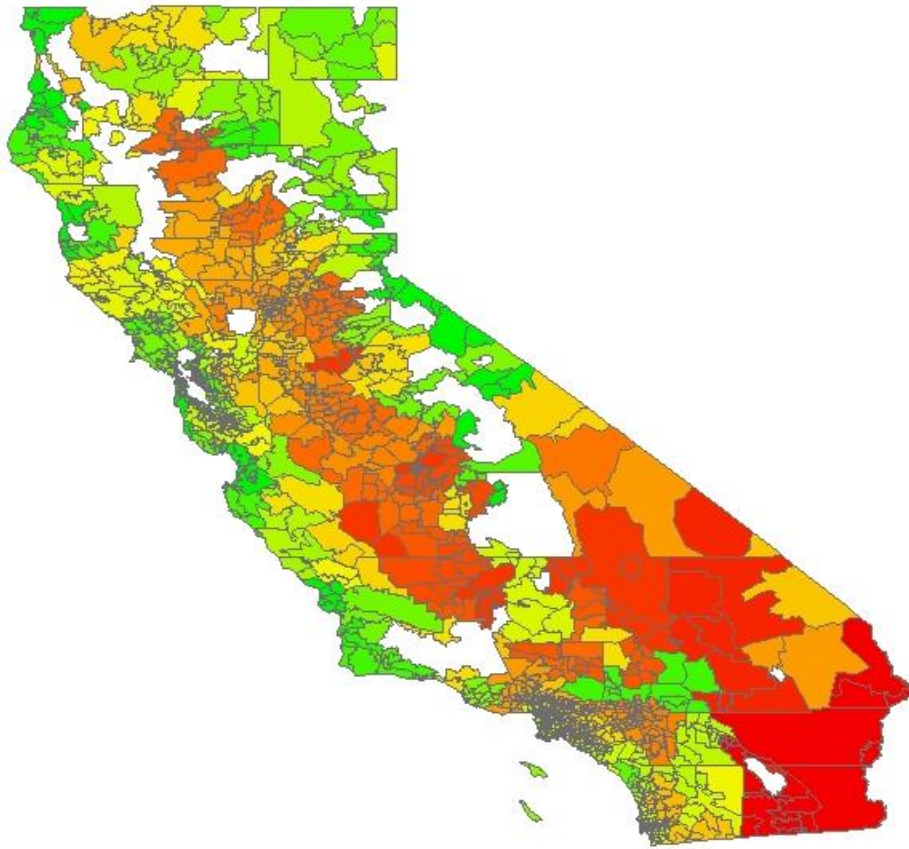
Note: Households who opened their account on or before the cutoff date in 2004 received a notice letter around April, 2005 and were automatically enrolled in the 2005 California 20/20 electricity rebate program. These households were eligible for a 20% discount on their summer electricity bills if they reduced their electricity consumption by 20% relative to their consumption in 2004. Households who opened their account after the cutoff date were excluded from the program. The three electric utilities have slightly different cutoff dates.

