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# Do Consumers Respond to Marginal or Average Price? Evidence from Nonlinear Electricity Pricing[†]

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*Nonlinear pricing and taxation complicate economic decisions by creating multiple marginal prices for the same good. This paper provides a framework to uncover consumers' perceived price of nonlinear price schedules. I exploit price variation at spatial discontinuities in electricity service areas, where households in the same city experience substantially different nonlinear pricing. Using household-level panel data from administrative records, I find strong evidence that consumers respond to average price rather than marginal or expected marginal price. This suboptimizing behavior makes nonlinear pricing unsuccessful in achieving its policy goal of energy conservation and critically changes the welfare implications of nonlinear pricing.* (*JEL* D12, L11, L94, L98, Q41)

A central assumption in economics is that firms and consumers optimize with marginal price. For example, consider taxpayers faced with a nonlinear income tax schedule. The theory of optimal taxation assumes that taxpayers respond to their marginal tax rate by making the right connection between their income and nonlinear tax schedule (Mirrlees 1971; Atkinson and Stiglitz 1976; and Diamond 1998). Likewise, empirical studies in economics generally take this assumption as given when estimating key parameters in a variety of markets that involve nonlinear price, subsidy, and tax schedules.[1]

However, evidence from many recent studies suggests that consumers may not respond to nonlinear pricing as the standard theory predicts. Many surveys find that few people understand the marginal rate of nonlinear price, subsidy, and tax

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[1] For example, the market for cellular phone (Huang 2008), energy (Reiss and White 2005), labor (Hausman 1985), and water (Olmstead, Hanemann, and Stavins 2007).

schedules.[2] Subjects in laboratory experiments show cognitive difficulty in understanding nonlinear price systems and respond to average price.[3] While the response to nonlinear pricing affects welfare implications of many economic policies, there is no clear empirical evidence from the field on the question: To what price of nonlinear price schedules do consumers respond?

In this paper, I provide a framework to uncover consumers' *perceived price* of nonlinear price schedules. Economic theory provides at least three possibilities about the perceived price. The standard model of nonlinear budget sets predicts that consumers respond to *marginal price*. However, in the presence of uncertainty about consumption, rational consumers respond to *expected marginal price* (Saez 1999; Borenstein 2009). Alternatively, consumers may use *average price* as an approximation of marginal price if the cognitive cost of understanding complex pricing is substantial. This suboptimization is described as "schmeduling" by Liebman and Zeckhauser (2004).

My analysis exploits price variation at spatial discontinuities in electricity service areas. Because the territory border of the two power companies in this study lies within city limits, households in the same city experience very different nonlinear pricing. This research design addresses long-discussed identification problems in the literature (Heckman 1996; Blundell, Duncan, and Meghir 1998; Goolsbee 2000; Saez, Slemrod, and Giertz 2012) by using nearly identical groups of households experiencing different price variation.

Access to the full administrative data on electricity billing records allows me to construct household-level monthly panel data for essentially all households in the study area from 1999 to 2007. The sample period provides substantial cross-sectional and time-series price variation because the two companies changed their prices independently multiple times. The billing data include each customer's nine-digit zip code, with which I match census data to show that demographic and housing characteristics are balanced across the territory border of the two power companies.

Results from my three empirical strategies provide strong evidence that consumers respond to average price rather than marginal or expected marginal price. First, I examine whether there is bunching of consumers at the kink points of nonlinear price schedules. Such bunching must be observed if consumers respond to marginal price (Heckman 1983; Saez 2010; Chetty et al. 2011). I find no bunching anywhere in the consumption distribution despite the fact that the marginal price discontinuously increases by more than 80 percent at some kink points. The absence of bunching implies either that (i) consumers respond to marginal price with *zero elasticity* or that (ii) they respond to *alternative price*. To explore this point, I use the encompassing test (Davidson and MacKinnon 1993) to examine whether consumers respond to marginal, expected marginal, or average price. I find that average price has a significant effect on consumption, while the effects of marginal price and expected marginal price become statistically insignificant from zero once I control for the effect of average price. Finally, I propose a strategy that estimates the perceived price directly. My model nests a wide range of potential perceived prices by allowing consumers to have different weights on prices at different parts

[2] See Liebman (1998) and Fujii and Hawley (1988) on tax rates; Brown, Hoffman, and Baxter (1975) on electricity price; and Carter and Milon (2005) on water price.

[3] For example, see de Bartolome (1995) for evidence from laboratory experiments.

of their nonlinear price schedule. I empirically estimate the weights, from which I can recover the shape of the perceived price. I find that the resulting shape of the perceived price is nearly identical to the average price.

This suboptimizing behavior changes the policy implications of nonlinear pricing. First, I show that the suboptimal response makes nonlinear pricing unsuccessful in achieving its policy goal of energy conservation. Many electric, natural gas, and water utilities in the United States have adopted nonlinear pricing similar to California's residential electricity pricing.[4] Policy makers often claim that higher marginal prices for excessive consumption can create an incentive for conservation. Contrary to the policy objective, I show that if consumers respond to average price, nonlinear tariffs may result in a slight *increase* in aggregate consumption compared with an alternative flat marginal rate. Second, the suboptimal response changes the efficiency cost of nonlinear pricing. I show that it *reduces* the efficiency cost, given a reasonable range of assumptions on the private marginal cost of electricity. However, it *increases* the efficiency cost when the social marginal cost of electricity is substantially high because of negative environmental externalities from electricity generation.

The findings also have important implications for US climate change legislation. According to the cap-and-trade program proposed in the American Clean Energy and Security Act of 2009, about 30 percent of emission permits would be given to electric utilities for free. The proposal prohibits distributing the value of the free allowance based on each customer's electricity consumption. Instead, it recommends providing a fixed credit on electricity bills. The rationale behind the policy is to preserve the marginal incentive to conserve electricity. However, if customers respond to average price, the fixed credit on electricity bills still discourages conservation and increases electricity consumption. Thus, the compensation scheme would need to be reconsidered.[5]

Although the possibility of this suboptimizing behavior has been long discussed in public finance, industrial organization, and environmental economics, previous studies provide inconclusive results because of several empirical challenges.[6] First, while access to extensive individual-level data is necessary to examine the question, it is rarely available to researchers.[7] Second, Heckman (1996) notes that usual nonexperimental data do not provide a clean control group because all comparable individuals usually face exactly the same nonlinear price schedule. Third, many studies do not have sufficient exogenous price variation to statistically distinguish the effects of alternative forms of price. My analysis addresses the challenges by exploiting substantial cross-sectional and time-series price variation at the spatial discontinuity of electricity service areas and provides robust empirical findings.

[4] British Columbia Utilities Commission (2008) conducts a survey of 61 US utilities and finds that about one-third of them use increasing block pricing for residential customers.

[5] The use of allowances is described on page 901 of US Congress (2009). Burtraw (2009) and Burtraw, Walls, and Blonz (2010) also 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.

[6] For example, see Shin (1985); Nieswiadomy and Molina (1991); Liebman and Zeckhauser (2004); Feldman and Katuščák (2006); Borenstein (2009).

[7] For example, the price and consumption data used in Shin (1985) are annual data aggregated at the company level. Without individual-level monthly data, it is not possible to identify each consumer's actual marginal and average price.

My findings are consistent with those of studies that explore consumer inattention to complex pricing.[8] While many studies test the hypothesis that consumers misperceive complex prices, the actual perceived price that consumers use for their optimization is not explicitly examined and remains unknown. My empirical strategy provides a way to nest a wide range of potential perceived prices, from which researchers can estimate the true shape of the perceived price by examining consumer behavior in response to price variation.

