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

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Abstract

Standard economic theory predicts that individuals optimize their consumption based on the marginal price and marginal utility of a good. With limited understanding of complex price schedules, however, consumers may make sub-optimal choices by responding to a simplified price. This paper exploits exogenous variations in nonlinear electricity rates across the geographical border of two California electric utilities. The utility border exists inside city limits and zip code boundaries. As a result, households sharing nearly identical demographics and weather conditions experienced substantially different nonlinear price schedules from 1999 to 2006. Using household-level monthly billing data, I find statistically significant price elasticity between -0.18 and -0.20 during the California electricity crisis, and between -0.13 to -0.26 under five-tier increasing-block price schedules between 2001 and 2006. Estimation results suggest that households are more likely to respond to the average price rather than the marginal price of nonlinear rate schedules. The response to average prices distorts consumption less, and hence reduces the deadweight loss under a certain range of marginal costs of electricity. Finally, switching from a uniform pricing to the current nonlinear rate schedule in California may result in a slight increase in aggregate consumption in the presence of the sub-optimal response.

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1 Introduction

Empirical studies of nonlinear budget sets generally rely on the standard economic model where agents make decisions based on the marginal price and marginal utility of a good. Taxpayers facing progressive income taxes, for example, determine their labor supply with respect to the marginal tax rate for an extra hour of work. The standard model serves as the basis of econometric equations that estimate the behavioral response to nonlinear rate schedules, such as income taxes and the price of electricity, water, and cell phone services.

An underlying assumption of the model, however, may be flawed if individuals do not respond to the marginal price of nonlinear rates. In fact, survey evidence suggests that individuals have limited understanding of the marginal rates and kink points of nonlinear price schedules.[1] In addition, most studies do not find bunching of individuals around the kink points on nonlinear rate schedules that the standard model predicts with convex and smoothly distributed preferences.[2] Finally, laboratory experiments find that many subjects use average rates as if they are marginal rates unless examiners explicitly explain their rate structures.[3]

Liebman and Zeckhauser (2004) suggest an alternative model, "schmeduling", where individuals with limited understanding of multi-part rate schedules respond to the average price at the point where they consume. The model implies that individuals may make a sub-optimal choice by responding to a simplified price, particularly when responding to their actual marginal price is costly. Yet the empirical evidence of schmeduling in the field is limited because non-experimental data rarely provide sufficient exogenous price variations that statistically separate the sub-optimal and optimal responses. [4]

This study examines how households respond to nonlinear price schedules by using exogenous variations in electricity prices across the geographical border of two California utilities. The utility border exists inside city limits and zip code boundaries. As a consequence, households sharing nearly identical demographics and weather conditions experienced substantially different price schedules from 1999 to 2006. During the California electricity crisis in 2000, for instance, households on one

[1] For example, Fujii and Hawley (1988) shows that many taxpayers do not know their marginal tax rate.

[2] Saez (2009) uses individual tax return micro data in the US and finds no bunching across wage earners in income tax schedules. Borenstein (2009) uses household-level electricity billing data and finds no bunching in nonlinear electricity rates. On the other hand, Chetty et al. (2010) find substantial bunching for self-employed workers and small but significant bunching for wage earners in their Danish tax recode data.

[3] See de Bartolome (1995) for a laboratory experiments of responses to marginal and average tax rates.

[4] For example, in the literature of residential electricity demand, most studies focus on the response to marginal prices except for Shin (1985).

side of the border experienced a 100% price increase whereas households on the other side had no price change. Furthermore, since each utility changed its nonlinear price schedules independently after 2001, customers experienced significantly different changes in their marginal and average prices of electricity over time. Using household-level monthly electricity billing data from 1999 to 2006, I estimate household electricity demand and test whether they respond to the marginal price or average price of nonlinear price schedules.

This paper includes the following preliminary findings. First, I find statistically significant price elasticity of -0.18 to -0.20 during the California electricity crisis in 2000. I also show that, for my sample households, the elasticity does not vary much across households with different levels of consumption during the crisis. Second, the empirical distribution of electricity consumption does not show bunching around the kink points of nonlinear rate schedules, which is predicted by the response to marginal prices. Third, under the five-tier increasing-block price schedules introduced in 2001, I estimate the demand models where households respond to either marginal or average prices. Price elasticity estimates are statistically significant for both models. The point estimate is between -0.135 to -0.211 for marginal prices, and between -0.153 to -0.262 for average prices. However, when both price variables are jointly estimated, average prices have statistically significant effects, whereas marginal prices turn to have statistically insignificant impacts on consumption. Fourth, I demonstrate a welfare analysis under the assumption that the marginal cost of electricity is 15.92¢/kWh. The sub-optimal response distorts consumption less than the marginal price response, and hence reduces deadweight loss. I show that the difference in the deadweight loss is $132M per year in a utility, which equals 2.53% of its revenue. Finally, my conclusions suggest that, contrary to popular belief, switching from uniform pricing to the current nonlinear schedule may slightly increase aggregate consumption in the presence of this sub-optimal response.

The present study has the following advantages compared to previous studies. First, the cross-sectional price variation across the utility border allows for nonparametric controls of time-variant unobservables such as local economic shocks, weather conditions, and mean reversion that affect electricity consumption. It is particularly important to use a cross-sectional price variation to prevent distributional shifts and mean reversion in consumption from confounding the behavioral response to a price change. Previous studies, by contrast, use time-series price variations in nonlinear rate schedules: when the prices applicable at certain consumption levels change more substantially than the prices at other levels, some households are more likely to face large changes in the applicable price than others. This standard differences-in-difference estimation tends to produce inconsistent estimates because an overall shift of distributions as well as mean reversion at the individual levels are highly likely to be correlated with changes in the applicable price. Cross-sectional price variations, in contrast, are free from this bias given that a distributional shift and mean reversions are not systematically different across the utility border. Second, since the utilities changed their rates independently, households across the utility border experienced substantially different changes in their marginal and average price of electricity. In particular, between some sample periods, subgroups of households experienced a relative decrease in marginal prices but a relative increase in average prices. Since the direction of changes in marginal and average prices is opposite, a simple differences-in-difference estimation sufficiently identifies household responses to the two types of prices without imposing strong functional form assumptions on electricity demand.

2 Background and Research Design

2.1 Geographical Border of the Two Electric Utilities

Southern California Edison (SCE) and San Diego Gas & Electric (SDG&E) provide electricity for most of the southern California areas. Figure 1 presents their service area border in Orange County. The border exists inside city limits and zip code boundaries, contrasting with typical utility borders that exist across cities, counties, or states.[5]

The basic idea of my research design is to examine changes in electricity consumption in relation to changes in nonlinear electricity rates using comparable households across the utility border. I focus on the six cities that contain both SCE and SDG&E service areas. In each city, I keep zip code areas that include both SCE and SDG&E customers to restrict my samples to be further near the utility border. This procedure leaves twelve zip code areas and 104,020 premises in the data.

Table 1 summarizes some demographic characteristics and the mean electricity consumption across the border. I match households' nine-digit zip codes with US Census blocks, and calculate the mean of each variable from the Census in 2000 on each side of the border. The table also includes the households' mean electricity consumption in 1999 when the residential electricity rates were nearly identical between the utilities. The household characteristics and their electricity consumption in 1999 are comparable across the utility border except that the SDG&E side includes more households within the top income level.

[5] According to utility officials, the utility border in this area exists inside city limits primarily because of the historical development of distribution systems.

2.2 Residential Electricity Rates from 1999 to 2009

In each utility, most customers are billed on an increasing block rate schedule where the marginal price of electricity is a step function of their monthly consumption relative to their baseline. Figure 2 presents each utility's standard residential rates in August 2006. 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. To determine the baseline, each utility defines several climate zones across their service areas. Customers within a climate zone have the same baseline with a minor exception that I describe in the next section. The baseline changes between summer and winter, but rarely changes over years. For the samples in this study, the baselines are exactly the same or only slightly different across the utility border at any given period.

