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

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Abstract

This paper examines how consumers respond to nonlinear price schedules, which are widely used in taxation, retail sales, and utility pricing. Standard economic theory predicts that consumers optimize their consumption based on marginal prices. However, under complex price schedules, they may make a sub-optimal choice by responding to a simplified price. To explore empirical evidence, I exploit geographical discontinuity in electric utility service areas in California. The service area border exists inside city limits. As a result, households sharing nearly identical demographics and weather conditions experienced substantially different price schedules. Using household-level monthly billing data, I find that households are more likely to respond to their average price of nonlinear electricity rates rather than the actual marginal price they are paying. The sub-optimal response distorts consumption less, and therefore reduces the deadweight loss of nonlinear pricing under a certain range of marginal costs of electricity. Finally, switching from uniform pricing to the current nonlinear pricing 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

How do people respond to nonlinear price schedules? The answer to this question plays a significant role in many areas of economics. In public and labor economics, taxpayers make decisions under nonlinear income tax schedules. In industrial organization, consumers often make choices under nonlinear price schedules in electricity, natural gas, telecommunication, transportation, water, and other markets. In each case, the welfare effects of nonlinear pricing largely depend on how people respond to the price schedules.

Empirical studies face two major challenges to answer the question. First, researchers hardly have counterfactual groups that experience a different price schedule from the group of interest. For example, all comparable taxpayers are usually on the same tax schedule in non-experimental data. The lack of clean control groups creates several identification problems in previous studies.\(^1\) Second, economic theory and evidence from laboratory experiments provide different implications about what price of nonlinear price schedules people are responding to. With standard utility maximization, they would respond to the actual marginal price they are paying. Laboratory experiments find, however, that people have limited understanding of nonlinear price structures and tend to respond to the average price at the point where they consume.\(^2\) Liebman and Zeckhauser (2004) provide an alternative theory, “schmeduling”, where people under complex price schedules make a sub-optimal choice by responding to the average price. Nevertheless, most empirical studies assume the standard theory, primarily because non-experimental data rarely provide sufficient exogenous price variations to test which price they are responding to.

This paper exploits geographical discontinuity in electric utility service areas to explore how consumers react to nonlinear pricing. The service area border of two electric utilities exists inside city limits. As a result, households in the same city have substantially different nonlinear electricity price schedules. Their demographics and weather conditions are nearly identical. Their electricity prices, in contrast, change differently because each utility sets the price independently. I use household-level monthly billing records to examine how electricity consumption changes when households experience different price changes.

I present the following preliminary findings. First, I investigate the price response during the California electricity crisis in 2000 in which the relative electricity price across the utility border increased by 100%. I find that households in fact changed their electricity consumption with price elasticity estimates between -0.18 and -0.20. Second, I examine whether the

\(^1\)Heckman (1996), Blundell et al. (1998), Goolsbee (2000), and Saez et al. (2009) describe why identification assumptions in common natural experiment approaches may not hold.

\(^2\)Fujii and Hawley (1988) find that many taxpayers do not know their marginal tax rate. de Bartolome (1995) finds that many subjects in his lab experiment use the average tax rate as if it is the marginal rate.
empirical distribution of electricity consumption shows bunching of households across the kink points of nonlinear price schedules. If households respond to their marginal price, many demand curves intersect with the kinks, therefore relatively more samples should be found around the kinks. Although both utilities introduced steep five-tier increasing price schedules after the electricity crisis, I do not find evidence of the bunching in any period of the data. No bunching implies either that households do not respond to the nonlinear electricity price schedules at all or that they react to other price of electricity rather than their marginal price. To explore how their consumption changes with their marginal price and average price, I use nearly unique price variations across the utility border where households face substantially different changes in their marginal and average price from 2001 to 2006. When both of marginal and average prices are estimated in the demand model, the average price has statistically significant effects, whereas the marginal price turns to have economically smaller and statistically insignificant impacts on consumption. Finally, I investigate how the response to average prices may change the welfare impacts of nonlinear pricing. I show that the sub-optimal response distorts consumption less than the marginal price response, and hence reduces deadweight loss under a certain range of marginal costs of electricity. The difference in the deadweight loss is $132M per year for a utility, which equals 2.53% of its revenue. The sub-optimal response also may make nonlinear price schedules less successful to reduce aggregate consumption. In fact, I show that switching from uniform pricing to the current nonlinear schedule may slightly increase aggregate consumption when households respond to the average price of their electricity bills.

