

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

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Abstract

Economic theory generally assumes that consumers respond to marginal prices when making economic decisions, but this assumption may not hold for complex price schedules. This paper 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.

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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 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.

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 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 (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 electricity, Borenstein (2009) finds no bunching in household-level electricity billing data.

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 “scheduling” 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 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

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.

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

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 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.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 a flat rate schedule to a nonlinear price schedule.⁸ I show that the sub-optimal response makes nonlinear

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.

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.

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 (2009) 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 (2009) 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 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

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.

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

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.

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.

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

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, 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.

additional consumption. Suppose that the consumer has wealth W and quasilinear utility:¹⁴

$$u(x, y) = W + V(x). \tag{1}$$

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

$$\max_x u(x) = W - (p_1 \cdot x_1 + p_2 \cdot x_2) + V(x), \tag{2}$$

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

$$x_{MP}^* = \begin{cases} x^*(p_1) & \text{if } x^*(p_1) \leq k \\ k & \text{if } x^*(p_2) \leq k \leq x^*(p_1) \\ x^*(p_2) & \text{if } x^*(p_2) \geq k, \end{cases} \tag{3}$$

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.

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%.

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

$$\max_x E[u(x)] = W - E[(p_1 \cdot x_1 + p_2 \cdot x_2)] + E[V(x)]. \quad (4)$$

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.

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:

$$\max_x u(x) = W - AP(x) \cdot x + V(x). \quad (5)$$

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

$$x(p)^{**} = \begin{cases} x_{MP}^* & \text{if } \Delta u(p) \equiv u(x_{MP}^*) - u(x_{AP}^*) \geq c \\ x_{AP}^* & \text{otherwise.} \end{cases} \quad (6)$$

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:

$$V(x) = \begin{cases} a_i \frac{1}{1+1/\beta} x^{1+1/\beta} & \text{if } \beta \neq -1 \\ a_i \ln(x) & \text{if } \beta = -1. \end{cases} \quad (7)$$

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

$$x_{MP}^*(p) = \left(\frac{MP(x_{MP}^*)}{a_i} \right)^\beta \quad (8)$$

$$x_{AP}^*(p) = \left(\frac{AP(x_{MP}^*)}{a_i} \right)^\beta. \quad (9)$$

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.

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

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.

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 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 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

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.

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. 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.

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 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

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.

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.

3.3 Price Variation

Households across the utility border experience substantially different nonlinear price schedules. Figure 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 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.

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 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, the utilities have different sunk losses from the 2000-01 California electricity crisis that is need to be collected from ratepayers. Third, as Figure 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 nonlinear 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 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.

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.

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:

$$\ln x_{it} = \alpha_i + \beta \ln p_t(x_{it}) + \eta_{it}, \quad (10)$$

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:

$$\Delta \ln x_{it} = \alpha'_i + \beta \Delta \ln p_t(x_{it}) + \varepsilon_{it}, \quad (11)$$

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.

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 $\varepsilon_{it} = \eta_{it} - \eta_{it_0}$.

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 particularly 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.

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

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.

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 2009). 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

$$\ln x_{it} = \beta \ln p_t(x_{it}) + \lambda + Z'_{it} \delta + \varepsilon_{it}, \quad (12)$$

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

$$\ln x_{it} = \beta \ln p_{ut}(x_{it}) + \gamma_u + \lambda_t + Z'_{it} \delta + \varepsilon_{it}, \quad (13)$$

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 (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

$$\ln x_{it} = \beta \ln p_{ut}(x_{it}) + \gamma_{ut} + \lambda_{gt} + \theta_{gu} + Z'_{it} \delta + \varepsilon_{it}, \quad (14)$$

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

$$\ln x_{it} = \beta_1 \ln mp_{ut}(x_{it}) + \beta_2 \ln ap_{ut}(x_{it}) + \gamma_{ut} + \lambda_{gt} + \theta_{gu} + Z'_{it} \delta + \varepsilon_{it}. \quad (15)$$

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 $Cycle_t$.

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.

5.1 Bunching Around Kink Points

The standard model of nonlinear budget sets predict that consumers choose demand based on equation (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 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 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 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.

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 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 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 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 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

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.

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 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 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 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 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 continu-

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

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

ous control functions of the forcing variable, or by narrowing the range of the sample sufficiently close to its discontinuity point (e.g. Angrist and Lavy 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 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 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 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

which of the two utilities provides electricity.

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 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 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 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.

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 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 2 shows results of the difference-in-difference-in-differences (DDD) estimation described in equation (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

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 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 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 2 for each decile of consumption distribution separately. Table 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 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 different 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.

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.

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 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 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

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 elasticity estimate -0.112 in Table 2 and the medium long run price elasticity estimate -0.201 in Table 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 $16.73\text{¢}/\text{kWh}$. 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 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 6 suggests, however, that the policy outcome depends on both the price elasticity and what type of price perception consumers have.