By contrast, tier rates change frequently and differently between the utilities. Figure 3 displays each utility's tier rates for their standard tariff customers from 1999 to 2009. In 1999 and early 2000, both utilities had essentially the same two-tier rate schedule. The first price shock occurred during the California electricity crisis in the summer of 2000. The rates for SDG&E customers started to increase in the May billing cycle because of increases in wholesale electricity prices. In the August billing cycles, the first and second tier rates increased to 22¢ and 25¢. This increase translated into a 100% rate increase for SDG&E customers relative to their rates in 1999. The rates for SCE customers, however, stayed at their 1999 level since their retail rates were not affected by the wholesale prices. In 2001, SCE introduced its five-tier increasing block rates. Four months later, SDG&E introduced its five-tier rates that were less steep than SCE's. Since each utility changed their tier rates independently, customers across the border experienced different changes. For example, consider the top tier rate that affect customers with large consumption. It was similar in 1999, 100% higher for SDG&E in 2000, 20% higher for SCE in 2002 and 2003, 20% higher for SDG&E in 2004 and 2005, and again 20% higher for SCE in 2006.

Thus, across the utility border, households sharing nearly identical demographics and weather conditions experienced substantially different nonlinear price schedules from 1999 to 2009. This quasi-experiment provides a similar research platform as a randomized experiment where different price schedules are introduced to comparable households to examine their behavioral response to rate schedules.[6]

[6] It is unlikely that households inside zip code boundaries sort across the utility border because of electricity prices.

3 Data

The primary data of this study consist of household-level monthly electricity billing records between 1999 and 2009 for nearly all residential customers in the two utilities. Each record includes a customer's account number, account type, climate zone, tariff, start and end date of a billing period, monthly consumption, monthly payment, baseline allowance, and nine-digit zip code. Customers choose from standard, all-electric, and medical-need account types as well as their tariff from several tariff schedules. Since over 70% are on the standard tariff with the standard account type, this study first focuses on the standard customers. In addition, 20 to 25% of each utility's customers are on the California Alternate Rates for Energy (CARE) program, a mean-tested program that provides relatively lower rates than the standard rates if household income is less than a regulatory determined level. The following analysis includes estimation for the standard and CARE customers separately.

The billing records do not include information on electricity rates and customers' demographic characteristics. I construct each utility's rate schedules for each billing period using the utilities' official documents. I match households' nine-digit zip code with US Census blocks to collect demographic information including income, household sizes, and housing characteristics.

4 Identification and Estimation

This section describes the econometric models that estimate the behavioral response to nonlinear electricity rates. 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 introduce the present study's identification strategy.

4.1 Difference-in-Differences Methods with Changes in Rate Structures

Let y_{it} denote household i's average daily electricity consumption during billing month t and $p_t(y_{it})$ be the price of electricity, which is either the marginal or average price of y_{it}. Suppose that the

To make sure about this potential self-selection, I use samples that moved-in before 1999, when electricity prices were virtually the same between the utilities.

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:

$$\ln y_{it} = \alpha_i + \beta \ln p_t(y_{it}) + \eta_{it}, \tag{1}$$

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 prices 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 come back to these assumptions.

The Ordinary Least Squares (OLS) produces an inconsistent estimate of β because $p_t(y_{it})$ is a function of y_{it}. Under increasing block price schedules, η_{it} is positively correlated with $p_t(y_{it})$.[7] 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 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 y_{it_0} may predict the price change that each household will face. Let $\triangle \ln y_{it} = \ln y_{it} - \ln y_{it_0}$ 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 $\triangle \ln p_t(y_{it}) = \ln p_t(y_{it}) - \ln p_{t_0}(y_{it_0})$ the log change in the price. Consider the two-stage least squares (2SLS) estimation for the equation:

$$\triangle \ln y_{it} = \alpha_i + \beta \triangle \ln p_t(y_{it}) + \varepsilon_{it}, \tag{2}$$

instrumenting for $\triangle \ln p_t(y_{it})$ with $\triangle \ln \widehat{p_t(y_{it})} = \ln p_t(y_{it_0}) - \ln p_{t_0}(y_{it_0})$ where $p_t(y_{it_0})$ is the predicted price in period t with household i's consumption in t_0. Given that the price schedule $p_t()$ itself is exogenous to the household, the 2SLS produces a consistent estimate of β if $E[\varepsilon_{it}|y_{it_0}] = 0$. That is, y_{it_0} needs to be uncorrelated with $\varepsilon_{it} = \eta_{it} - \eta_{it_0}$.

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

4.2 Econometric Identification Problems

The condition $E[\varepsilon_{it}|y_{it_0}] = 0$ requires a parallel trend assumption on changes in electricity consumption between households with different levels of y_{it_0}. That is, in the absence of rate changes, households with different levels of y_{it_0} would have equivalent changes in their consumption. There are two concerns for this condition.[8]

First, in panel data of household electricity consumption, mean reversion produces a negative correlation between ex-ante consumption y_{it_0} and the shock ε_{it}. Households with lower consumption in t_0 systematically consume more in t and vice versa. This systematic negative correlation produces substantial bias particularly when a rate 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.

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

4.3 Identification Strategy Using Price Variations across the Utility Border

I propose the following estimation method using panel data of household electricity consumption across the utility border. Consider two households with the same level of ex-ante consumption in year y_{t_0}. Suppose that they are in the same zip code area, but on a different side of the utility border. In year t, they experience different rate changes because the utilities introduce different rate schedules. By including non-parametric controls for each level of y_{t_0}, the following estimation controls for any systematic changes specific to y_{t_0} such as mean reversion.

Define a set of dummy variables:

[8] Saez et al. (2009) provides a detail discussion of similar identification problems in empirical studies of labor supply response to income taxes.

$$D_{ij} = 1\{j < y_{it_0} \leq j + k\}, \tag{3}$$

which equals one if household i's consumption in year t_0 falls between j and $j+k$. I use bandwidth $k = 1$ for the main result, which is equivalent to creating dummy variables of y_{it_0} rounded to the nearest whole integer.

First, let $p_t(y_{it})$ denote either the marginal or average price of nonlinear rates. For each type of price, I estimate the following 2SLS equation:

$$\triangle \ln y_{it} = \alpha + \beta \triangle \ln p_t(y_{it}) + \sum_{j=0}^{J} \gamma_j \cdot D_{ij} + \sum_{z=1}^{Z} \delta_z \cdot zip_z + \sum_{c=1}^{C} \zeta_c \cdot cycle_c + \varepsilon_{it}, \tag{4}$$

with the first stage equation:

$$\triangle \ln p_t(y_{it}) = \alpha_1 + \sum_{j=0}^{J} \theta_j \cdot D_{ij} \cdot SCE_i + \sum_{j=0}^{J} \gamma_{1j} \cdot D_{ij} + \sum_{z=1}^{Z} \delta_{1z} \cdot zip_z + \sum_{c=1}^{C} \zeta_{1c} \cdot cycle_c + \eta_{it}, \tag{5}$$

where $SCE_i = 1\{i \in \text{SCE customers}\}$. I include dummy variables zip_z and $cycle_c$ that control for weather and economic shocks to zip code area z and billing cycle c. In addition, $\sum_{j=0}^{J} \gamma_j \cdot D_{ij}$ non-parametrically control for mean reversion, distributional changes, and other shocks specific to y_{t_0}. Even with these non-parametric controls, the interactions $D_{ij} \cdot SCE_i$ identify parameters of interest. The identification assumption is that the parallel trend assumption holds between households across the utility border once conditional on D_{ij}, zip_z, and $cycle_c$.