Figure 3.2: Electric Utility Service Areas in California



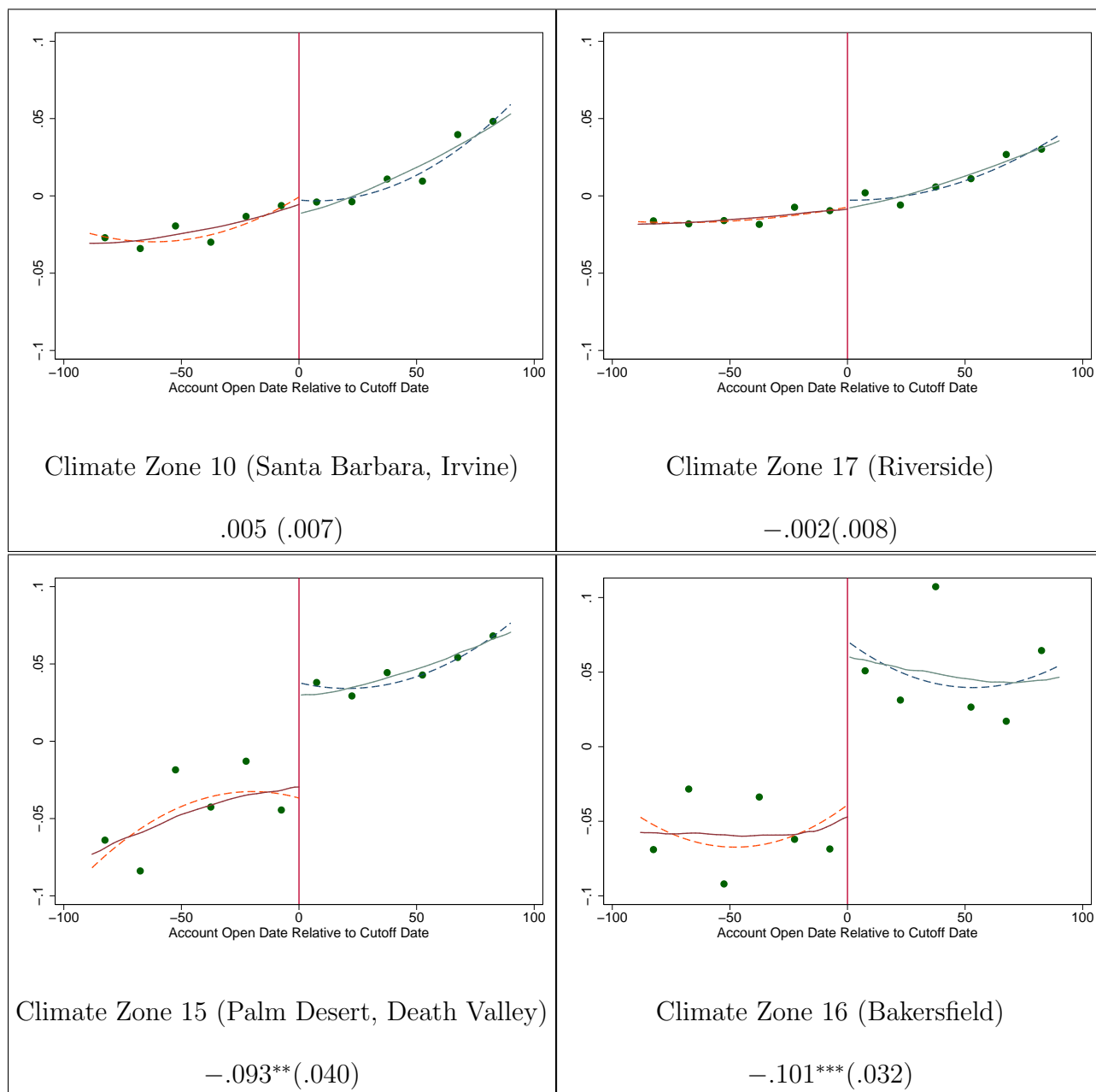
Note: This figure shows the service areas of electric utilities in California. The original source file is available at the California Energy Commission's website. Three investor owned electric utilities, Pacific Gas & Electric, Southern California Edison, and San Diego Gas & Electric, participated in the 2005 California 20/20 electricity rebate program program.