This 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.

The findings in the welfare analysis indicate that the policy implications of nonlinear pricing may change in the presence of the sub-optimal response. The efficiency cost is likely to be less when consumers respond to their average price given a certain assumption on the marginal cost of electricity supply. This implication is similar to the one in de Bartolome (1995) and Liebman and Zeckhauser (2004) that show that the efficiency cost of nonlinear income tax schedules is smaller when taxpayers respond to their average tax rate. For the same reason, however, the sub-optimal response makes nonlinear pricing less successful to reduce aggregate consumption. Therefore, to achieve a certain level of consumption reduction, the price has to be set steeper when consumers respond to their average price. This implication is particularly important for electricity pricing because most electric utilities that adopted or plan to adopt an increasing block price schedule aim to reduce their aggregate consumption. Therefore, to achieve a certain level of consumption reduction, the price has to be set steeper when consumers respond to their average price. This implication is particularly important for electricity pricing because most electric utilities that adopted or plan to adopt an increasing block price schedule aim to reduce their aggregate consumption by introducing the schedule.\(^3\)

Finally, the findings are relevant to a discussion in the American Clean Energy and Security Act of 2009, the Waxman-Markey Bill. In the cap-and-trade program, about 30% of emission permits are given to electric utilities as a free allowance. The proposal explicitly prohibits electric utilities from distributing the value to their customers based on a customer’s electricity consumption. Instead, it recommends providing a fixed credit on electricity bills. The rationale behind the idea is that customers still have an incentive to conserve electricity because the fixed credit does not change their 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.\(^4\)

\(^3\)BC 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.

\(^4\)Use 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 et al. (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.
2 Research Design

2.1 Geographical Discontinuity in Electric Utility Service Areas

Southern California Edison (SCE) and San Diego Gas & Electric (SDG&E) provide electricity in southern California. Figure 1 presents their service area border in Orange County. The border exists inside city limits. It contrasts with other utility borders in the US, which usually exist across cities, counties, or states. Importantly, households cannot choose their electric utility in this area. Their premises determine which utility provides their electricity.

I focus on the six cities that contain the service areas of both utilities. 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 seven 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 each household’s nine-digit zip code with US Census blocks, and calculate the mean of each demographic variable on each side of the border. The table also includes the mean electricity consumption in 1999, in which residential electricity prices were nearly identical between the utilities. 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.

2.2 Price Variations Across the Utility Border

Figure 2 shows standard residential electricity price schedules in each utility. The marginal price of electricity is a step function of monthly consumption. About 80% of households are on the standard price schedules, although they can choose alternative tariffs on request. I focus on households that are on the standard price schedules. The utilities assign “baselines” to households. 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. Although the baseline can be different between climate zones and seasons, households in this study have the same or only slightly different baselines.

The tier rates, in contrast, change differently between the utilities. Figure 3 presents the tier rates from 1999 to 2009. In 1999 and early 2000, both utilities had essentially the same two-tier price 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 May in
response to increases in wholesale electricity prices. In August, 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, in contrast, stayed at their 1999 level because their retail prices were not affected by wholesale prices. The second price shock happened in 2001, when SCE introduced five-tier price schedules in June, and SDG&E followed four months later, although their rates were different. Afterwards, the utilities change the tier rates differently over time.