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 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.

$$\begin{aligned}
 dwl(p^*) &= \int_{mc}^{p^*} x(p) dp - x(p^*) \cdot p^* && \text{if } p^* \geq mc \\
 &= x(p^*) \cdot p^* - \int_{p^*}^{mc} x(p) dp && \text{if } p^* \leq mc.
 \end{aligned} \tag{16}$$

First, I obtain $dwl(ap)$ using the observed consumption by assuming that consumers are currently responding to their average price. Second, I calculate the counterfactual 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 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 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 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 excessive consumption obtained from the average price response has larger negative impacts on the social welfare compared to the marginal price response.

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

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).

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.

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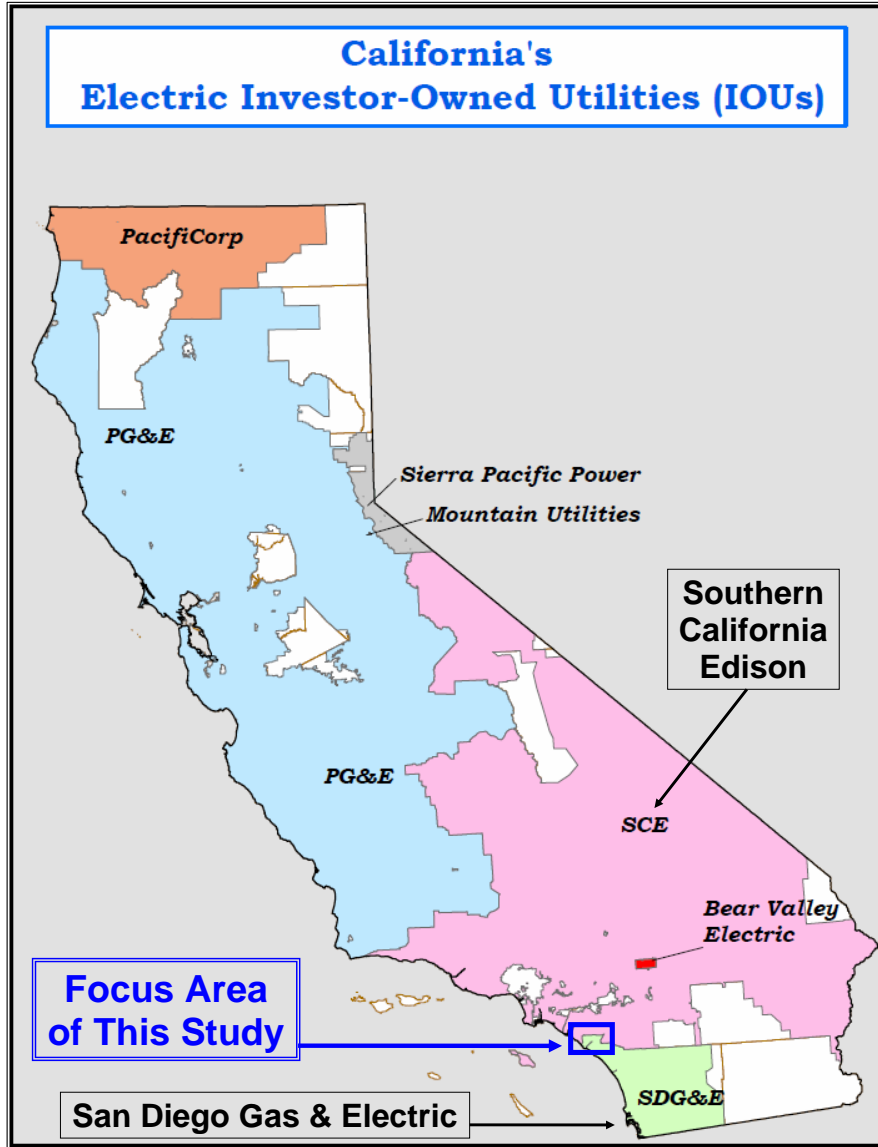
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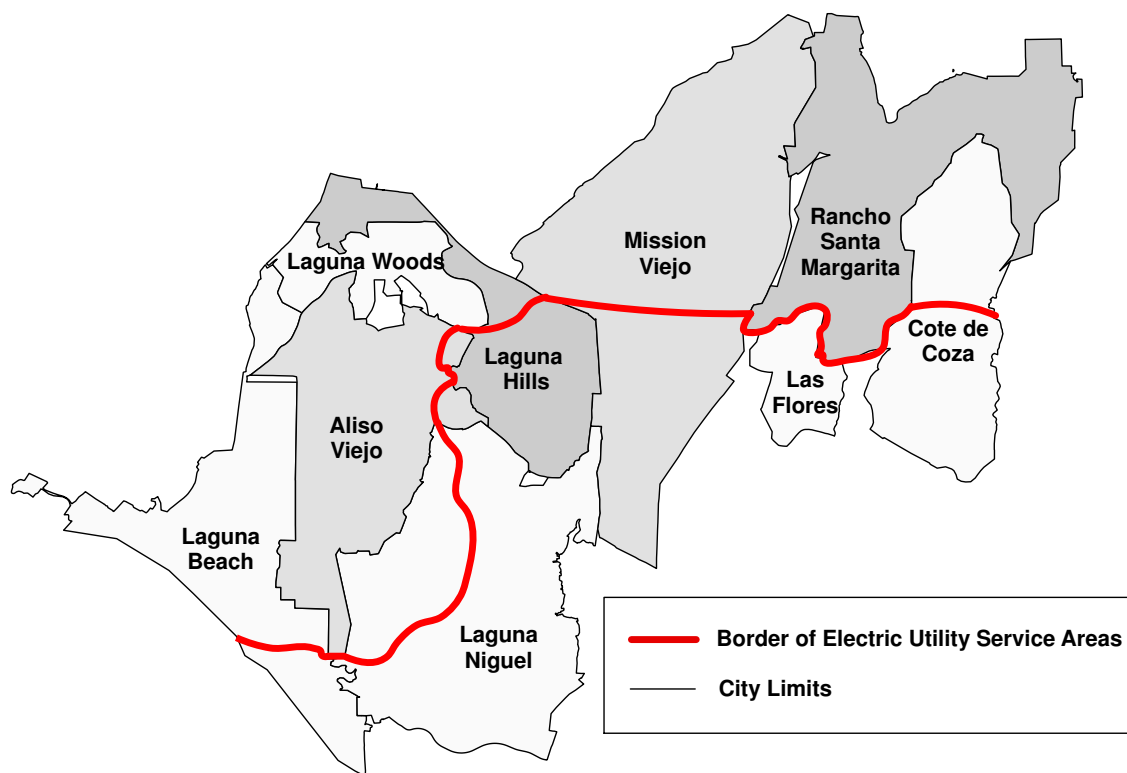
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Figure 1: Service Territories of California's Investor-Owned Electric Utilities