Figure 3.3: Cooling Degree Days in August 2005 in California



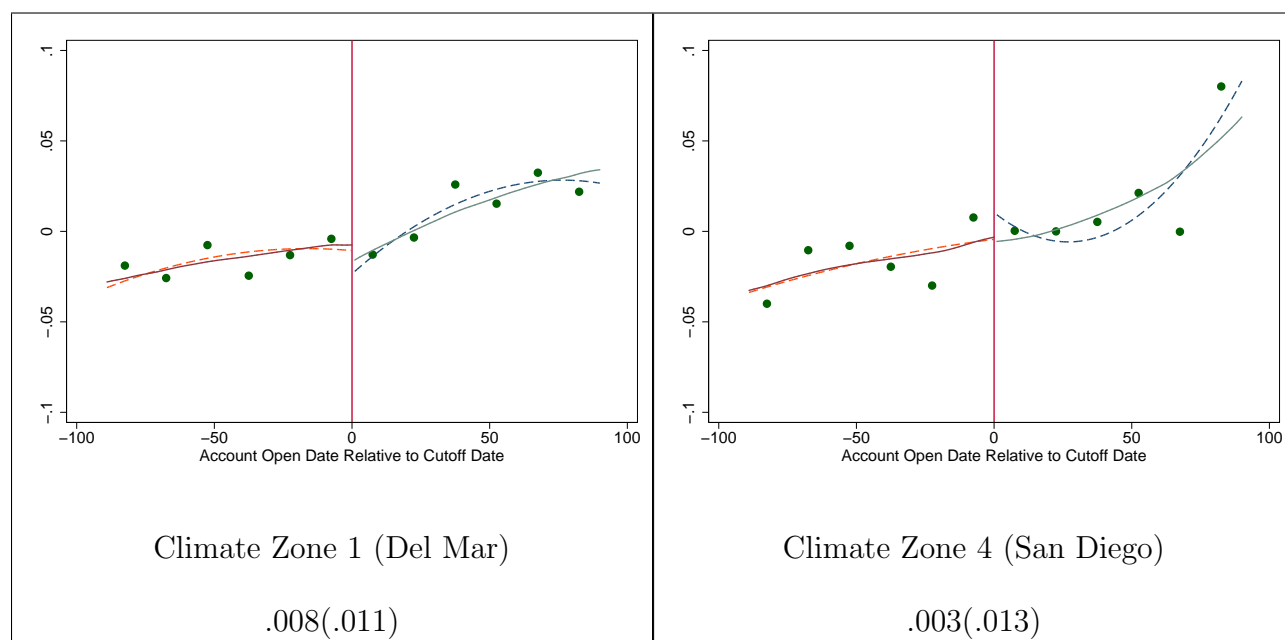
Note: This figure shows the cooling degree days (CDD) in August 2005 in California by zip code boundaries.

Figure 3.4: Regression Discontinuity Estimates: SCE September Billing Month



Note: This figure presents the regression discontinuity estimates for the September billing month in SCE by its climate zones. The horizontal axis shows households' account open date relative to the cutoff date for the program eligibility. The vertical axis shows the log change in September consumption from 2004 to 2005 where zip code level mean and billing cycle level mean are subtracted. Each dot presents the local mean using fifteen days window and the solid and dashed lines are the fitted lines by equation (3.3) and (3.4), respectively. I also include representative cities for each climate zone in parentheses. Finally, the figure includes the point estimate of the treatment effect with the robust standard errors in parentheses.

Figure 3.5: Regression Discontinuity Estimates: SDG&E September Billing Month



Note: This figure presents the regression discontinuity estimates for the September billing month in SDG&E by its climate zones. The horizontal axis shows households' account open date relative to the cutoff date for the program eligibility. The vertical axis shows the log change in September consumption from 2004 to 2005 where zip code level mean and billing cycle level mean are subtracted. Each dot presents the local mean using fifteen days window and the solid and dashed lines are the fitted lines by equation (3.3) and (3.4), respectively. I also include representative cities for each climate zone in parentheses. Finally, the figure includes the point estimate of the treatment effect with the robust standard errors in parentheses.

Table 3.1: Aggregate Consumption and Rebates in the Summer Billing Months in 2005

Utility	Consumption (kWh)	Revenue (\$)	Rebated Households	Rebate (\$)
PG&E	10,065,216,512	1,320,995,584	8.24%	10,786,594
SCE	9,401,883,648	1,257,056,768	7.91%	10,609,540
SDG&E	2,284,046,848	363,180,320	9.07%	4,325,000

Note: This table reports the statistics based on the actual residential billing data in the June, July, August, and September billing months in 2005. I include customers who maintained their account both in the summer of 2004 and 2005. The rebate expenditure does not include the administrative and advertising costs of the program. All expenditures are in nominal 2005 dollars.

Table 3.2: Changes in Summer Electricity Consumption in SCE

Year	Changes in Summer Weather	Median of % Changes in Consumption	% Households with 20% or More Reduction
From 2003 to 2004	Cooler in 2004	-1.7%	14.3%
From 1999 to 2000	Hotter in 2000	7.7%	6.8%

Note: This table reports statistics of within-household changes in summer electricity consumption in Southern California Edison (SCE). I first calculate the change in consumption for each household between the two years. I then calculate the median value of the change and the percentage of households who reduced their consumption more than 20%. Note that SCE customers did not encounter a price spike during the California electricity crisis in 2000 because their retail rates are capped.