The price variations have three advantages features in estimating the response to nonlinear price schedules. First, the magnitude of the variation is substantial. Cross-sectionally, households across 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 across the utility border is often significantly different from the difference in average prices. Figure 4, 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 forth tier. The marginal price is higher for SCE customers, whereas the average price is higher for SDG&E customers. These price variations help identifying which of the marginal or average price households are responding to.

3 Data

The primary data consist of household-level monthly electricity billing records. The data cover all households in each utility except for a small number of customers that are not individually metered. Each monthly record includes a household’s account number, account type, climate zone, tariff, start and end date of the billing period, consumption, baseline, total bill, and nine-digit zip code.

The billing records do not include electricity prices and demographic characteristics. I collect price information from official documents published by the utilities. To ensure the preciseness of the price information, I verify that it is consistent with each household’s total bill in the billing data. For demographic information, I match nine-digit zip codes with US Census blocks to collect Census data such as income, household size, 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 Using 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 household has a quasi-linear utility function and responds to electricity prices with a constant elasticity $\beta$. Then, the demand function can be described as:

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

with a household fixed effect $\alpha_i$ and an error term $\eta_{it}$. 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 $\beta$ because $p_t(y_{it})$ is a function of $y_{it}$. Under increasing block price schedules, $\eta_{it}$ is positively correlated with $p_t(y_{it})$. 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 $y_{ito}$ may predict the price change that each household will face. Let $\Delta \ln y_{it} = \ln y_{it} - \ln y_{ito}$ 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 $\Delta \ln p_t(y_{it}) = \ln p_t(y_{it}) - \ln p_{t_0}(y_{ito})$ the log change in the price. Consider the two-stage least squares (2SLS) estimation for the equation:

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5For example, if a household has a positive shock in $\eta_{it}$ (e.g. a friend visit) that is not observable to researchers, the household will locate in the higher tier of its nonlinear rate schedule.
\[ \Delta \ln y_{it} = \alpha_i + \beta \Delta \ln p_t(y_{it}) + \varepsilon_{it}, \]  

(2)

instrumenting for \( \Delta \ln p_t(y_{it}) \) with \( \Delta \ln \hat{p}_t(y_{it}) = \ln p_t(y_{it}) - \ln p_{t0}(y_{it}) \) where \( p_t(y_{it}) \) 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 \( \beta \) if \( y_{it0} \) is uncorrelated with \( \varepsilon_{it} = \eta_{it} - \eta_{it0} \).

### 4.2 Econometric Identification Problems

The condition \( \text{Cov}(\varepsilon_{it}, y_{it0}) = 0 \) requires a parallel trend assumption on changes in electricity consumption between households with different levels of \( y_{it0} \). That is, in the absence of rate changes, households with different levels of \( y_{it0} \) would have equivalent changes in their consumption. There are two concerns for this condition.

First, in panel data of household electricity consumption, mean reversion produces a negative correlation between ex-ante consumption \( y_{it0} \) and the shock \( \varepsilon_{it} \). 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 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 \( y_{t0} \). Suppose that they are in the same city, but their electric utilities

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6Saez et al. (2009) provides a detail discussion of similar identification problems in empirical studies of labor supply response to income taxes.
are different. In year $t$, they experience different changes in electricity price when the utilities introduce different price 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 and changes in distribution of consumption over time.

Define a set of dummy variables:

$$D_{ij} = 1\{j < y_{t_0} \leq j + k\},$$

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 $y_{t_0}$ rounded to the nearest whole integer.