Second, to examine whether households respond to the marginal or average price of nonlinear price schedules, I estimate the following equation:

$$\triangle \ln y_{it} = \alpha + \beta_m \triangle \ln mp_t(y_{it}) + \beta_a \triangle \ln ap_t(y_{it}) + \sum_{j=0}^{J} \gamma_j \cdot D_{ij} + \sum_{z=1}^{Z} \delta_z \cdot zip_z + \sum_{c=1}^{C} \zeta_c \cdot cycle_c + \varepsilon_{it}. \tag{6}$$

Note that in general, it is difficult to separately identify β_m and β_a because changes in marginal prices and average prices are typically highly correlated in nonlinear rate schedules. The price variation across the utility border, however, potentially provides a sufficient statistical power to make inferences about the response to two types of prices. Between some sample periods, some households experienced a relative decrease in marginal prices but a relative increase in average prices compared to households on the other side of the border. Consider the following simple example. Suppose that utility A does not change their tier rates. Utility B, however, imposes large increases on their lower tier rates and decreases on higher tier rates. When the increase in the lower tier rate is larger than the decrease in the higher tier rate, the households falling in the higher tiers in utility B will have a relative decrease in marginal price and a relative increase in average price compared to households in utility A. Since the direction of relative price changes is opposite between marginal and average prices, these price variation may allow for the identification of two types of price response without imposing a strong functional form assumption on electricity demand.

For the following analysis, I use $t_0 = 1999$. That is, D_{ij} are defined based on consumption levels in 1999. An advantage of this approach is that households across the utility border had essentially the same rate schedules in 1999. Thus, their consumption $y_{i,1999}$ was not affected by price differences in 1999. An alternative approach is to use $y_{i,t-1}$ to determine D_{ij}. This approach, however, may be confounded by the fact that $y_{i,t-1}$ itself if affected by different rate schedules between the utilities in $t-1$.

5 Results

This section describes estimation results. As a preliminary analysis, I mostly focus on the August billing months from 1999 to 2006 for standard tariff customers. That is, the following analysis does not include CARE customers or all-electric customers.

5.1 Responses to the Price Spike in 2000

First, I present estimation results for the price spike during the California electricity crisis in 2000. In 1999 and 2000, each utility had two-tier increasing block price schedules, but the second tier rate was only 16% higher than the first tier rate. That is, the rate schedule was almost equivalent to a uniform price. The first part of Figure 5 shows the relative changes in log tier rates across the utilities between 1999 and 2000. Regardless of consumption levels, SDG&E customers experienced a 60% to 100% increase in both marginal and average price relative to SCE customers during the summer billing months.

There are several advantages and disadvantages to the price change in 2000 for estimating the electricity demand. First, there is less concern about simultaneity bias between prices and consumption because the difference between the first and second tier rates is small. Second, the equivalent price change over all consumption levels allows for a clear comparison of the price elasticity among different consumption levels. On the other hand, because the change in marginal and average price is virtually equivalent, the price spike in 2000 does not allow for a test for the responses to marginal or average prices. Finally, the electricity crisis brought on many other changes than electricity rates, including public appeals for conservation. In this study's research design, these factors do not confound estimates as far as public appeals did not differ within the same zip code areas across the utility border. However, public appeals also potentially made rate changes more salient to customers. Therefore, the results from this time period may not be generalized to the effect of typical rate changes.

The second part of Figure 5 presents graphical evidence of the effect of the price spike on consumption. I first calculate the percent change in individual household consumption from 1999 to 2000. I then make difference-in-differences estimates by subtracting the mean percent change of SCE customers from the mean percent change of SDG&E customers. The range bars show the 95% confidence intervals for the point estimates. The relative price started to increase in the July billing cycle, but households started to reduce consumption in the August billing cycle.[9]

Table 2 provides regression results for the August billing month in which the price spike was likely to be known to most customers. Column 1 and 2 do not include the nonparametric controls for mean reversion whereas column 3 and 4 include the control. The price elasticity estimate is numerically the same for the marginal and average price because the two prices were essentially equivalent under the moderately steeped increasing block rate schedule in 1999 and 2000. Excluding controls for mean reversion biases the estimates, but the bias is small since the price change from 1999 to 2000 was uniform across all consumption levels. Table 3 compares the price elasticity estimates for subsets of households by their consumption level in 1999. Households with smaller ex-ante consumption have slightly larger price elasticity, but the difference among the subgroups is in the range of 2%.

The results confirm that households do respond to electricity prices and that the price elasticity estimate is approximately -0.2.[10] In addition, the estimates do not significantly differ among house-

[9]Bushnell and Mansur (2005) find a similar result of lagged price responses during the California electricity crisis.

[10]The estimated price elasticity is slightly larger than but not significantly different from the previous studies of

holds with different levels of consumption. In the following sections, I examine whether the price response persists with the five-tier increasing pricing introduced in 2001 and whether households respond to the marginal or average price of nonlinear rate schedules.

5.2 Responses to the Five-Tier Increasing Block Pricing

One way to estimate the behavioral response to nonlinear rate schedules is to find bunching of samples around the kink points where a marginal rate discontinuously increases.[11] Suppose that preferences for electricity consumption are convex and smoothly distributed in the population. Then, if households respond to marginal prices, many demand curves intersect with the kinks, therefore relatively more samples should be found around the kinks. Figure 6 displays a histogram of consumption across SCE customers in the August billing month of 2006. The vertical lines show the locations of the kink points presented in Figure 2. Although the steps around the second and third kinks are substantially steep, the empirical distribution is smooth across all consumption levels. The result indicates either that households do not respond to any price under the five-tier increasing block pricing, or that households respond to a price other than marginal prices. I provide graphical and statistical evidence for these hypotheses.

The basic idea of the 2SLS estimation in equation (4) is that households with the same level of y_{i1999} potentially experience different changes in their marginal and average price across the utility border. To graphically examine the relation between the relative changes in price and consumption conditional on y_{i1999}, I calculate the mean percent changes in price and consumption from 1999 for households whose y_{i1999} fall in the third tier in 1999[12]. First, for each side of the border, I calculate the mean percent changes in price and consumption. Second, I make difference-in-differences by subtracting the mean percent change of SCE customers from the mean percent change of SDG&E customers.

The first graph in Figure 7 shows the difference-in-differences in the mean percent changes in price and consumption for households whose y_{i1999} fall in the third tier in 1999. That is, the figure shows how the prices and consumption of SDG&E customers change over time relative to SCE customers conditional on their y_{i1999}. Relative to SCE customers, the mean percent change

the California electricity crisis (e.g. Bushnell and Mansur (2005) and Reiss and White (2008)).

[11] For example, see Saez (2009), Borenstein (2009), and Chetty et al. (2010) for more detail descriptions of how to estimate elasticity from bunching in distributions.

[12] Note that third and fourth tiers did not exist in 1999 because the utilities had two-tier block rates. I use "third tier" and "fourth tier" here just to group households by y_{i1999}.

in average prices are larger for SDG&E customers for all years. The changes in marginal prices, however, are lower for SDG&E customers in 2001, 2006, and 2007. Except for 2004 and 2005, the relative change in marginal and average prices are different by 10 to 20 percentage points. The graph indicates that the relative changes in consumption move in line with the relative changes in average prices rather than marginal prices. For example, in 2001, 2006, and 2007, the changes in marginal prices are lower for SDG&E customers, but the changes in consumption show that their relative consumption is also lower compared to SCE customers. In addition, relative marginal prices substantially increase in 2004 and 2005, but the relative consumption does not seem to respond to the change in the same magnitude. On the other hand, the relative change in average prices seem to show a negative relation with the relative change in consumption over time. I present the same graph for households whose y_{i1999} fall in the fourth tier in 1999 in the second panel. The implications are similar to the first graph. Particularly, the relative change in marginal prices does not show a negative relation with the relative change in consumption in 2001, 2002, 2006, and 2007.

To statistically test the relation, I estimate the 2SLS equations described in equation (5) and (6). Table 4 presents regression results for each year between 2001 and 2006. First, when the regression includes only marginal or average prices, the 2SLS estimation produces statistically significant price elasticity between -0.135 to -0.211 for marginal prices and between -0.153 to -0.262 for average prices. Second, when both price variables are jointly estimated, average prices have statistically significant effects, whereas marginal prices turn to have statistically insignificant impacts on consumption. Finally, in 2004 and 2005, the joint estimation produces too noisy estimates to distinguish the two price effects. This is because the relative changes of the two prices are highly positively correlated for all consumption levels in the two years.