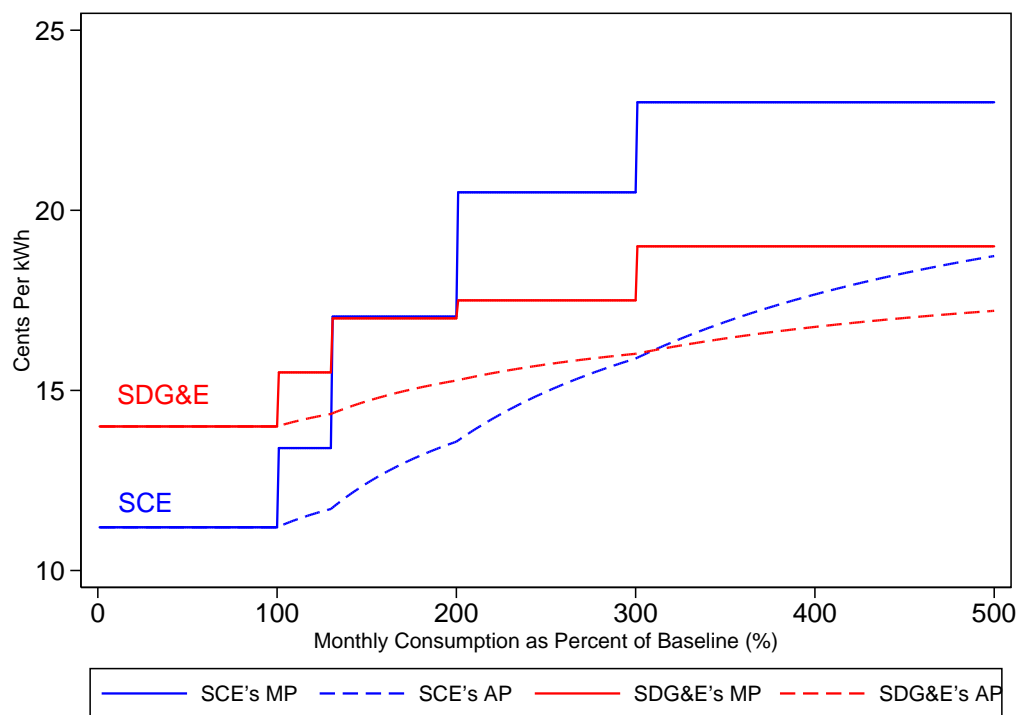
Notes: This figure shows a service territory map of California's investor-owned electric utilities. The original map is provided by the California Energy Commission. Blank areas indicate that these areas are served by electric utilities that are not investor-owned. In this study, I use two electric utilities: 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 2.