Let $p_t(y_{it})$ denote either the marginal or average price of nonlinear rates for consumption $y_{it}$. Define a dummy variable for SCE customers, $sce_i = 1\{i \in $SCE$ customers\}$. For each of the marginal and average price, I estimate the following 2SLS equation:

$$\Delta \ln y_{it} = \alpha + \beta \Delta \ln p_t(y_{it}) + \gamma \cdot sce_i + \sum_{j=0}^{J} \delta_j \cdot D_{ij} + \sum_{z=1}^{Z} \zeta_z \cdot zip_z + \sum_{c=1}^{C} \theta_c \cdot cycle_c + \epsilon_{it},$$

using $\sum_{j=0}^{J} D_{ij} \cdot sce_i$ as instruments for $\Delta \ln p_t(y_{it})$. The dummy variable $sce_i$ controls for unobservable shocks that are specific to SCE customers. I also include dummy variables $zip_z$ and $cycle_c$ that capture weather and economic shocks specific to zip code area $z$ and billing cycle $c$. Finally, $D_{ij}$ control for mean reversion, distributional changes, and other shocks specific to ex-ante consumption levels, $y_{t_0}$. The intuition behind the instrument is that households with the same ex-ante consumption levels experience different exogenous shocks to their price because each utility changes the price schedules differently. The identification assumption is that $\text{Cov}(D_{ij} \cdot sce_i, \epsilon_{it}) = 0$. In other words, it requires the following parallel trend assumption: absent the change in price schedules, changes in log consumption would be the same for households with the same ex-ante consumption levels across the utility border.

When multi-year data are available, I can further weaken the identification assumption. Suppose that multi-year data are available for $t = 1, ..., T$. By pooling the first differenced data, I estimate the following 2SLS equation:

$$\Delta \ln y_{it} = \alpha_t + \beta_t \Delta \ln p_t(y_{it}) + \sum_{j=0}^{J} \eta_j \cdot D_{ij} \cdot sce_i + \sum_{j=0}^{J} \delta_{ij} \cdot D_{ij} + \sum_{z=1}^{Z} \zeta_{tz} \cdot zip_z + \sum_{c=1}^{C} \theta_{tc} \cdot cycle_c + \epsilon_{it},$$

(5)
using \( \sum_{j=0}^{J} D_{ij} \cdot sce_i \cdot year_t \) as instruments where \( year_t = 1\{i \in t\} \). Note that I allow all coefficient to be year specific except for \( \beta \). This regression allows the mean reversion to be different across the utility border as long as the difference does not change over time. Still, I need the identification assumption that \( Cov(D_{ij} \cdot sce_i \cdot year_t, \varepsilon_{it}) = 0 \).

To examine whether households respond to the marginal or average price of nonlinear price schedules, I include both of \( \Delta \ln mp_t(y_{it}) \) and \( \Delta \ln ap_t(y_{it}) \) in the regression. Note that in general, it is difficult to separately identify the partial effect of these two prices because changes in marginal 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. For example, some households experienced a relative decrease in marginal prices but a relative increase in average prices compared to households with similar ex-ante consumption levels 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 is affected by different rate schedules between the utilities in \( t-1 \).

## 5 Results

This section presents estimation results. I show the results for the year of the California electricity crisis and for years after the crisis separately. The electricity crisis brought on large public appeals and media campaigns. Therefore, households may react differently to the price change during this period and others. In addition, the marginal and average prices were essentially the same during the electricity crisis because households were on two-tier price schedules that were close to flat rate schedules. Thus, the price variation during this
period does not allow me to separately identify the response to the marginal price and average price.

### 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 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.

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

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7Bushnell and Mansur (2005) find a similar result of lagged price responses during the California electricity crisis.
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. In addition, the estimates do not significantly differ among households 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. 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 idea of the 2SLS estimation in equation (5) is that households with the same ex-ante consumption levels will experience different changes in price when their electric utilities change their price schedules differently. First, I graphically examine the relation between the change in price and consumption using August billing months from 2001 to 2006. The first graph in Figure 7 shows the difference-in-differences in price and consumption for households