5.3 Welfare Analysis

This section explores the welfare effect of the sub-optimal response to nonlinear rate schedules. Examining the deadweight loss from increasing block pricing requires an assumption about the marginal cost of electricity supply. As a preliminary exercise, I follow Borenstein (2010) and assume that the marginal cost of quantity changes equals the average cost under the existing tariffs. Thus, I assume that the marginal cost is the flat rate that the utility would have if the five-tier pricing is replaced by uniform pricing given that total revenue remains unchanged. For SCE's residential electricity bills in 2006, the flat rate is 15.92¢/kWh. However, note that it could be too high because the retail electricity price includes sunk losses from the California electricity crisis. On the other hand, it could be too low because we are not taking into account of the externalities from electricity generation.

Under the assumption of the uniform marginal cost, uniform pricing of 15.92¢ maximizes the social welfare. Introducing nonlinear pricing would distort consumption, and thus induce deadweight loss. Figure 5 provides a graphical example for a SCE customer that is in the fourth tier of the increasing-block schedule in August 2006. The deadweight loss equals d1 + d2 if the household responds to the marginal price, whereas it equals d2 if the household responds to the average price. I calculate the deadweight loss using the Harberger-Browning approximation,

$$DWL \simeq \frac{1}{2} Y |\beta| \frac{(p - MC)^2}{MC}, \tag{7}$$

where Y is the monthly electricity consumption when the demand curve intersects the marginal cost, β is the price elasticity of demand, and p is either marginal or average price.

Table 5 presents the aggregate annual deadweight loss calculated by the individual households' billing records in SCE in 2006.[13] I include only customers on the standard tariff, so the statistics do not include other customers on the CARE program. If households respond to marginal prices, the DWL would equal $186M. However, the actual DWL with the response to average prices is $54M. The difference is $132M, which is 2.53% of the annual revenue. The sub-optimal response substantially reduces the DWL.

In addition, the sub-optimal response alters the effect on the aggregate consumption. Under the price schedule in 2006, if households respond to the marginal price, they would reduce their consumption by 6.57% compared to the uniform pricing where the price equals the marginal cost. However, the actual consumption based on the average price model is slightly larger than the consumption under the uniform pricing. This is because the households in lower tiers increase their consumption under the increasing block pricing, and this increase is larger than the reduction by the households in higher tiers. Thus, if the five-tier increasing block pricing aims to reduce negative externalities from excessive consumption such as greenhouse gas emissions, the tier rates need to be set higher than current levels in the presence of the sub-optimal response to nonlinear price schedules.

[13] This exercise assumes that the price elasticity is homogeneous within SCE.

6 Conclusion and Future Work

This paper examines how households respond to nonlinear price schedules and test whether they respond to marginal prices as the standard economic model predicts. I use exogenous variations in electricity prices across the geographical border of two California utilities. The utility border exists inside city limits and zip code boundaries. As a consequence, households sharing nearly identical demographics and weather conditions experienced substantially different price schedules from 1999 to 2006. I estimate household electricity demand across the utility border using household-level monthly electricity billing records.

First, I find statistically significant price elasticity of -0.18 to -0.20 during the California electricity crisis in 2000. I also show that, for my sample households, the elasticity does not vary much across households with different levels of consumption during the crisis. Second, the empirical distribution of electricity consumption does not show bunching around the kink points of nonlinear rate schedules, which is predicted by the response to marginal prices. Third, under the five-tier increasing-block price schedules introduced in 2001, I estimate the demand models where households respond to either marginal or average prices. Price elasticity estimates are statistically significant for both models. The point estimate is between -0.135 to -0.211 for marginal prices, and between -0.153 to -0.262 for average prices. However, when both price variables are jointly estimated, average prices have statistically significant effects, whereas marginal prices turn to have statistically insignificant impacts on consumption. Fourth, I demonstrate a welfare analysis under the assumption that the marginal cost of electricity is 15.92¢/kWh. The sub-optimal response distorts consumption less than the marginal price response, and hence reduces deadweight loss. I show that the difference in the deadweight loss is $132M per year in a utility, which equals 2.53% of its revenue. Finally, my conclusions suggest that, contrary to popular belief, switching from uniform pricing to the current nonlinear schedule may slightly increase aggregate consumption in the presence of this sub-optimal response.

This preliminary version leaves the following questions for future work. First, I focus on the August billing months between 1999 to 2006 using customers on standard tariff schedules. The next analysis needs to incorporate the data excluded from the present paper such as customers on the CARE program and billing records from other billing months. Second, although I examine exclusively the marginal price response model and the average price response model, alternative models may better explain household behavior under nonlinear rate schedules.[14] Third, the welfare analysis needs to include more detail discussions about the social marginal cost of electricity including externalities from electricity generation.

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[14]Saez (2009) describes the model incorporating uncertainty in taxable income and Borenstein (2009) estimates the response to expected marginal prices. In addition, lagged prices may have substantial effects on consumption as suggested by Bushnell and Mansur (2005) and other previous studies.

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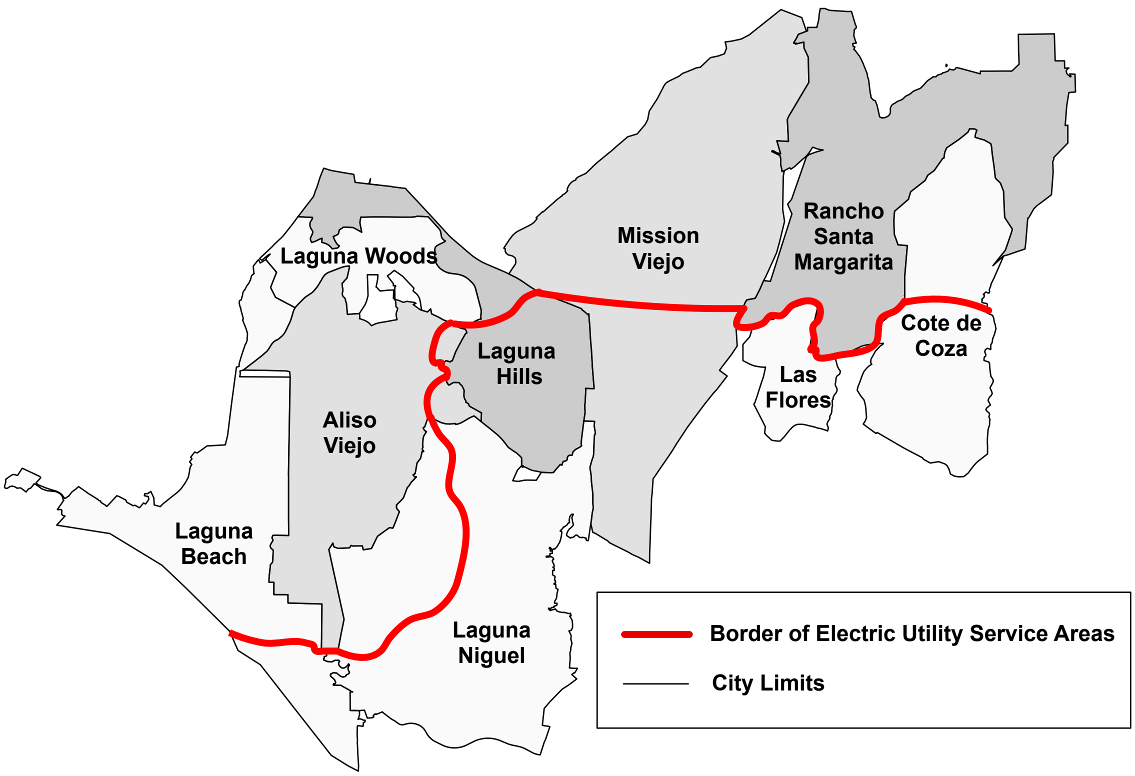
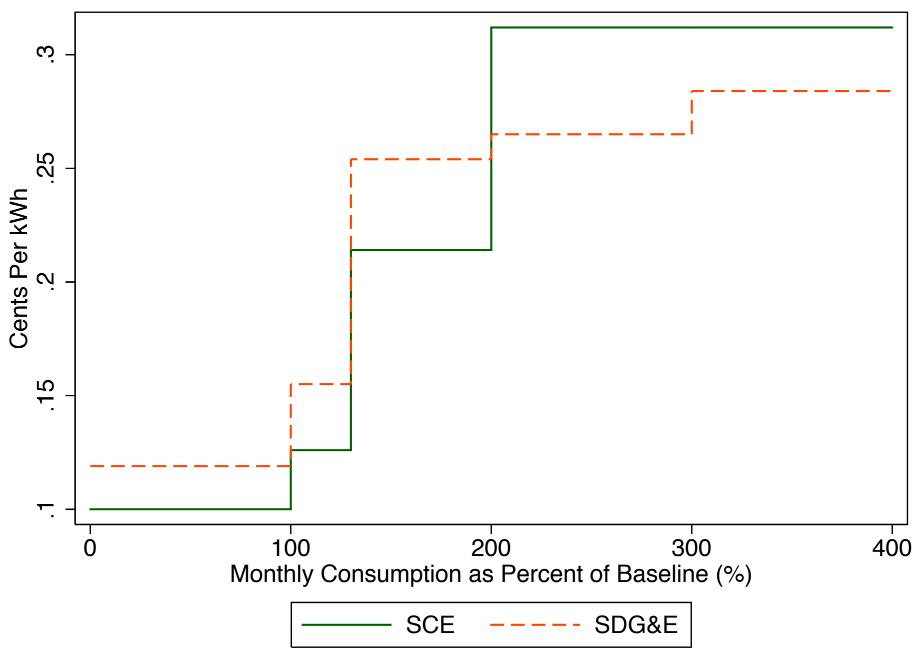
Figure 1: Geographical Border of Electric Utility Service Areas in Orange County, California