## I. Theoretical Predictions

Economic theory provides three predictions about consumers' perceived price of nonlinear price schedules. To characterize the predictions, consider a price schedule $p(x)$ in Figure 1. The marginal price of $x$ equals $p_1$ for $x \leq k$ and $p_2$ for $x > k$. This form of nonlinear pricing is widely used in many economic policies. For example, $p(x)$ can be seen as an income tax schedule of annual income (Moffitt 1990), a price schedule of medical utilization (Aron-Dine et al. 2012), or a price schedule of monthly electricity, phone, or water usage.

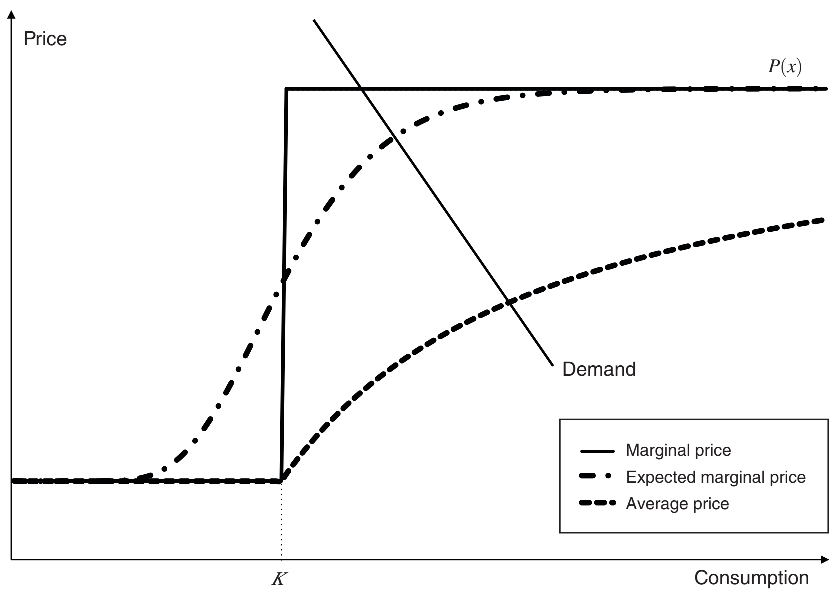
The standard model of nonlinear budget sets predicts that consumers optimize $x$ based on the true marginal price schedule $p(x)$. That is, the perceived price is identical to $p(x)$. This response requires two implicit assumptions: (i) consumers have no uncertainty about $x$, and (ii) they fully understand the structure of the nonlinear price schedule. Saez (1999) and Borenstein (2009) relax the first assumption. In reality, individuals often have random shocks to $x$. For example, electricity consumers have weather shocks to electricity demand during a billing month. Likewise, income earners have wage bonuses, dividends, and capital gains that are unknown when labor supply decisions are made. As a result, it is unrealistic to assume that consumers know $x$, with certainty and respond to their *exact* marginal price of $x$. In the uncertainty models by Saez (1999) and Borenstein (2009), consumers incorporate uncertainty about $x$ and respond to their *expected* marginal price.[9] Finally, Liebman and Zeckhauser (2004) relax the second assumption by allowing inattention to complex price schedules. Their model predicts that if the cognitive cost of understanding complex pricing is substantial, consumers respond to the *average* price of total payment as an approximation of their marginal price. Compared to marginal price or expected marginal price, much less information is required to calculate average price. Total payment and quantity are sufficient information and the knowledge of the nonlinear price schedule is not necessary.

I consider a general form of perceived price that encompasses all three theoretical predictions. Suppose that consumers care about $p(x + \epsilon)$ for a range of $\epsilon$, because

[8] See DellaVigna (2009) for a comprehensive survey. Examples include Busse, Silva-Risso, and Zettelmeyer (2006); Gabaix and Laibson (2006); Hossain and Morgan (2006); Chetty, Looney, and Kroft (2009); Finkelstein (2009); Brown, Hossain, and Morgan (2010); Gabaix (2011); Malmendier and Lee (2011); Chetty (2012).

[9] Consumers, including samples in this study, usually do not have information about their day-to-day consumption. The lack of this information is another reason for their difficulty in responding to their *exact* marginal price. In contrast, the calculation of their *expected* marginal price does not necessarily require this information. Consumers can calculate their expected marginal price based on the distribution of predicted random shocks that will occur during a billing month, as described in Saez (1999) and Borenstein (2009). For example, if a consumer knows that there is a 50/50 chance that her monthly consumption will end up in the first tier and the second tier of her nonlinear price schedule, her expected marginal price is the average of the two marginal prices, which can be calculated without knowing her day-to-day consumption.

Panel A. Three theoretical predictions




Panel B. The shape of density functions of $w(\epsilon)$ that convert $\tilde{p}(x)$ to the three prices

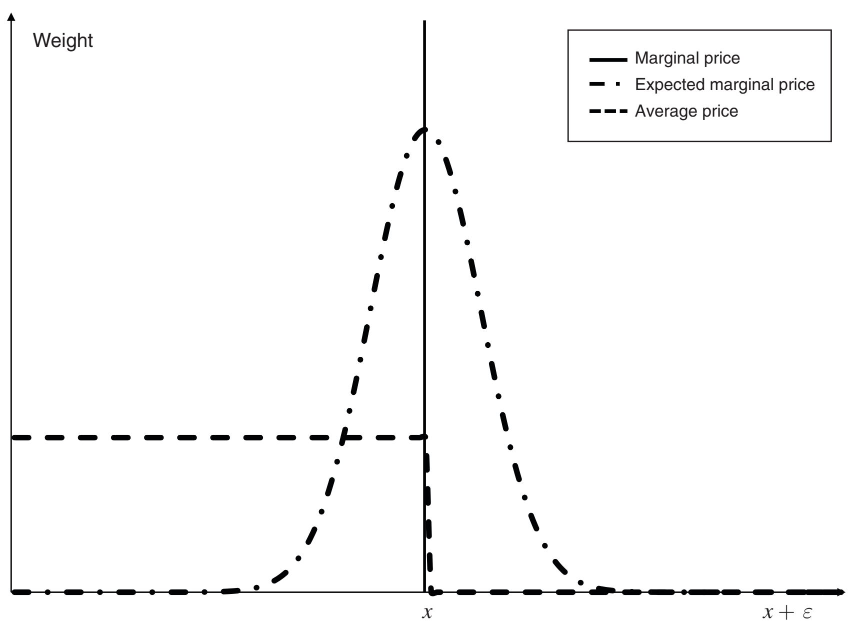



Figure 1. Theoretical Predictions about Consumers' Perceived Price

*Notes:* Panel A uses a simple example of nonlinear price schedules to describe the three theoretical predictions about perceived price. Panel B shows the density functions of $w(\epsilon)$ that convert $\tilde{p}(x)$ to the the corresponding prices presented in panel A.

they consider uncertainty about $x$, or they are inattentive to the price schedule. They construct the perceived price $\tilde{p}(x)$ by deciding relative weights $w(\varepsilon)$ on $p(x + \varepsilon)$:

$$(1) \qquad \tilde{p}(x) = \int p(x + \epsilon) w(\epsilon)\, d\epsilon,$$

where $\int w(\epsilon)\, d\epsilon = 1$. Panel B of Figure 1 shows the density functions $w(\epsilon)$ that convert $\tilde{p}(x)$ to marginal, expected marginal, and average prices. In the standard model, consumers care about the price only at $x$. It implies that $w(\epsilon) = 1$ for $\epsilon = 0$ and, therefore, $\tilde{p}(x) = p(x)$. In the uncertainty model, risk-neutral consumers replace $w(\epsilon)$ by the density function of their uncertainty about $x$. The resulting $\tilde{p}(x)$ is their expected marginal price. In the inattention model, consumers replace $w(\epsilon)$ by the uniform distribution $\mathcal{U}[0, x]$.