Figure 2: A Spatial Discontinuity in Electric Utility Service Areas in Orange County, California



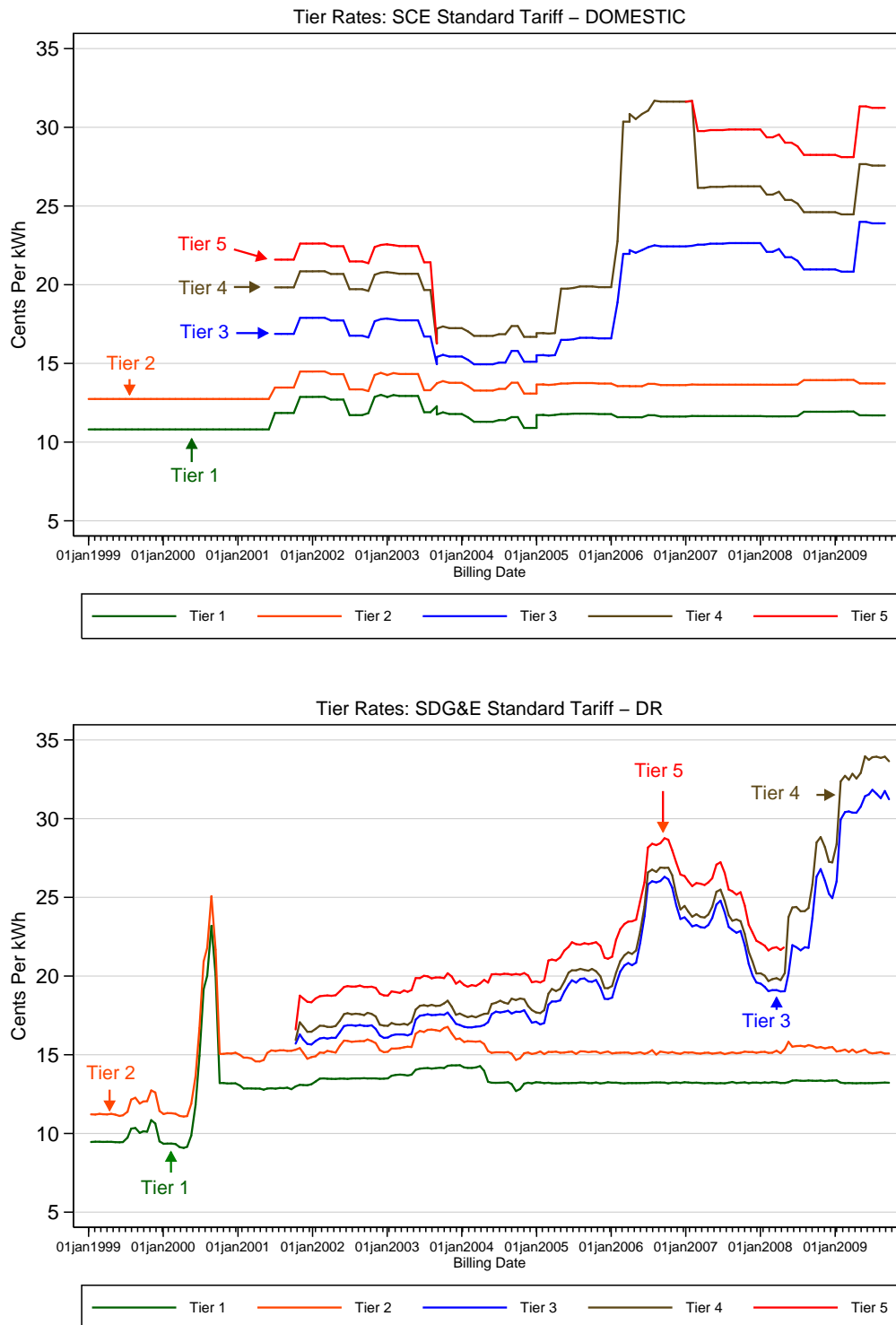
Notes: The bold line shows the service area border of Southern California Edison and San Diego Gas & Electric. SCE provides electricity for the north side of the border and SDG&E covers the south side. The map also presents city limits. The utility border exists inside the city limits in Laguna Beach,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

Figure 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 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.