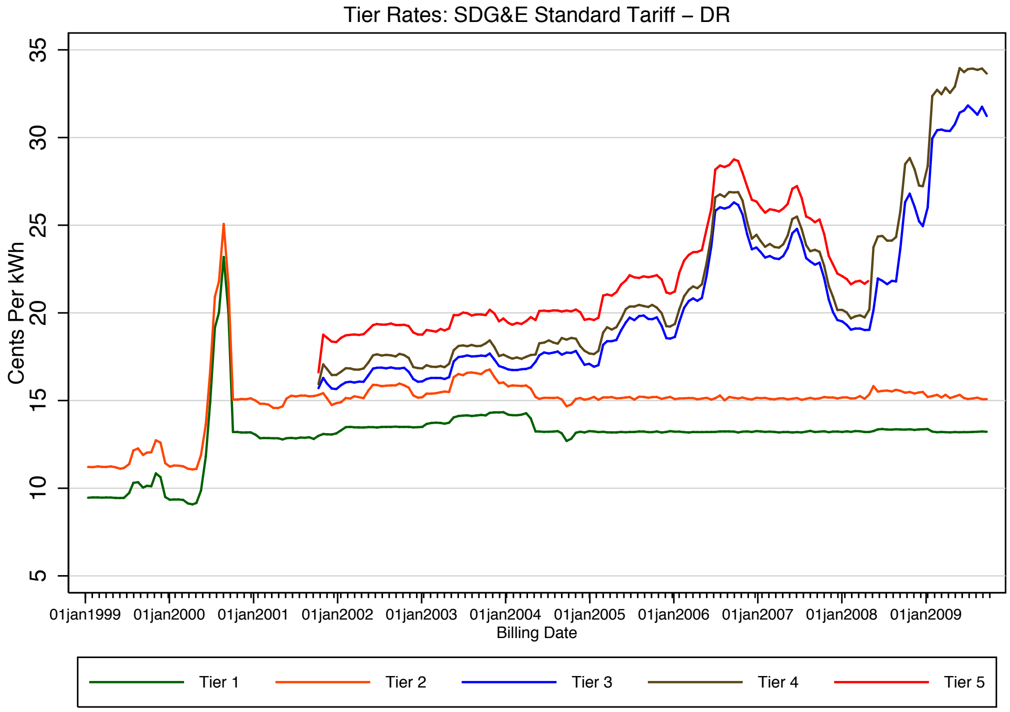
Note: The bold line shows the service area border of Southern California Edison and San Diego Gas & Electric. SCE provides electricity for the north side of the border and SDG&E covers the south side. The map also presents city limits. The utility border exists inside the city limits in Laguna Beach,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

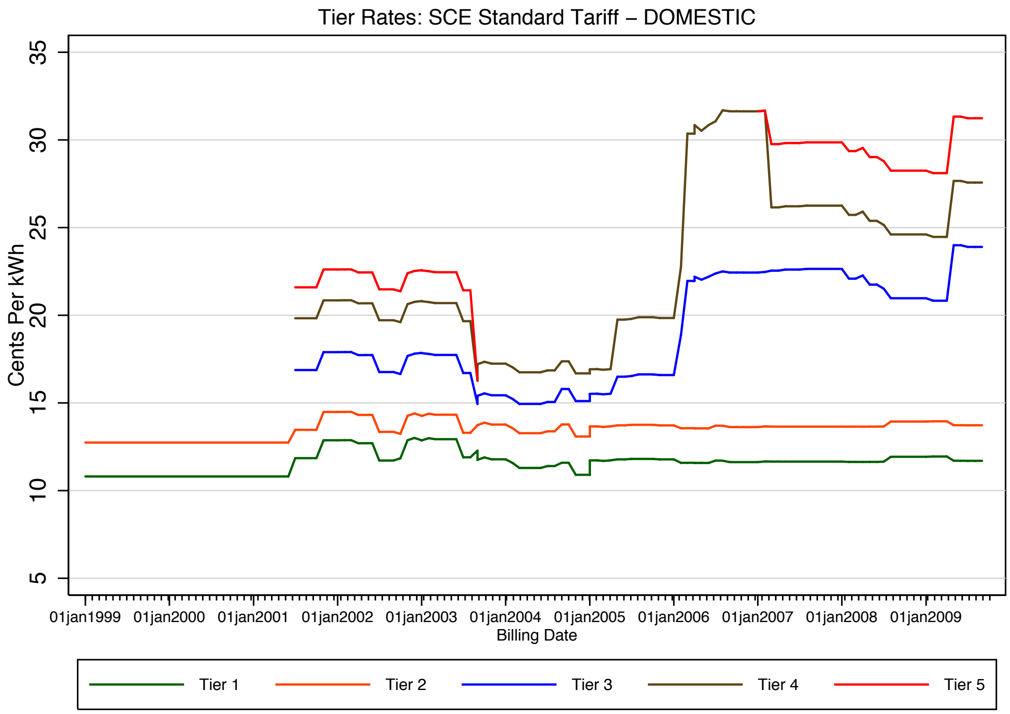
Figure 2: Standard Residential Rates in SCE and SDG&E in 2006



Note: The figure displays standard residential electricity rates in August 2006 for Southern California Edison (SCE) and San Diego Gas & Electric (SDG&E). The marginal price of 1 kWh electricity is a step function of customers' monthly consumption as a percent of their baseline. For example, customers pay the first tier rate for their consumption less than 100% of the baseline, the second tier rate for their consumption larger than 100% and less than 130% of the baseline, and so forth.