Empirically, there are two ways to uncover $\tilde{p}(x)$. The first approach is to assume a certain shape of $w(x)$ based on economic theory and test if it is consistent with data. The second approach is to directly estimate $w(\epsilon)$ to find $\tilde{p}(x)$. I use both approaches. Regardless of which approach I use, there are two empirical challenges to identify $\tilde{p}(x)$. First, it requires sufficient exogenous price variation in order to distinguish competing predictions about the shape of $\tilde{p}(x)$. Second, it requires a well-identified control group to distinguish the effect of price from other factors that also affect consumption. The next section describes how I address the two challenges by exploiting spatial discontinuities in electricity service areas.

## II. Research Design and Data

This section describes two key features of my research design. First, households in the same city experience different nonlinear pricing because the territory border of two power companies lies within city limits. Second, they experience substantially different price variation because the power companies change the price schedules independently.

### A. *Spatial Discontinuities in Electricity Service Areas*

Southern California Edison (SCE) provides electricity to a large part of Southern California, and San Diego Gas & Electric (SDG&E) provides electricity to most of San Diego County and the southern part of Orange County (Figure A.1 in the online Appendix). Californian households are generally not allowed to choose their retail electricity provider; this is predetermined by their address. I focus on the territory border between SCE and SDG&E in Orange County, because this is the only border in populated areas that does not correspond to city boundaries.

Figure 2 shows the territory border in Orange County. Because the border lies within city limits, households in the same city are served by different power companies. This border contrasts with typical territory borders of utility companies, which correspond to city, county, or state boundaries. Why does the border lie within city limits? In the 1940s, SCE and SDG&E connected their transmission lines in this area and established the territory border (Crawford and Engstrand 1991; Myers 1983).

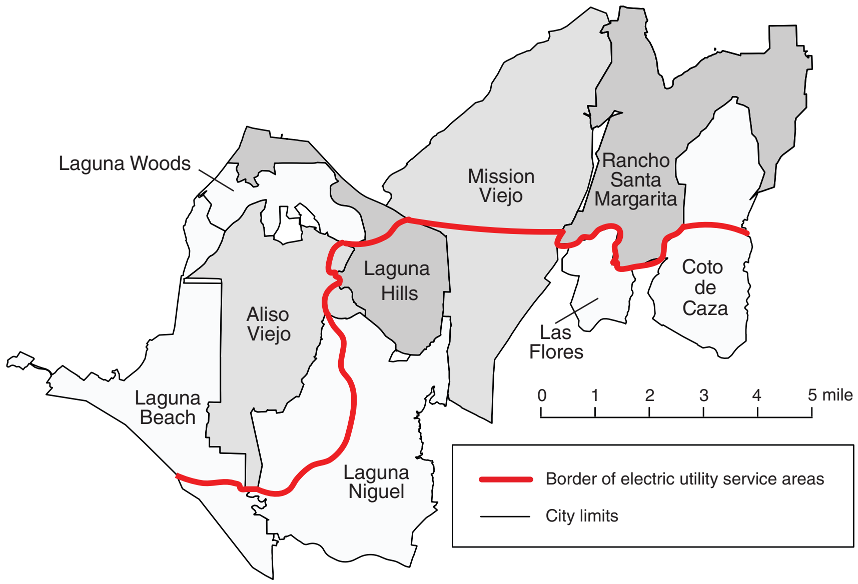



FIGURE 2. BORDER OF ELECTRICITY SERVICE AREAS IN ORANGE COUNTY, CALIFORNIA

*Notes:* The border of electricity service areas lies within city limits in six cities. SCE serves the north side of the border and SDG&E serves the south side of the border.

The border does not correspond to the city limits because the city limits in this area were established around the 1980s.

Lee and Lemieux (2010) note that geographical discontinuity designs (Black 1999) should be used with careful investigation of potential sorting and omitted variables at the border. My research design is unlikely to be confounded by such factors for several reasons. First, time-invariant unobservable factors do not affect my results because I use panel data with household fixed effects. Second, households in this area are not allowed to choose their electricity provider. The only way to choose one provider or another is to live in its service area. It is nearly impossible for households to sort based on their expected electricity bill because the *relative* electricity price between SCE and SDG&E changes frequently; the price is higher for SCE in some years and for SDG&E in other years, as presented in the next section. Third, the next section shows that demographic and housing characteristics are balanced across the territory border, suggesting that systematic sorting is unlikely to have occurred. Finally, it would be a concern if households receive natural gas, a substitute for electricity, from different providers. However, this is not the case in this area because all households are served by the same natural gas provider, Southern California Gas Company.

## B. *Nonlinear Electricity Pricing and Price Variation*

Figure 3 shows the standard residential tariff for SCE and SDG&E in 2002. The marginal price is a step function of monthly consumption relative to a "baseline" consumption level. The baseline differs by climate regions. However, because households in this study belong to the same climate region, the baseline is essentially the same for

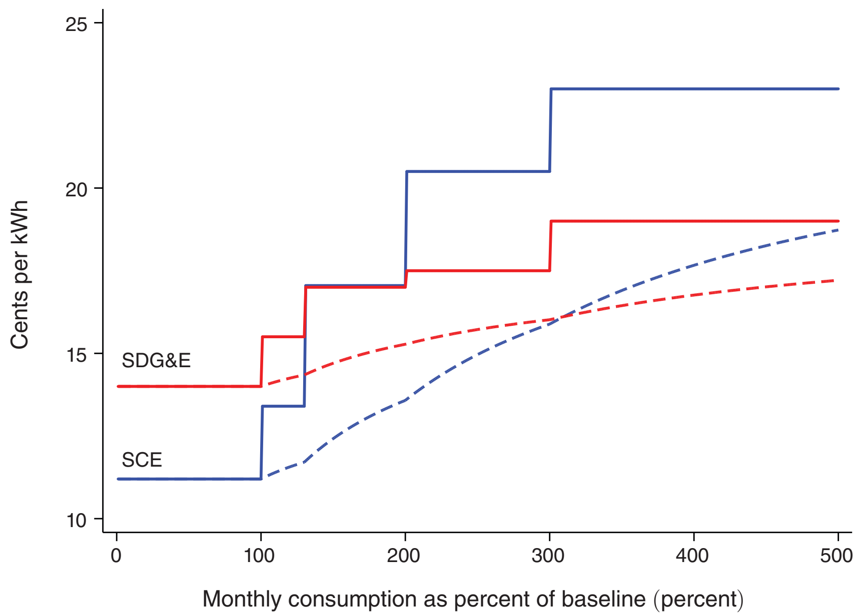



Figure 3. An Example of Cross-Sectional Price Variation in Nonlinear Electricity Pricing

*Note:* To show an example of cross-sectional price variation, this figure presents the marginal price (solid line) and the average price (dashed line) for SCE and SDG&E in 2002.

everyone. The baseline is about 10 kWh/day, with a slight difference between summer and winter billing months.[10]