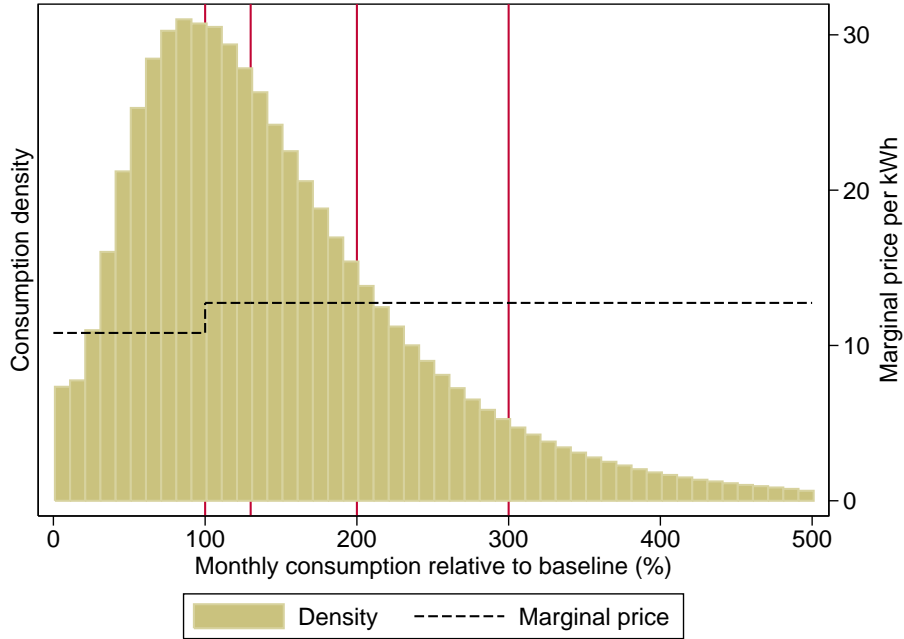
Figure 4: Tier Rates for Standard Price Schedules from 1999 to 2009



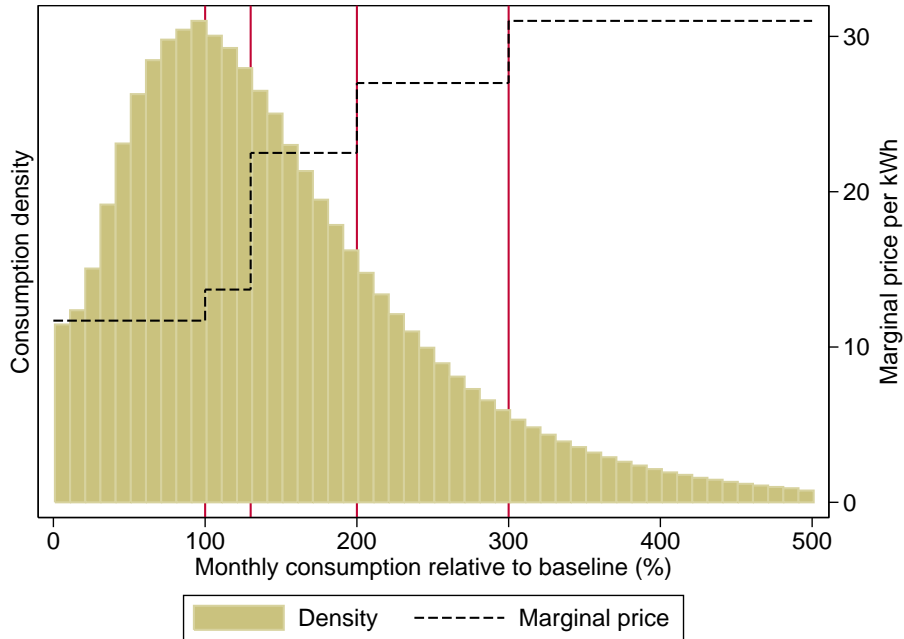
Notes: The figures display how residential electricity prices changed over time in Southern California Edison and San Diego Gas & Electric. Each of the five tier rates corresponds to the tier rates in the five-tier increasing block price schedules presented in Figure 3. The third, fourth, and fifth tiers did not exist before 2001. The fifth tier did not exist between 2004 and 2006 in SCE, and after 2008 in SDG&E.