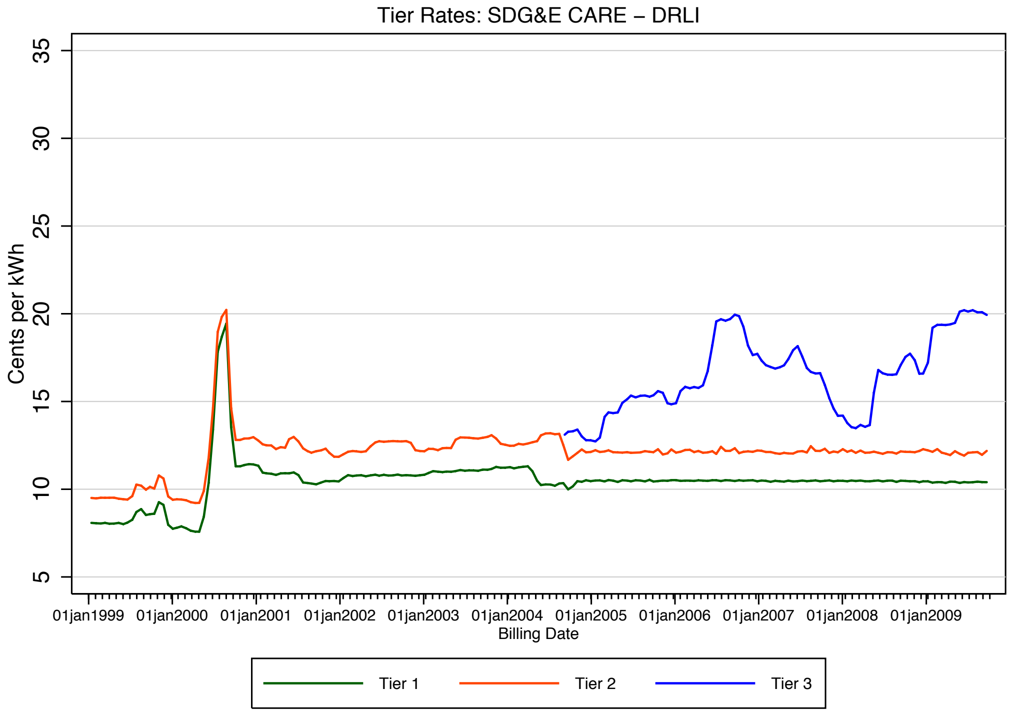
Figure 3: Tier Rates for Standard Tariff Customers from 1999 to 2009

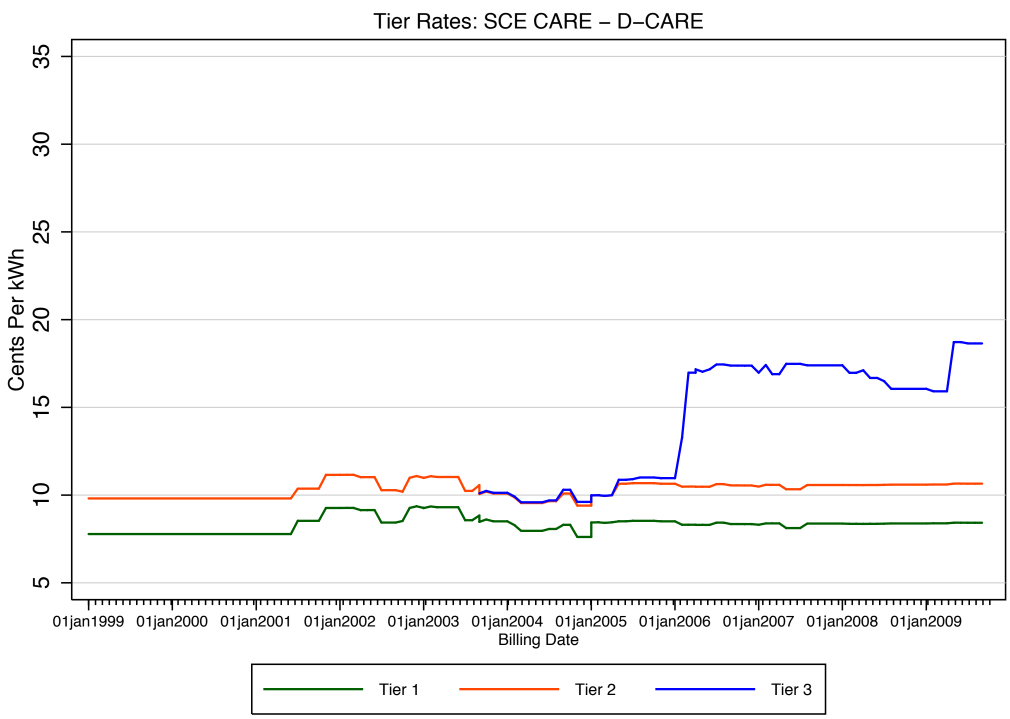




Note: The figures display each tier rate of the five-tier increasing-block price schedules for Southern California Edison and San Diego Gas & Electric from 1999 to 2009. The third, fourth, and fifth tiers did not exist before the utilities introduced the five-tier block schedules in 2001. For SCE between 2004 and 2006, and for SDG&E after 2008, the fifth tier rates were equivalent to the fourth tier rates.

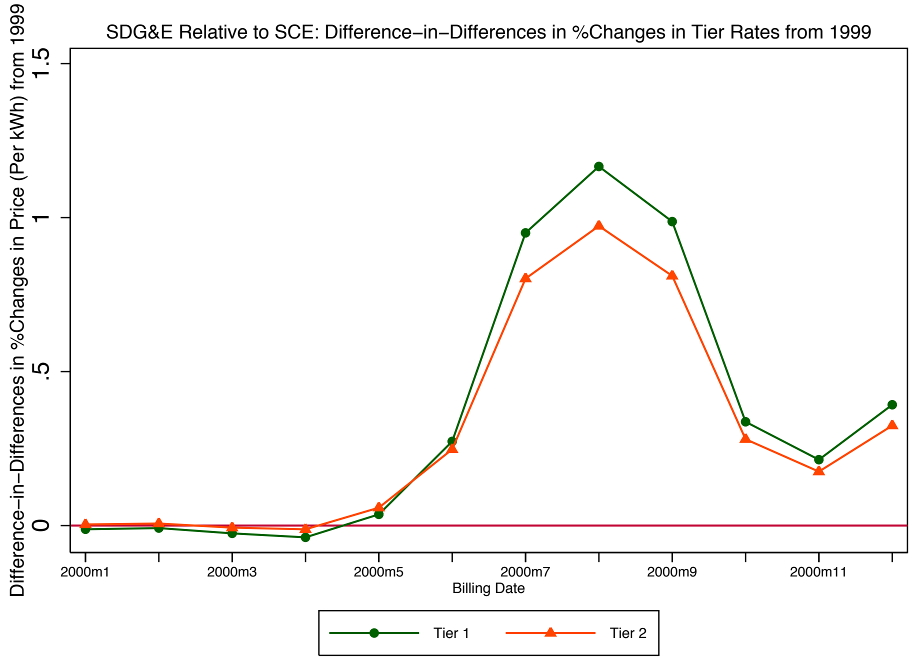
Figure 4: Tier Rates for CARE Customers from 1999 to 2009

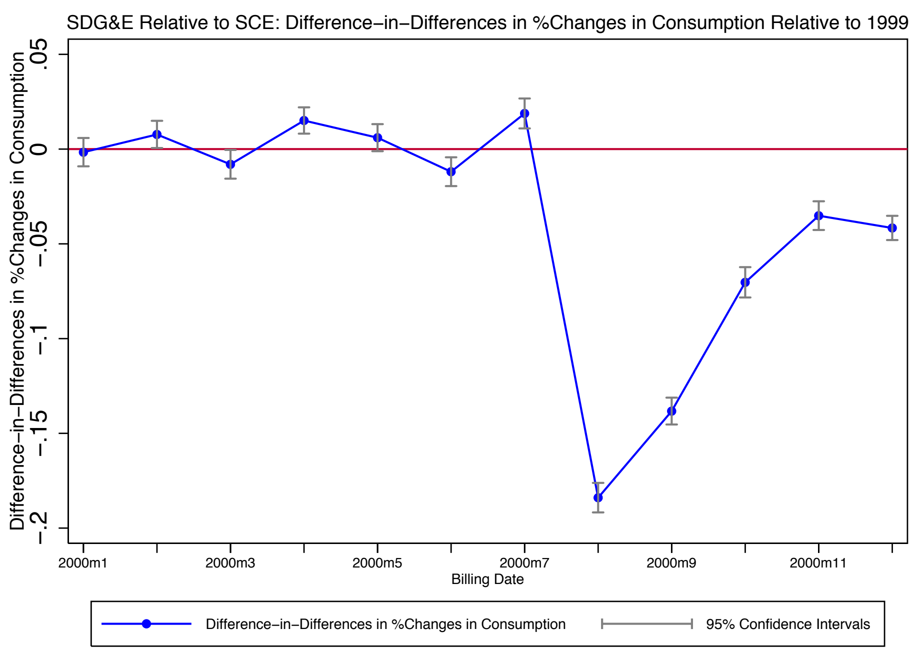




Note: The figures present each tier of the three-tier increasing-block price schedules for customers on the CARE (California Alternative Rates for Energy) program. CARE customers had two-tier block rates before three-tier rates were introduced in 2005.