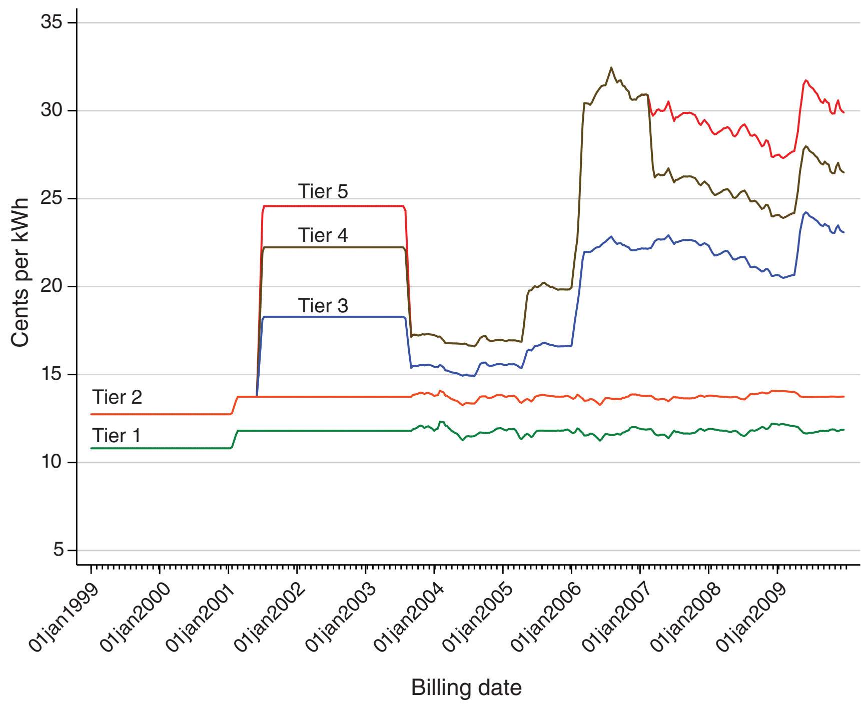
Figure 4 shows that the cross-sectional price variation between SCE and SDG&E also changes quite substantially over time. Until the summer of 2000, SCE and SDG&E had nearly the same two-tier nonlinear price schedules. The first price shock occurred during the California electricity crisis in the summer of 2000.[11] The price for SDG&E customers started to increase in May in response to increases in the wholesale electricity price. In August, the first and second tier rates increased to 22 cents and 25 cents per kWh. This increase translated into a 100 percent price increase for SDG&E customers relative to their price in 1999. In contrast, the price for SCE customers stayed at the 1999 level, because their retail price was protected from changes in wholesale price during this period. The second price shock occurred in 2001, when SCE introduced a five-tier price schedule in June, and SDG&E followed four months later. Thereafter, they made different changes to the five-tier rates over time.

How is the price determined and why is it different for SCE and SDG&E? Retail electricity prices in California are regulated by the California Public Utility

[10] The baseline for the summer billing months is 10.2 kWh of electricity per day for both SCE and SDG&E customers in this area. The baseline for the winter billing months is 10.1 kWh per day for SCE customers and 10.8 kWh per day for SDG&E customers. Monthly bills and prices are calculated based on the exact baseline of each individual bill.

[11] By August of 2000, wholesale electricity prices had more than tripled since the end of 1999. See Joskow (2001); Borenstein, Bushnell, and Wolak (2002); Bushnell and Mansur (2005); Puller (2007); and Reiss and White (2008) for details.

Panel A. Southern California Edison (SCE)




Panel B. San Diego Gas & Electric (SDG&E)

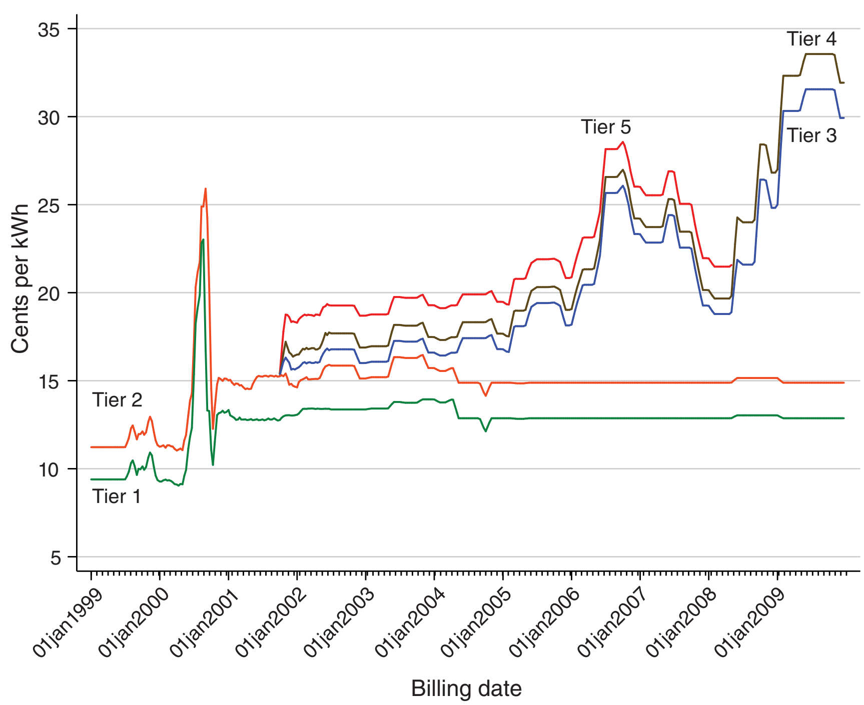



Figure 4. Time-Series Price Variation in Nonlinear Electricity Pricing

*Notes:* The figure shows how SCE and SDG&E changed their residential electricity prices over time. Each of the five-tier rates corresponds to the corresponding tier rates in the five-tier increasing block price schedules presented in Figure 3. The third, fourth, and fifth tiers did not exist before 2001. The fifth tier did not exist between 2004 and 2006 for SCE, and after 2008 for SDG&E.

Commission. When regulated utilities change their price, they need to provide evidence of changes in cost to receive approval. SCE and SDG&E make different changes to their electricity prices for several reasons. First, they have different generation portfolios of power plants, such as natural gas, nuclear, and coal. Changes in input costs of each type of plant lead to different changes in procurement costs for the two companies. Second, they have built their distribution systems in different areas and at different times, which leads to different cost structures for their distribution charges. Finally, they have different amounts of sunk losses from the 2000–2001 California electricity crisis that are required to be collected from ratepayers.

The price variation provides three advantages compared with previous studies. First, the magnitude of the variation is substantial. Cross-sectionally, households have significantly different nonlinear pricing. Second, the cross-sectional price variation changes over time. Third, the *difference* in marginal prices between SCE and SDG&E is often quite different from the *difference* in average prices between SCE and SDG&E. For example, consider consumers in the fourth tier in Figure 3. While the marginal price is higher for SCE customers, the average price is higher for SDG&E customers. This price variation is key to empirically distinguish the response to alternative forms of price.

### C. *Data and Summary Statistics*

Under a confidentiality agreement with SCE and SDG&E, I obtained the household-level billing history of all residential customers from 1999 to 2007. Each monthly record includes each customer's account ID, premise ID, billing start and end date, monthly consumption, monthly bill, tariff type, climate zone, and nine-digit zip code. It does not include customer names, addresses, and demographic information. To obtain demographic information, I match each customer's nine-digit zip code to a census block group in the 2000 US Census. In my sample, the mean number of households in a nine-digit zip code area is 4.9 and that in a census block group is 217.3. Therefore, the nine-digit zip code allows precise neighborhood matching with census data.