Figure 5: Consumption Density in 1999 and 2007: Bunching Around Kink Points

Panel A. Consumption density and price schedule in 1999

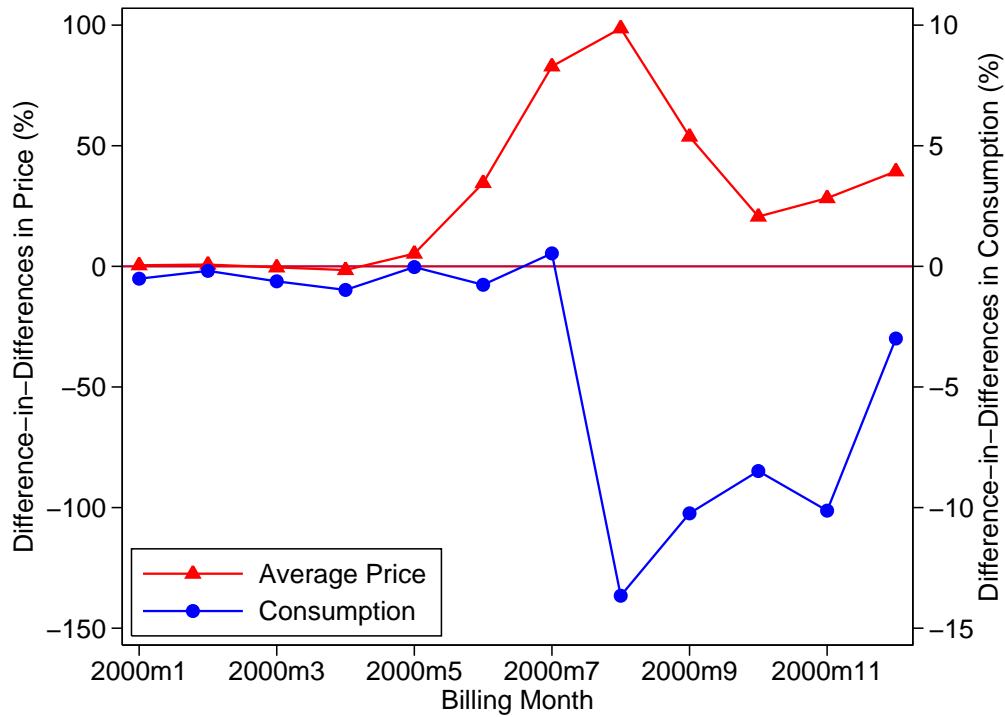


Panel B. Consumption density and price schedule in 2007



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.

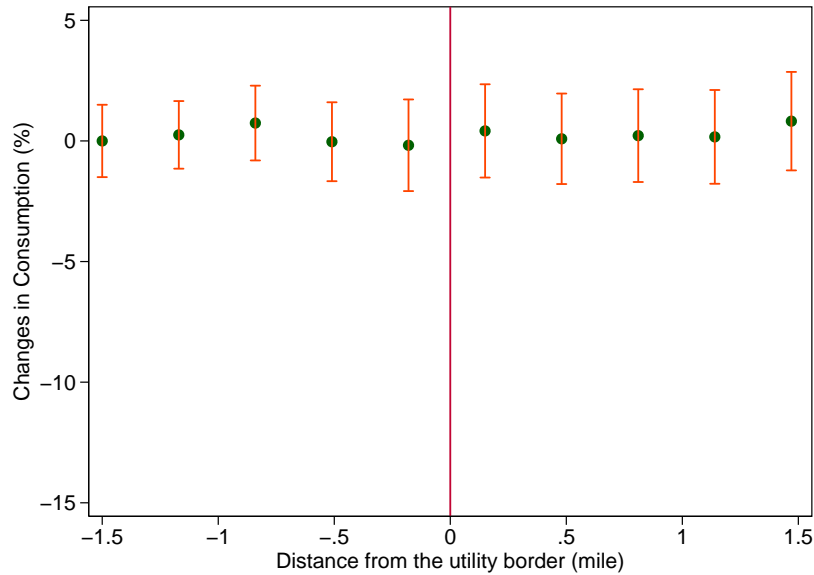
Figure 6: Difference-in-Differences in Price and Consumption in 2000



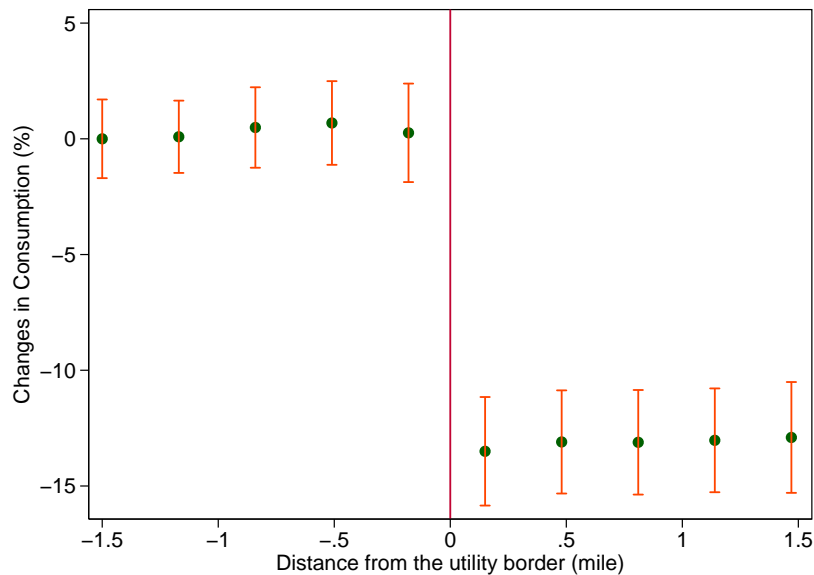
Notes: The first figure shows relative percent changes in tier rates for SDG&E customers relative to SCE customers. I first calculate changes in each tier rate from 1999 to 2000. Then, I calculate its difference-in-differences by subtracting the change in SCE's tier rates from the change in SDG&E's tier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