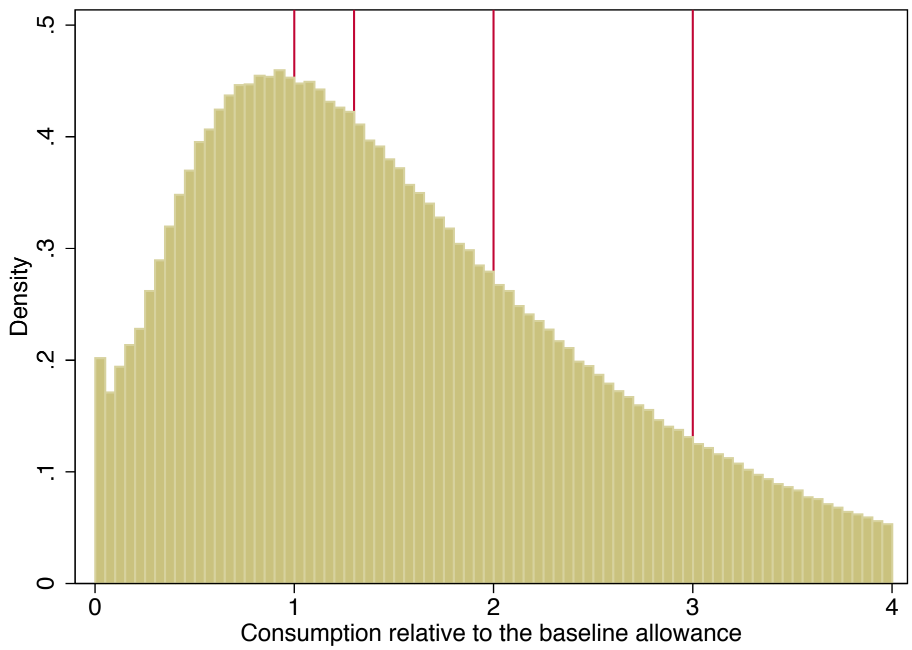
Figure 5: Relative Changes in Price and Consumption in 2000





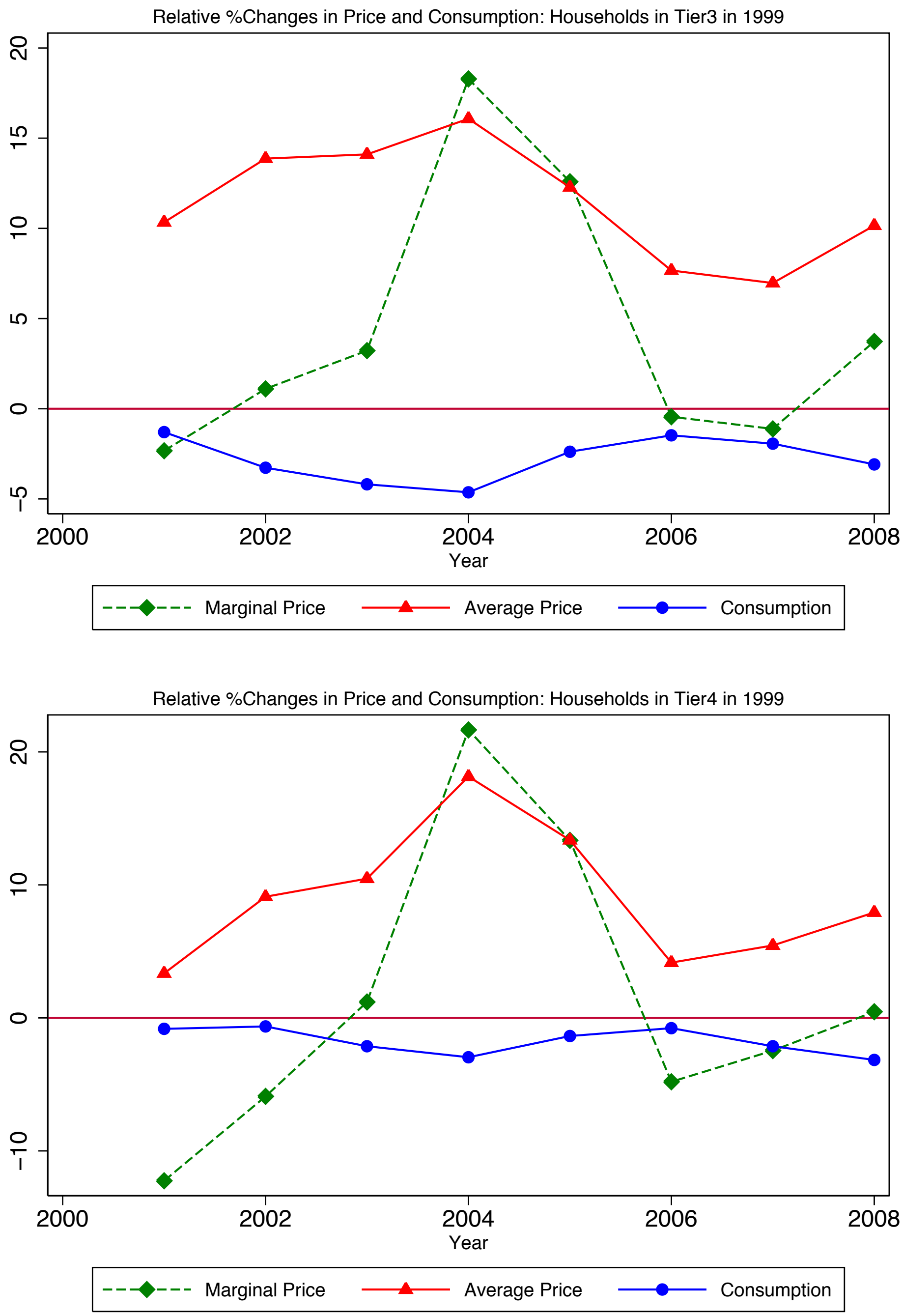
Note: The first figure shows relative percent changes in tier rates for SDG&E customers relative to SCE customers. I first calculate changes in each tier rate from 1999 to 2000. Then, I make its difference-in-differences by subtracting the change in SCE's tier rates from the change in SDG&E's tier rates. Similarly, the second figure presents the relative percent change in consumption. The range bars show the 95% confidence intervals for the difference-in-differences estimates.