My empirical analysis uses the samples that satisfy the following criteria. First, I focus on customers that are on the default standard tariff.[12] Second, I focus on the six cities where the border of electricity service areas lies within city limits: Laguna Beach, Laguna Niguel, Aliso Viejo, Laguna Hills, Mission Viejo, and Coto de Caza. Third, to be conservative about potential sorting that could have occurred because of the price changes after 2000, my main analysis focuses on the panel data of households that are at the same premise throughout the sample period.[13] This procedure results in 40,729 households.

Table 1 provides summary statistics. I show the means and standard errors for SCE customers and SDG&E customers separately. The last column shows the difference in the means with the standard error of the difference. I cluster standard

[12] Over 85 percent of households are on the standard tariff. About 15 percent of households are on the California Alternative Rate for Energy (CARE) Program, a means-tested tariff for low-income households. About 5 percent of households have other tariffs such as time-of-use pricing.

[13] I show that using unbalanced panel data of all households does not change results.

Table 1—Summary Statistics and Differences in Means

| | SCE | | SDG&E | | Difference | |
|---|---|---|---|---|---|---|
| | Mean | (SE) | Mean | (SE) | Mean | (SE) |
| *Data from census 2000* | | | | | | |
| Income per capita ($) | 40,773 | (1,591) | 40,832 | (1,627) | 59 | (2,261) |
| Median home value ($) | 391,508 | (19,987) | 404,887 | (19,768) | 13,379 | (27,849) |
| Median rent ($) | 1,364 | (41) | 1,385 | (62) | 21 | (74) |
| Population density/mile$^2$ | 6,084 | (362) | 5,423 | (360) | −662 | (508) |
| Household size | 2.71 | (0.07) | 2.81 | (0.05) | 0.11 | (0.09) |
| Median age | 47.71 | (1.23) | 45.73 | (0.55) | −1.98 | (1.35) |
| Percent owner occupied housing | 81.86 | (1.65) | 84.27 | (1.93) | 2.41 | (2.53) |
| Percent male | 49.12 | (0.41) | 48.65 | (0.32) | −0.46 | (0.52) |
| Percent employment of males | 74.90 | (2.14) | 78.67 | (1.13) | 3.78 | (2.41) |
| Percent employment of females | 57.75 | (1.83) | 58.54 | (1.22) | 0.79 | (2.19) |
| Percent college degree | 50.31 | (1.28) | 52.96 | (1.22) | 2.65 | (1.76) |
| Percent high school degree | 35.25 | (1.11) | 32.27 | (0.93) | −2.98 | (1.44) |
| Percent no high school degree | 4.28 | (0.29) | 4.07 | (0.33) | −0.21 | (0.44) |
| Percent white | 85.53 | (0.86) | 83.74 | (0.94) | −1.79 | (1.27) |
| Percent Hispanics | 9.33 | (0.58) | 9.70 | (0.74) | 0.37 | (0.93) |
| Percent Asian | 6.97 | (0.61) | 8.23 | (0.66) | 1.26 | (0.90) |
| Percent black | 1.19 | (0.15) | 0.86 | (0.16) | −0.32 | (0.22) |
| *Electricity billing data* | | | | | | |
| Electricity use (kWh/day) | 21.37 | (0.07) | 22.48 | (0.09) | 1.11 | (0.12) |
| ln(electricity use) | 2.89 | (0.00) | 2.89 | (0.01) | 0.00 | (0.00) |
| ln(electricity use) in 1999 | 2.86 | (0.00) | 2.86 | (0.01) | 0.01 | (0.01) |

*Notes:* For each variable, I show the mean and standard error for SCE customers and SDG&E customers in the six cities that have the territory border of SCE and SDG&E within the city limits. The last column shows the difference in the mean with the standard error of the difference. I cluster standard errors at the census block group level for the census data and at the customer level for the electricity billing data.

errors at the census block group level for the census data and at the customer level for electricity billing records. The demographic and housing characteristics between SCE and SDG&E customers are balanced. The mean of electricity consumption during the sample period is about 22 kWh/day and 23 kWh/day for SCE and SDG&E customers. SCE and SDG&E had nearly identical price schedules until 1999, before the first major price change in the summer of 2000. The last row shows that the mean of log consumption in 1999 is not statistically different between SCE and SDG&E customers.

## III. Empirical Analysis and Results

### A. *Bunching at Kink Points of Price Schedules*

My first empirical strategy is to examine bunching of consumers at the kink points of nonlinear price schedules (Heckman 1983; Saez 2010; Chetty et al. 2011). In Figure 1, suppose that preferences for electricity consumption are convex and smoothly distributed across the kink point $K$. Then, if consumers respond to the true marginal price $p(x)$, a disproportionate share of demand curves intersect with the vertical part of the schedule. I thus expect a disproportionate share of consumers bunching around the kink point in the data. The amount of bunching should be larger when (i) the discrete jump in marginal price at $K$ is large, and (ii) the price elasticity of demand is large.

*Bunching Analysis Results*.—In 1999, consumers faced an essentially flat marginal rate with a small step between the first and second tiers. Therefore, the distribution of consumption in 1999 can provide a baseline case, where there is no steep kink point in the price schedule. Panel A of Figure 5 presents a histogram of consumption for SCE customers in 1999. I use monthly consumption data from all 12 months in 1999. The histogram shows that the consumption is smoothly distributed.

After 2001, SCE introduced a five-tier price schedule. Steep steps in the price schedule should translate into a consumption distribution that differs from the baseline case observed in 1999. Panel B shows the histogram of consumption for SCE customers in 2007, when SCE had the steepest five-tier price schedule. The distribution is as smooth as the distribution in 1999, and there is no bunching around the kink points. In particular, there is no bunching even at the second kink, where the marginal price increases more than 80 percent. I also find no bunching for any year of the data in SCE and SDG&E.

The absence of bunching implies two possibilities. First, consumers may respond to marginal price with *nearly zero elasticity.* Saez (2010) and Chetty et al. (2011) provide statistical methods to estimate the price elasticity with respect to marginal price from the bunching analysis. When I apply the methods to my SCE data in 2007, both methods produce estimates of nearly zero price elasticity with tight standard errors.[14] Second, consumers may respond to *alternative price*. If consumers respond to any "smoothed" price such as average price, the price has no more kink points. Thus, there can be no bunching even if consumers have nonzero price elasticity. The next section examines these possibilities by exploiting panel price variation between SCE and SDG&E.

## B. *Encompassing Tests of Alternative Prices*

My second empirical strategy is to test whether consumers respond to marginal, expected marginal, or average price by using the encompassing test (Davidson and MacKinnon 1993). Let $x_{it}$ denote consumer $i$'s average daily electricity use during billing month $t$. Suppose that they have quasilinear utility for electricity consumption.[15] I allow the possibility that they may respond to marginal price or average price by characterizing their demand by $x_{it} = \lambda_i \cdot MP_{it}^{\beta_1} \cdot AP_{it}^{\beta_2}$ with the price elasticity with respect to marginal price ($\beta_1$) and average price ($\beta_2$). I define $\Delta \ln x_{it} = \ln x_{it} - \ln x_{it_0}$, where $t_0$ is the same billing month of the previous year. This first-difference eliminates household-by-month fixed effects. Consider the estimating equation:

$$\Delta \ln x_{it} = \beta_1 \Delta \ln MP_{it} + \beta_2 \Delta \ln AP_{it} + \gamma_{ct} + \eta_{it}, \tag{2}$$

[14] For example, when I apply the method in Saez (2010), the point estimate and standard error of the elasticity is −0.001 (0.002) for the largest kink point for SCE's price schedule in 2007.