Figure 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



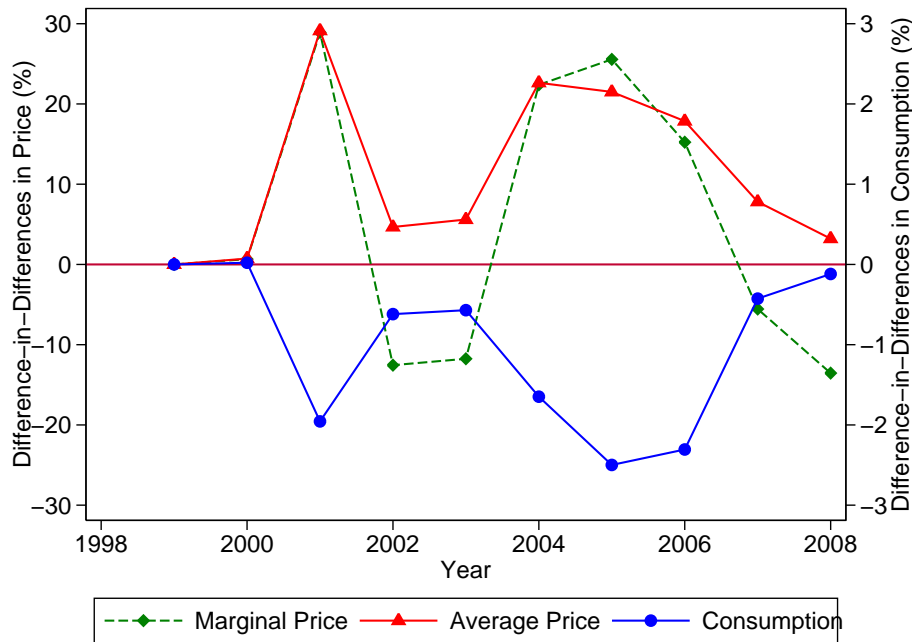
Panel B. Changes in Consumption from August 1999 to August 2000



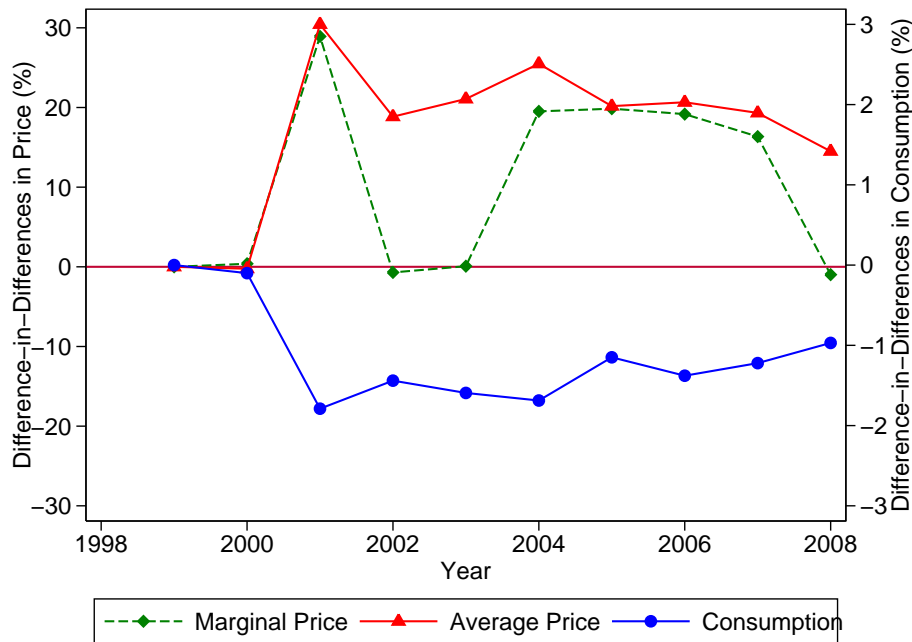
Notes: The figures show the changes in consumption from a billing month in 1999 to the same billing month in 2000 by the distance from the utility border. The horizontal axis shows miles from the border as negative values for SCE's territory and positive values for SDG&E's territory. That is, the left 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 8: Difference-in-Differences in Price and Consumption in January Billing Months