Figure 6: Bunching in the Distribution of Consumption



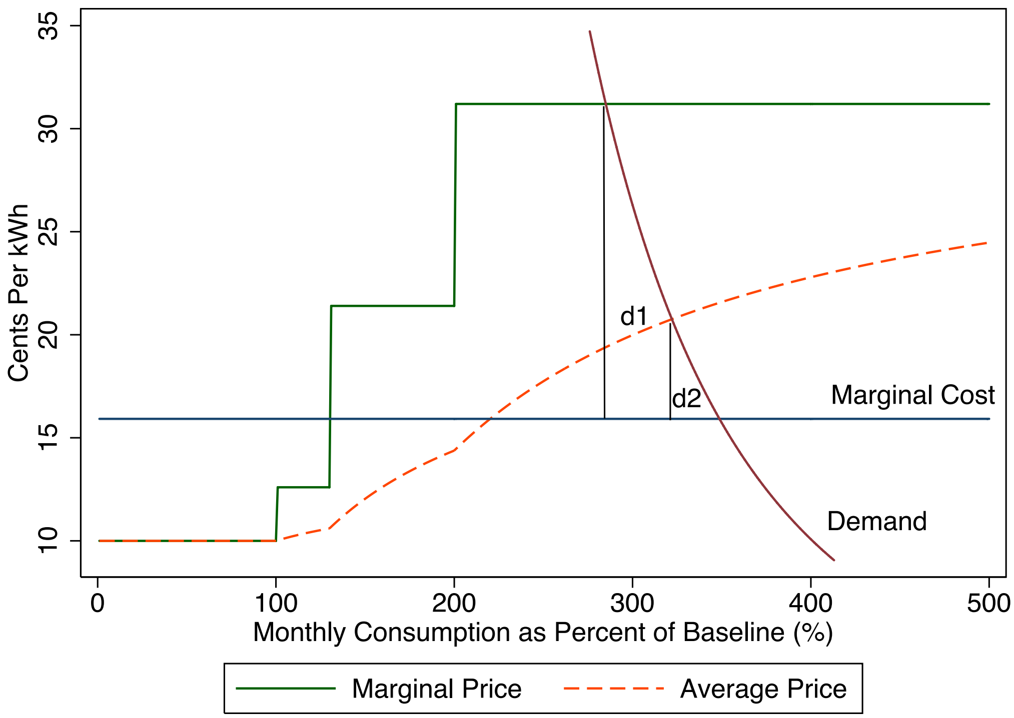
Note: This figure presents the histogram of electricity consumption in the 2006 August billing month for SCE. The horizontal axis shows consumption relative to customers' baseline. The solid lines display locations of the kinks in the five-tier increasing block rates.

Figure 7: Relative Changes in Price and Consumption by 1999 Consumption Levels



Note: The figures show the relative changes in price and consumption conditional on y_{i1999}. For the top graph, I calculate the mean percent changes in price and consumption from 1999 for households whose y_{i1999} fall in the third tier in 1999. First, for each side of the border, I calculate the mean percent changes in price and consumption. Second, I make difference-in-differences by subtracting the mean percent change of SCE customers from the mean percent change of SDG&E customers. The second graph shows the same variables for households whose y_{i1999} fall in the fourth tier in 1999.

Figure 8: Welfare Effect of Sub-optimal Price Responses to Nonlinear Price Schedules



Note: 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 August 2006 and the dashed line presents its average price. I assume the marginal cost of electricity equals $15.92 per kWh. The deadweight loss equals d1 + d2 if a household respond to marginal prices and equals d2 if the household responds to average prices.

Table 1: Household Demographics and Electricity Consumption in 1999 Across the Utility Border

	SCE Side	SDG&E Side
Income per capita	38809	39690
%Households with Annual Income bellow 20k	6.85	6.14
%Households with Annual Income 20-40k	13.37	11.45
%Households with Annual Income 40-60k	15.53	14.87
%Households with Annual Income 60-100k	29.72	25.69
%Households with Annual Income over 100k	34.52	41.85
% Renter Occupancy	24.78	21.71
Median Home Value	364143	385695
Median Monthly Rent	1273	1324
Average Household Size	2.62	2.77
Average Daily Electricity Use (kWh) in 1999		
Jan	18.85	20.01
Feb	18.1	18.67
Mar	17.75	17.8
Apr	17.38	17.65
May	16.4	16.9
Jun	16.38	16.42
Jul	20.03	18.97
Aug	21.88	21.89
Sep	20.85	21.16
Oct	20.62	20.47
Nov	19.47	20.26
Dec	18.64	19.49

Note: The first part presents household demographics across the utility border. I match households' nine-digit zip code with Census blocks to calculate the mean of each variable from UC Census 2000. The second part shows the mean consumption for each billing month in 1999.

Table 2: Instrumental Variable Estimates of Price Elasticity of Electricity Demand in 2000

	Dependent Variable: $\triangle$ln(Electricity Consumption)			
	(1)	(2)	(3)	(4)
$\triangle$ln(MP)	-.160		-.191	
	(.008)		(.008)	
$\triangle$ln(AP)		-.159		-.183
		(.008)		(.008)
Control for mean reversion	No	No	Yes	Yes
Zip code dummy	Yes	Yes	Yes	Yes
Billing cycle dummy	Yes	Yes	Yes	Yes
Observations	104020	104020	104020	104020

Note: This table presents results of the 2SLS regression in equation (5) in 2000. The dependent variables are log changes in electricity consumption relative to 1999. Robust standard errors are in parentheses.

Table 3: Price Elasticity of Electricity Demand in 2000 for Different Consumption Levels in 1999

	Dependent Variable: $\triangle$ln(Electricity Consumption)					
Subgroup	Tier1 in1999		Tier3 in1999		Tier5 in1999	
	(1)	(2)	(3)	(4)	(5)	(6)
$\triangle$ln(MP)	-.200		-.198		-.185	
	(.026)		(.014)		(.013)	
$\triangle$ln(AP)		-.198		-.195		-.181
		(.026)		(.014)		(.013)
Control for mean reversion	Yes	Yes	Yes	Yes	Yes	Yes
Zip code dummy	Yes	Yes	Yes	Yes	Yes	Yes
Billing cycle dummy	Yes	Yes	Yes	Yes	Yes	Yes
Observations	18208	18208	25647	25647	24567	24567

Note: This table presents results of the 2SLS regression in equation (5) in 2000 for subgroups defined by consumption level in 1999. The dependent variables are log changes in electricity consumption relative to 1999. Robust standard errors are in parentheses.

Table 4: Instrumental Variable Estimates of Price Elasticity of Electricity Demand under Increasing-Block Rate Schedules

	Dependent Variable: $\triangle\ln$(Electricity Consumption)								
Year		2001			2002			2003	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\triangle\ln$(MP)	-.166		.082	-.156		-.054	-.211		-.081
	(.017)		(.042)	(.031)		(.047)	(.076)		(.106)
$\triangle\ln$(AP)		-.219	-.286		-.251	-.215		-.262	-.218
		(.029)	(.069)		(.044)	(.065)		(.054)	(.073)
Control for mean reversion	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Zip code dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Billing cycle dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	104020	104020	104020	102238	102238	102238	100688	100688	100688
Year		2004			2005			2006	
	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
$\triangle\ln$(MP)	-.135		-2.59	-.116		-2.48	-.183		.070
	(.046)		(2.14)	(.057)		(2.23)	(.069)		(.105)
$\triangle\ln$(AP)		-.153	3.26		-.224	3.29		-.238	-.316
		(.052)	(2.64)		(.069)	(2.71)		(.080)	(.127)
Control for mean reversion	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Zip code dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Billing cycle dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	99568	99568	99568	98741	98741	98741	97123	97123	97123

Note: This table presents results of the 2SLS regressions in equation (5) and (6) between 2001 and 2006. The dependent variables are log changes in electricity consumption relative to 1999. For each year, I estimate the average price response model and the marginal price response model separately. These results are shown in the first two columns in each year. In addition, I include both prices in the regressions. I present the results in the last column in each year. Robust standard errors are in parentheses.

Table 5: Deadweight Loss and Aggregate Consumption under Five-Tier Block Price Schedules

Revenue (\$M)	DWL (\$M)		$\triangle$DWL	Consumption (Gwh)		
	MP Model	AP Model		if P=MC	MP model	Actual
5207	186	54	132	30779	28757	30954
	3.58%	1.04%	2.53%		-6.57%	0.57%

Note: The table presents annual revenue, deadweight loss, and aggregate consumption using individual household billing records for SCE in 2006. Note that I impose two assumptions: price elasticity $\beta = 0.2$ and the marginal cost of electricity equals 15.92¢/kWh . I include only standard tariff customers. The second row for the DWL shows the percent of the DWL to the annual revenue. The second row of the consumption presents the percent change in consumption relative to the consumption when the price is set to be the marginal cost, 15.92.