[15] Quasilinear utility functions assume no income effect. In the case of residential electricity demand, income effects are likely to be extremely small. In my sample, a median consumer pays a monthly electricity bill of \$60. A 30 percent change in *all five tiers* would produce an income change of \$18 per month, about 0.2 percent of the monthly median household income in my sample. In the literature, the income elasticity estimates of residential electricity demand lie between 0.1 and 1.0. The income effect of this price change would thus result in a change of 0.02 percent to 0.2 percent in consumption.

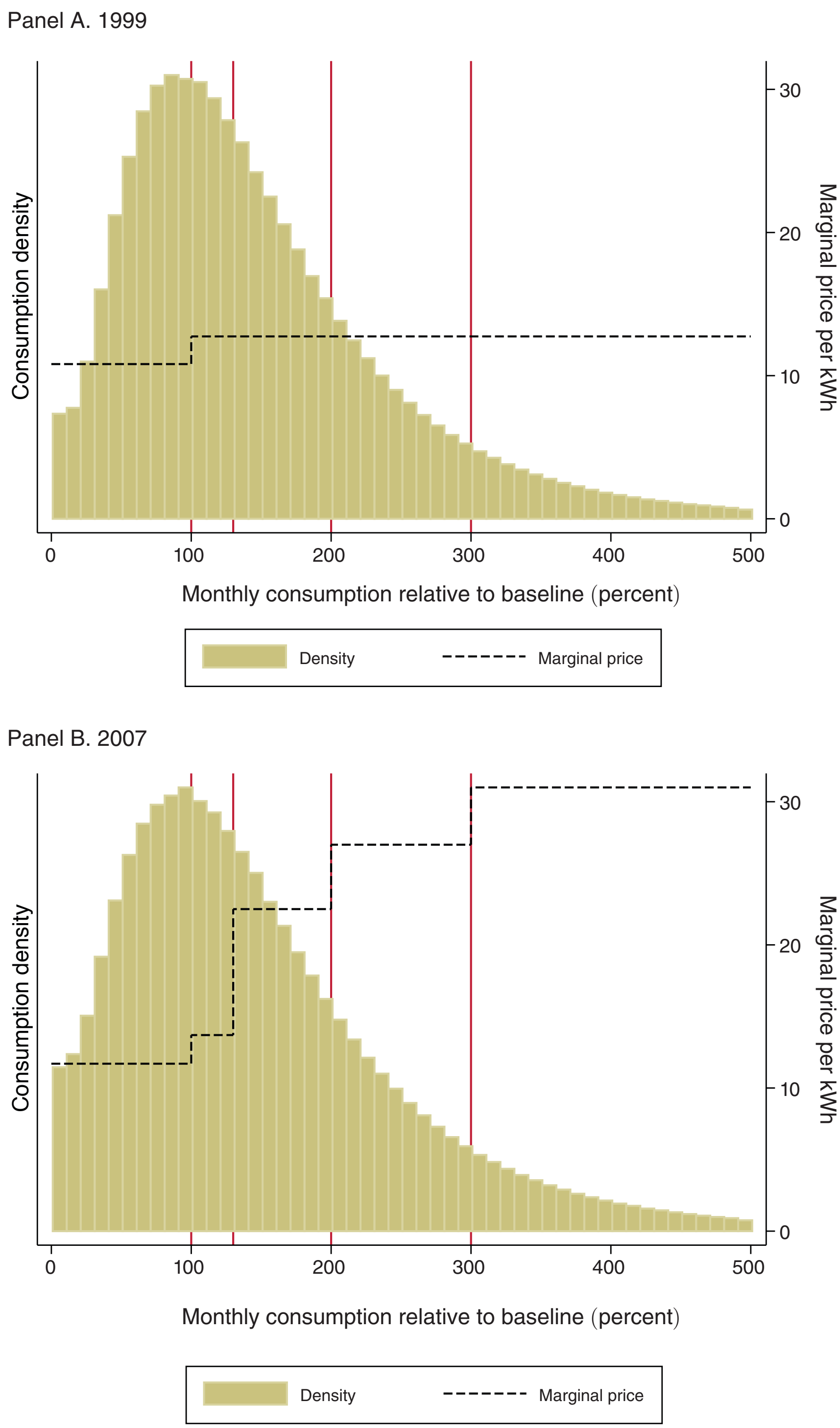



Figure 5. Consumption Distributions and Nonlinear Price Schedules

*Notes:* The figure shows the histogram of household-level monthly electricity consumption for SCE in 1999 (panel A) and in 2007 (panel B). The figure also shows the nonlinear price schedule for each year. The vertical solid lines show the kink points of the nonlinear price schedule.

with city-by-time fixed effects $\gamma_{ct}$ and error term $\eta_{it} = \varepsilon_{it} - \varepsilon_{it_0}$. An encompassing test examines if one model encompasses an alternative model. For example, if consumers respond to marginal price and do not respond to average price, one expects $\hat{\beta}_2 = 0$ because average price should not affect demand conditional on the effect of marginal price.

A common identification problem of nonlinear pricing is that the price variables are functions of consumption and hence, are correlated with unobserved demand shocks $\eta_{it}$. To address the endogeneity, previous studies use a policy-induced price change as an instrument: $\Delta \ln MP_{it}^{PI} = \ln MP_t(\tilde{x}_{it}) - \ln MP_{t_0}(\tilde{x}_{it})$.[16] This instrument, also called a simulated instrument, computes the predicted price change at a consumption level $\tilde{x}_{it}$. The instrument thus captures the price change induced by the policy change in the nonlinear price schedule for the consumption level $\tilde{x}_{it}$. To be a valid instrument, $\tilde{x}_{it}$ has to be uncorrelated with $\eta_{it}$. Many studies use the base year's consumption $x_{it_0}$ for $\tilde{x}_{it}$. However, $x_{it_0}$ is likely to be correlated with $\eta_{it}$ because the mean reversion of consumption creates a negative correlation between $\varepsilon_{it_0}$ and $\eta_{it} = \varepsilon_{it} - \varepsilon_{it_0}$. Blomquist and Selin (2010) and Saez, Slemrod, and Giertz (2012) suggest that consumption in a period midway between $t_0$ and $t$ can be used to address the mean reversion problem. Because my analysis uses monthly consumption data, the middle period and its consumption are $t_m = t - 6$ and $x_{it_m}$.[17]

Even if the mean reversion problem is addressed, the instrument based on the level of consumption can still be correlated with $\eta_{it}$ if high and low electricity users have different growth patterns in consumption. For example, if there is an underlying distributional change in electricity consumption over time, I cannot expect a parallel trend between high and low electricity users. Exactly the same problem has been long discussed in the literature of nonlinear taxation (Heckman 1996; Blundell, Duncan, and Meghir 1998; Goolsbee 2000; Saez, Slemrod, and Giertz 2012). A usual quasi-experiment essentially compares the change in income between lower and higher income households. Because all comparable households usually face the same nonlinear tax schedule, there is no clean control group that can be used to control for differential underlying growth between lower and higher income households.