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

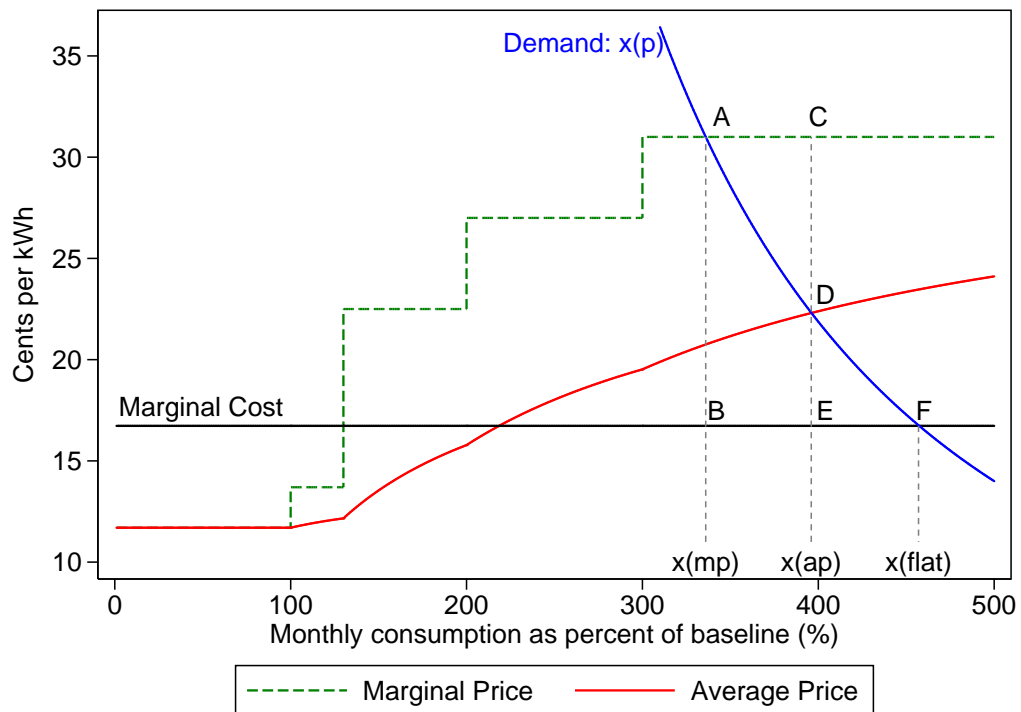


Panel B. Fifth Decile (40% - 50%) of Consumption Distributions



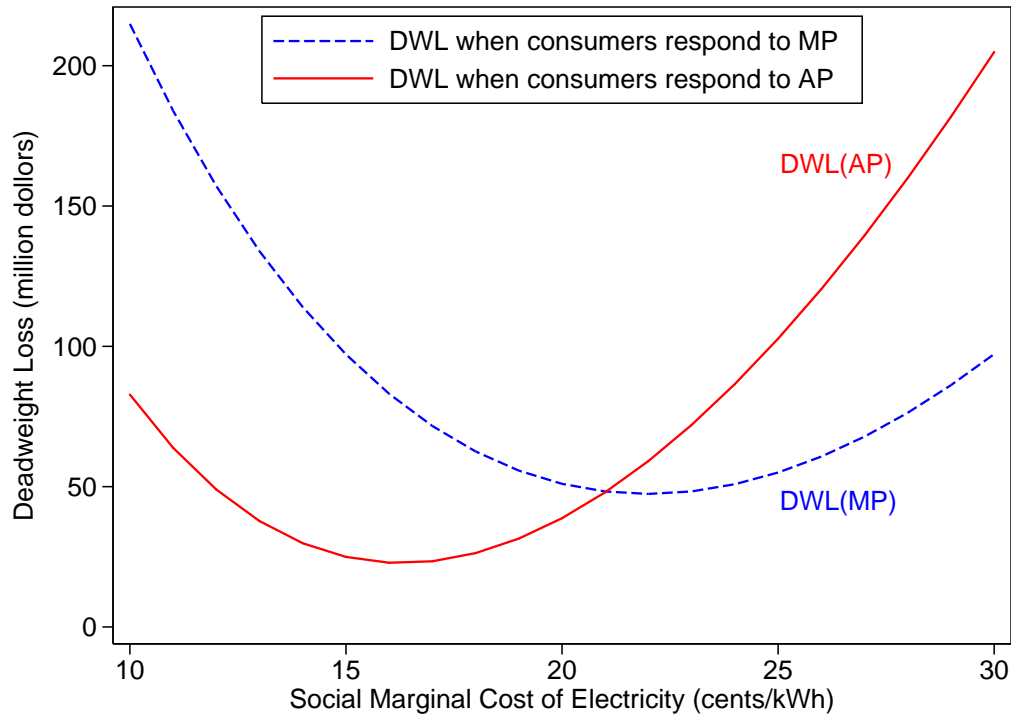
Notes: The figures show the difference-in-differences in price and consumption of January billing months relative to the initial year 1999. First, for each side of the border, I calculate the mean percent change in price and consumption from 1999. Second, I calculate difference-in-differences by subtracting 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 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 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: 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 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 (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 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 (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 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 (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 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 (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 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 7: Efficiency Costs of Nonlinear Pricing

	DWL (\$M)		Difference (\$M)
	MP Response	AP Response	
	(1)	(2)	
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 10 also presents the deadweight loss for different continuous values of the marginal cost assumptions.