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8The estimated price elasticity is slightly larger than but not significantly different from the previous studies of the California electricity crisis (e.g. Bushnell and Mansur (2005) and Reiss and White (2008)).
9For example, see Saez (2009), Borenstein (2009), and Chetty et al. (2010) for more detail descriptions of how to estimate elasticity from bunching in distributions.
whose consumption in 1999 falls in the third tier level. That is, in both utility service areas, I take households whose consumption in 1999 was in the third tier level, and look at how the price and consumption of SDG&E customers change over time relative to SCE customers. Relative to SCE customers, the mean percent change in average price is larger for SDG&E customers for all years. The change in marginal price, however, is lower for SDG&E customers in 2001, 2006, and 2007. Except for 2004 and 2005, the relative change in marginal and average prices is different by 10 to 20 percentage points. The graph indicates that the relative change in consumption move in line with the relative change in average price rather than marginal price. For example, in 2001, 2006, and 2007, the change in marginal prices is lower for SDG&E customers, but the change in consumption shows that their relative consumption is also lower compared to SCE customers. In addition, the relative marginal price increases substantially in 2004 and 2005, but the relative consumption does not seem to respond to the change by the same magnitude. On the other hand, the relative change in average price has a negative relation with the relative change in consumption over time. I present the same graph for households whose consumption in 1999 falls in the fourth tier level in the second panel. The implications are similar to the first graph. Particularly, the relative change in marginal price does not have a negative relation with the relative change in consumption in 2001, 2002, 2006, and 2007.

To statistically test the relation, I first estimate the 2SLS equations described in equation (4) for August billing months from 2001 to 2006. 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 the marginal price and between -0.153 to -0.262 for the average price. Second, when both price variables are jointly estimated, the average price has statistically significant effects, whereas the marginal price turns 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, in 2004 and 2005, the relative change in marginal and average price is highly positively correlated for all consumption levels so that multicolinearlity is severe in the estimation.

Second, I pool the first differenced data for all years and estimate equation (5). Table 5 shows estimation results for the summer billing months: May to October and the winter billing months: November to April. The results indicate that the price elasticity is larger for the summer billing months. Similar to the results in Table 4, when the regression includes both price variables, the average price has statistically significant effect, whereas the marginal price has economically smaller and statistically insignificant impacts on consumption.

The regression results along with the graphical evidence in Figure 7 indicate that households are more likely to respond to their average price of nonlinear electricity rates rather than
the actual marginal price. In the next section, I investigate how this sub-optimal response affects the welfare effects of nonlinear price schedules.

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 6 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,

\[
DWL \approx \frac{1}{2} Y|\beta| \frac{(p - MC)^2}{MC},
\]

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

Table 6 presents the aggregate annual deadweight loss calculated by the individual households’ billing records in SCE in 2006.\(^\text{10}\) 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

\(^{10}\)This exercise assumes that the price elasticity is homogeneous within SCE.
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.

6 Conclusion and Future Work

This paper explores how households respond to nonlinear price schedules, which are widely used in taxation, retail sales, and utility pricing. I exploit exogenous variations in electricity prices across the geographical border of two California utilities. The utility border exists inside city limits. As a result, 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 investigate the price response during the California electricity crisis in 2000 in which the relative electricity price across the utility border increased by 100%. I find that households in fact changed their electricity consumption with price elasticity estimates between -0.18 and -0.20. Second, I examine whether the empirical distribution of electricity consumption shows bunching of households across the kink points of nonlinear price schedules. If households respond to their marginal price, many demand curves intersect with the kinks, therefore relatively more samples should be found around the kinks. Although both utilities introduced steep five-tier increasing price schedules after the electricity crisis, I do not find evidence of the bunching in any period of the data. No bunching implies either that households do not respond to the nonlinear electricity price schedules at all or that they react to other price of electricity rather than their marginal price. To explore how their consumption changes with their marginal price and average price, I use nearly unique price variations across the utility border where households face substantially different changes in their marginal and average price from 2001 to 2006. When both of marginal and average prices are estimated in the demand model, the average price has statistically significant effects, whereas the marginal price turns to have economically smaller and statistically insignificant impacts on consumption. Finally, I investigate how the response to average prices may change the welfare impacts of nonlinear pricing. I show that the sub-optimal response distorts consump-
tion less than the marginal price response, and hence reduces deadweight loss under a certain range of marginal costs of electricity. The difference in the deadweight loss is $132M per year for a utility, which equals 2.53% of its revenue. The sub-optimal response also may make nonlinear price schedules less successful to reduce aggregate consumption. In fact, I show that switching from uniform pricing to the current nonlinear schedule may slightly increase aggregate consumption when households respond to the average price of their electricity bills.