To address the problem, I exploit the spatial discontinuity in electricity service areas. Because households in the same city experience different nonlinear pricing, I can use households on the other side of the border as a control group. My identification assumption is that confounding factors such as underlying distributional changes in consumption are not systematically different across the border. Consider the instrumental variable (IV) regression:

$$(3) \qquad \Delta \ln x_{it} = \beta_1 \Delta \ln MP_{it} + \beta_2 \Delta \ln AP_{it} + f_t(x_{it_m}) + \gamma_{ct} + \delta_{bt} + u_{it},$$

[16] For example, see Saez, Slemrod, and Giertz (2012) for discussions of this instrument.

[17] The instrument based on $x_{it_m}$ is not systematically affected by the mean reversion problem because $\varepsilon_{it}$ and $\varepsilon_{it_0}$ do not directly affect $x_{it_m}$. If there is no serial correlation, $\varepsilon_{it_m}$ and $\eta_{it} = \varepsilon_{it} - \varepsilon_{it_0}$ are uncorrelated. Moreover, Blomquist and Selin (2010) show that even if there is serial correlation, $\mathrm{Cov}(\varepsilon_{it_m}, \eta_{it})$ equals zero as long as the serial correlation depends only on the time difference between the error terms. This is because $\varepsilon_{it_m}$ is equally spaced from $\varepsilon_{it}$ and $\varepsilon_{it_0}$ and, thus, would be correlated with $\varepsilon_{it}$ and $\varepsilon_{it_0}$ in the same manner. Another option for $\tilde{x}_{it}$ is household $i$'s consumption in 1999. If the serial correlation of $\varepsilon_{it}$ has minimal impacts on the correlation between the error term in 1999 and the error term in $t$, the consumption in 1999 would not be systematically correlated with $\eta_{it} = \varepsilon_{it} - \varepsilon_{it_0}$. I find that using this instrument produces results that are virtually identical to my main results.

with instruments, $\Delta \ln MP_{it}^{PI} = \ln MP_t(x_{it_m}) - \ln MP_{t_0}(x_{it_m})$ and $\Delta \ln AP_{it}^{PI} = \ln AP_t(x_{it_m}) - \ln AP_{t_0}(x_{it_m})$. The error term $u_{it}$ is uncorrelated with $x_{it_m}$ as long as $f_t(x_{it_m})$ sufficiently controls for confounding factors such as underlying distributional changes in consumption. When all consumers face the same price schedule, flexible controls of $x_{it_m}$ absorb all price variation and destroy identification. In contrast, I can include any flexible controls of $x_{it_m}$ because households experience different nonlinear pricing.

There are many ways to define $f_t(x_{it_m})$. For example, I can include flexible polynomial functions in $x_{it_m}$. To prevent a functional form assumption as far as possible, I take a nonparametric approach. For each percentile of consumption in $t_m$, I define grouping dummy variables by $G_{j,t} = 1\{x_{j,t_m} < x_{it_m} \leq x_{j+1,t_m}\}$, which equal one if $x_{it_m}$ falls between $j$ and $j+1$ percentiles. These dummy variables are percentile-by-time fixed effects and control for underlying changes in consumption for each part of the consumption distribution. Although city-level economic shocks and weather shocks are absorbed by city-by-time fixed effects $\gamma_{ct}$, the weather impact can be slightly different between households with different billing cycles. To control for the effect, I include billing-cycle-by-time fixed effects $\delta_{bt}$.

*Encompassing Tests Results*.—Figure 6 provides a graphical illustration of the encompassing test. To show an example of year-to-year price variation, the figure uses the billing month of January and households whose $x_{it_m}$ is on the fourth tier of the five-tier price schedule.[18] The squared line shows the difference-in-differences (DD) in the mean of log marginal price ($\ln MP_{it}$) for SDG&E customers relative to SCE customers. For each customer, I calculate the change in log marginal price from 1999. Then, I obtain the DD by subtracting SCE's mean from SDG&E's mean. The DD estimate thus shows how SDG&E's marginal price evolved from 1999 relative to SCE. I call it the *relative* change in marginal price. In the same way, I calculate the DD in the means of predicted log marginal price ($\ln MP_{it}^{PI}$), log average price ($\ln AP_{it}$), predicated log average price ($\ln AP_{it}^{PI}$), and log consumption ($\ln x_{it}$).

Figure 6 provides several important insights. First, the predicted prices (the instruments) and the effective prices are strongly correlated, which implies a strong first-stage relationship. Second, the change in consumption from 1999 to 2000 provides a test for the parallel trend assumption between SDG&E and SCE customers. If the parallel trend assumption holds, I expect no difference in the change in consumption between SDG&E and SCE customers from 1999 to 2000 because they have nearly the same price change. The DD in consumption in 2000 verifies that this is in fact the case. Third, the relative change in marginal price and the relative change in average price are substantially different in 2002, 2003, and 2007. SDG&E's marginal price *decreases* more than SCE's marginal price, but its average price *increases* more than SCE's average price. If consumers respond to marginal price, SDG&E's consumption should increase more than SCE's consumption in these years. However, the figure shows the opposite result: SDG&E's consumption decreases more than SCE's consumption. Unless price elasticity is positive, the relative change in

[18] The mean consumption in the data (22 kWh/day) lies in the fourth tier of the five-tier price schedule.

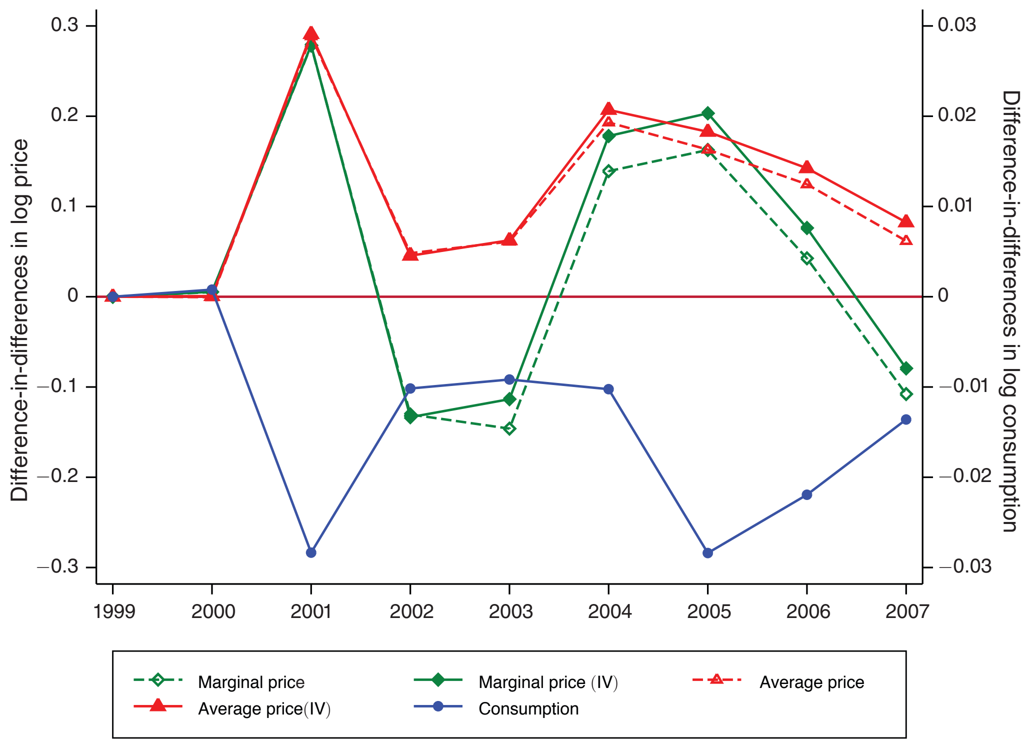



Figure 6. Difference-in-Differences in Price and Consumption

*Notes:* The figure shows the difference-in-differences (DD) in price and consumption for the billing month of January relative to year 1999 for customers whose consumption lies in the fourth tier of the five-tier price schedule. For example, the plot of marginal price presents how SDG&E's log marginal price evolved from 1999 relative to that of SCE. First, for each side of the border, I calculate the mean log change in price and consumption. Then, I calculate DD by subtracting the mean log change of SCE customers from the mean log change of SDG&E customers.

consumption is inconsistent with the relative change in marginal price. Rather, it is more consistent with the relative change in average price, although formal econometric estimation is required to discuss its statistical inference.