Table 3.3: Treatment Effects in Each Billing Months by Climate Zones

Billing Month	6	7	8	9
<hr/>				
PG&E				
Coastal Areas	-.002 (.004)	-.001 (.003)	.003 (.004)	-.002 (.005)
Inland Areas	-0.01 (.013)	-.016* (.011)	-.032*** (.011)	-.059*** (.012)
<hr/>				
SCE				
Coastal Areas	.001 (.009)	-.001 (.010)	-.001 (.009)	-.002 (.008)
Inland Areas	-.019* (.015)	-.032** (.016)	-.056*** (.016)	-.092*** (.015)
<hr/>				
SDG&E				
Coastal Areas	.005 (.009)	-.001 (.010)	-.002 (.009)	.008 (.011)
Mid-Inland Areas	-.002 (.011)	-.001 (.012)	.002 (.011)	.003 (.013)
<hr/>				

Note: This table presents the regression discontinuity estimates of the local linear regression of equation (3.5) with the triangular kernel and 90 days bandwidth. Each estimate comes from separate regressions for each billing month and climate zones. The number of observations is 535,741 (Coastal, PG&E), 168,162 (Inland, PG&E), 492,244 (Coastal, SCE), 86,118 (Inland, SCE), 138,718 (Coastal, SDG&E), and 100,450 (Mid-inland, SDG&E). Robust standard errors are in parentheses.***, **, and * show 1%, 5%, and 10% statistical significance respectively.

Table 3.4: Treatment Effect by Different Weather and Income Quartiles in Southern California Edison's Climate Zone 10

Quartile	1	2	3	4
<hr/>				
Cooling Degree Days				
Treat	.013 (.012)	-.005 (.009)	-.019 (.019)	-.030*** (.016)
<hr/>				
Income				
Treat	-0.017** (.009)	-.011 (.016)	-.005 (.010)	-.0003 (.0006)
<hr/>				

Note: This table presents the regression discontinuity estimates of the local linear regression of equation (3.5) with the triangular kernel and 90 days bandwidth for September 2005. The sample includes households in climate zone 10 in Southern California Edison. The number of observations is 231,318. The dependent variables is the log change in household daily electricity consumption from September 2004 to 2005. For the first row, I divide the samples into quartiles based on the cooling degree days (CDD) in September 2005 and run separate regressions for each quartile. Similarly for the second row, I divide the samples into income quartiles and run separate regressions for each quartile. Robust standard errors are in parentheses.***, **, and * show 1%, 5%, and 10% statistical significance respectively.

Table 3.5: Treatment Effect Interacted with Temperature and Income

	(1)	(2)	(3)
Treat	.095** (.051)	-.297*** (.055)	-.199*** (.077)
Treat*Ave.Temp.	-.0015** (.0007)		-.0016** (.0008)
Treat*ln(Income)		.027*** (.005)	.027*** (.005)
<hr/>			

Note: This table presents the regression discontinuity estimates of the local linear regression of equation (3.4) with the triangular kernel and 90 days bandwidth for September 2005. The sample includes households in all climate zones in each of the electric utilities. The number of observation is 1,521,433. The dependent variables is the log change in household daily electricity consumption from September 2004 to 2005. I calculate average temperature for each billing cycle by taking mean of the average temperature during the billing days. Robust standard errors are in parentheses.***, **, and * show 1%, 5%, and 10% statistical significance respectively.

Table 3.6: Cost-Benefit Analysis for SCE

	Customers	Consumption (kWh)	Rebate (\$)	Estimated Reduction (kWh)	Rebate/ Reduction (\$/kWh)
Coastal	3,190,027	8,247,457,920	9,358,919	10,323,778	0.907
Inland	299,178	1,154,292,248	1,250,621	61,486,108	0.020
Total	3,489,205	9,401,750,168	10,609,540	71,809,886	0.148

Note: This table reports the cost-benefit analysis of the 20/20 program for SCE's coastal areas, inland areas, and all service areas. Column 1 shows the number of residential customers that maintained their account in the summer of 2004 and 2005. Column 2 presents the aggregate consumption in the four summer months. Column 3 reports the aggregate amount of rebates. Column 4 shows the estimated kWh reduction by the program and the last column presents the rebate expenditure per kWh reduction.

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