This preliminary version leaves the following questions for future work. First, 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. For example, the model with uncertainty predicts that consumers may respond to their expected marginal price by taking into account the uncertainty about their monthly consumption. In addition, the response to the change in electricity price may have a time lag if consumers gradually acquire the information about their electricity price.\footnote{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.} Second, the welfare analysis needs to include more detail discussions about the social marginal cost of electricity production. For example, externalities from electricity generation would change the social marginal cost of electricity depending on the social marginal cost of carbon emissions.

References


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 Viejo, Laguna Hills, Mission Viejo, and Coto de Coza.
Figure 2: Standard Residential Electricity Price Schedules in SCE and SDG&E

Note: 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 electricity 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 August 2006 as an example. The utilities change the tier rates frequently as shown in Figure 3.
Figure 3: Tier Rates for Standard Price Schedules from 1999 to 2009

Note: 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 2. 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 4: Marginal and Average Prices under Nonlinear Electricity Price Schedules

Note: The figure presents a customer’s marginal and average price under the standard nonlinear electricity price schedules in August 2002. The average price is defined as a customer’s monthly bill divided by its 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 forth tier. The marginal price is higher for SCE customers, whereas the average price is higher for SDG& E customers.
Figure 5: Difference-in-Differences 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. The distribution is smooth and does not have visible bunching of customers around the kinks.
Figure 7: Difference-in-Differences in Price and Consumption by 1999 Consumption Levels

Note: The figures show the difference-in-differences in price and consumption of August billing months conditional on a household’s consumption level in 1999. For the top graph, I calculate the mean percent changes in price and consumption from 1999 for households whose 1999 consumption falls in the third tier level. 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 1999 consumption falls in the fourth tier level.
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 $d_1 + d_2$ if a household respond to marginal prices and equals $d_2$ if the household responds to average prices.
## Table 1: Demographics and Mean Electricity Consumption Across the Utility Border

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

Note: The first part presents household demographics across the service area border of Southern California Edison and San Diego Gas & Electric. 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. Note that in 1999, SCE and SDG&E had essentially the same electricity price schedules.

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

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>△ln(MP)</td>
<td>-.160</td>
<td>-.191</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(.008)</td>
<td>(.008)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>△ln(AP)</td>
<td>-.159</td>
<td></td>
<td>-.183</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(.008)</td>
<td></td>
<td>(.008)</td>
<td></td>
</tr>
<tr>
<td>Control for mean reversion</td>
<td>No</td>
<td>No</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Zip code dummy</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Billing cycle dummy</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Observations</td>
<td>104020</td>
<td>104020</td>
<td>104020</td>
<td>104020</td>
</tr>
</tbody>
</table>

Note: This table presents results of the 2SLS regression in equation (4) 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

<table>
<thead>
<tr>
<th>Subgroup</th>
<th>△ln(MP)</th>
<th>△ln(AP)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Tier1 in1999</td>
<td>-.200</td>
<td>-.198</td>
</tr>
<tr>
<td>Tier3 in1999</td>
<td>-.198</td>
<td>-.195</td>
</tr>
<tr>
<td>Tier5 in1999</td>
<td>-.185</td>
<td>-.181</td>
</tr>
<tr>
<td>(1)</td>
<td>(.026)</td>
<td>(.014)</td>
</tr>
<tr>
<td>(2)</td>
<td>(.013)</td>
<td></td>
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</table>

Control for mean reversion: Yes
Zip code dummy: Yes
Billing cycle dummy: Yes
Observations: 18208, 25647, 24567

Note: This table presents results of the 2SLS regression in equation (4) 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: IV Estimates of Price Elasticity of Electricity Demand: August Billing Months

<table>
<thead>
<tr>
<th>Year</th>
<th>2001</th>
<th>2002</th>
<th>2003</th>
<th>2004</th>
<th>2005</th>
<th>2006</th>
</tr>
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<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
<td>(4)</td>
<td>(5)</td>
<td>(6)</td>
</tr>
<tr>
<td>△ ln(MP)</td>
<td>-.166</td>
<td>.082</td>
<td>-.156</td>
<td>-.054</td>
<td>-.211</td>
<td>-.081</td>
</tr>
<tr>
<td></td>
<td>(.017)</td>
<td>(.042)</td>
<td>(.031)</td>
<td>(.047)</td>
<td>(.076)</td>
<td>(.106)</td>
</tr>
<tr>
<td>△ ln(AP)</td>
<td>-.219</td>
<td>-.286</td>
<td>-.251</td>
<td>-.215</td>
<td>-.262</td>
<td>-.218</td>
</tr>
<tr>
<td></td>
<td>(.029)</td>
<td>(.069)</td>
<td>(.044)</td>
<td>(.065)</td>
<td>(.054)</td>
<td>(.073)</td>
</tr>
<tr>
<td>Control for mean reversion</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Zip code dummy</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Billing cycle dummy</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Observations</td>
<td>104020</td>
<td>104020</td>
<td>104020</td>
<td>102238</td>
<td>102238</td>
<td>100688</td>
</tr>
</tbody>
</table>

Note: This table presents estimates of the 2SLS regressions in equation (4) using August billing month data. The dependent variable is log change in electricity consumption relative to 1999. For each year between 2001 and 2006, I estimate the average price response model and the marginal price response model separately. The first two columns of each year show these results. The third column of each year shows the regression results when both price variables are included. Robust standard errors are in parentheses.
Table 5: IV Estimates of Price Elasticity of Electricity Demand Using All Years of Data from 2001 to 2006

<table>
<thead>
<tr>
<th>Billing months</th>
<th>Dependent Variable: $\Delta \ln(\text{Electricity Consumption})$</th>
<th>Winter</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Summer (1) (2) (3)</td>
<td>Winter (4) (5) (6)</td>
</tr>
<tr>
<td>$\Delta \ln(\text{MP})$</td>
<td>-.127 (.009)</td>
<td>-.075 (.007)</td>
</tr>
<tr>
<td>$\Delta \ln(\text{AP})$</td>
<td>-.185 (.013)</td>
<td>-.104 (.009)</td>
</tr>
<tr>
<td>Observations</td>
<td>3515214</td>
<td>3516351</td>
</tr>
</tbody>
</table>

Note: This table presents estimates of the 2SLS regressions in equation (5) using all years of data from 2001 to 2006. The summer billing months include May to October billing months. The winter billing months include November to April billing months. The dependent variable is log change in electricity consumption relative to 1999. All regressions include month-year specific zip code dummy variables, billing cycle dummy variables, and controls for mean reversion. Robust standard errors are in parentheses.

Table 6: Deadweight Loss and Aggregate Consumption under Five-Tier Block Price Schedules

<table>
<thead>
<tr>
<th>Revenue ($M$)</th>
<th>$\Delta \text{DWL}$</th>
<th>Consumption (Gwh)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>MP Model</td>
<td>AP Model</td>
</tr>
<tr>
<td>5207</td>
<td>186</td>
<td>54</td>
</tr>
<tr>
<td></td>
<td>3.58%</td>
<td>1.04%</td>
</tr>
</tbody>
</table>

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.\]