Now, I run the instrumental variable estimation in equation (3) by using the entire monthly billing data from January 1999 to December 2007. Table 2 presents the regression results that examine whether consumers respond to marginal or average price. I cluster the standard errors at the household level to correct for serial correlation. First, I include only the marginal price of electricity as a price variable. Column 1 shows that the price elasticity with respect to marginal price is −0.034. This result contradicts the result in the bunching analysis, where I find nearly zero price elasticity with respect to marginal price. However, the encompassing test in column 3 implies that the significant price elasticity in column 1 comes from spurious correlation. Column 3 includes both marginal and average price as price variables. If consumers respond to marginal price as the standard theory predicts, I expect that average price would not affect demand conditional on the effect of marginal price. Column 3 reveals the opposite result. Once average price is included, adding marginal price does not statistically change the effect of average price. Moreover, the effect of marginal price becomes statistically insignificant from zero.

TABLE 2—ENCOMPASSING TESTS: MARGINAL PRICE VERSUS AVERAGE PRICE

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| $\Delta \ln(\textit{marginal price}_t)$ | −0.034 | | 0.002 | | | |
| | (0.004) | | (0.011) | | | |
| $\Delta \ln(\textit{average price}_t)$ | | −0.051 | −0.054 | | | |
| | | (0.005) | (0.015) | | | |
| $\Delta \ln(\textit{marginal price}_{t-1})$ | | | | −0.050 | | 0.006 |
| | | | | (0.004) | | (0.011) |
| $\Delta \ln(\textit{average price}_{t-1})$ | | | | | −0.074 | −0.082 |
| | | | | | (0.005) | (0.015) |

*Notes:* This table shows the results of the IV regression in equation (3) with fixed effects and control variables specified in the equation. The unit of observation is household-level monthly electricity usage. The dependent variable is the log change in electricity consumption in billing period $t$ from billing period $t - 12$. The sample period is from January 1999 to December 2007 and the sample size is 3,752,378. Standard errors in parentheses are clustered at the household level to adjust for serial correlation.

Because households receive electricity bills at the end of monthly billing periods, they may respond to lagged price rather than contemporaneous price. Columns 4 to 6 provide the results with one-month lagged price. Using lagged price does not change the main result. Households respond to lagged average price rather than lagged marginal price. The price elasticity with respect to lagged price is larger than that with respect to contemporaneous price, suggesting the possibility that consumers respond to lagged price more than contemporaneous price. Table 3 investigates this point. Column 1 shows that consumers respond to lagged prices and the effect of contemporaneous price is statistically insignificant from zero once the effects of lagged prices are controlled. Usually, the most policy-relevant price elasticity is the medium-long run elasticity that includes these lagged responses. Columns 2 to 4 include the averages of one-, two-, three-, and four-month lagged average prices. The estimated elasticity thus shows the percent change in consumption when consumers experience a persistent change in average price for the one- to four-month periods. The medium-long run price elasticity estimates are larger than the short-run elasticity estimate. I find that lagged prices with more than four-month lags have negligible effects and that the medium-long run elasticity estimates do not change when I include lags exceeding four months.

It can be unrealistic to expect that rational consumers respond to their *exact* marginal price for two reasons. First, they often have random shocks to their demand during a billing month. Second, they do not have information about their day-to-day consumption. As described in Section II, given uncertainty about consumption, the standard economic model of uncertainty predicts that consumers respond to their *expected* marginal price. I empirically examine this possibility. To find the degree of uncertainty for the monthly consumption of typical consumers, I estimate the variance of $\ln x_{it}$ conditional on household-by-month fixed effects and one-month lagged log consumption. The median of the root mean squared error is about 0.2, suggesting that with this information, the average consumer can predict her consumption with a standard error of about 20 percent. Based on this estimate, I calculate the expected marginal price by assuming that consumers have errors with a standard deviation of 20 percent of their consumption. Table 4 shows evidence that consumers respond to average price rather than expected marginal price. Column 3

Table 3—Lagged Responses and Medium-Long Run Price Elasticity

| | Lagged responses | Medium-long run responses | | | |
|---|---|---|---|---|---|
| | | 1 month | 2 month | 3 month | 4 month |
| | (1) | (2) | (3) | (4) | (5) |
| $\Delta \ln(\textit{average price}_t)$ | 0.001 | | | | |
| | (0.002) | | | | |
| $\Delta \ln(\textit{average price}_{t-1})$ | −0.049 | | | | |
| | (0.006) | | | | |
| $\Delta \ln(\textit{average price}_{t-2})$ | −0.026 | | | | |
| | (0.007) | | | | |
| $\Delta \ln(\textit{average price}_{t-3})$ | −0.011 | | | | |
| | (0.006) | | | | |
| $\Delta \ln(\textit{average of lag average prices})$ | | −0.071 | −0.082 | −0.087 | −0.088 |
| | | (0.005) | (0.005) | (0.006) | (0.006) |

*Notes:* See notes in Table 3. The dependent variable is the log change in electricity consumption in billing period $t$ from billing period $t - 12$. Because the four-month lag price is unknown for the first four months of the sample period, I include monthly bills from May 1999 to December 2007. The sample size is 3,598,571. Standard errors in parentheses are clustered at the household level to adjust for serial correlation.

shows that once average price is included, adding expected marginal price does not statistically change the effect of average price. Columns 4 to 6 show that using lagged price does not change the result.

The results in this section provide evidence that households respond to average price rather than other two prices predicted by theory. Figure A.2 and Table A.1 in the online Appendix show that the results are robust for (i) unbalanced panel data that include all households in my sample period, (ii) the samples restricted to households within a certain distance from the border, and (iii) alternative instruments. The encompassing test is simple and sufficient for testing competing theoretical predictions. However, it cannot completely eliminate other possibilities of the perceived price. For example, the previous analysis assumes that the average consumer can predict her consumption with a standard error of about 20 percent. If households have more or less information about their expected consumption, their expected marginal price can be different from the assumed expected marginal price. To address this point, the next section uses an approach that examines a general form of perceived price, instead of starting with a particular prediction of perceived price.

## C. *Estimation of the Shape of Perceived Price*

In the previous two sections, I begin with particular forms of perceived price derived from the theoretical predictions and examine which of the competing forms of perceived price is most consistent with the data. I take a different approach in this section. Consider that consumers have consumption $x_{it}$ and face a nonlinear price schedule $p(x_{it})$. I define a series of surrounding consumption levels around $x_{it}$ by $x_{k,it} = (1 + k/100)x_{it}$. That is, $x_{k,it}$ is the level of consumption that is $k$ percent away from $x_{it}$. Let $p_{k,it} = p(x_{k,it})$ denote the marginal price for $x_{k,it}$. Consumers may care about the surrounding marginal prices, either because of the uncertainty about their ex post consumption, or inattention to the true price schedule.

Table 4—Encompassing Tests: Expected Marginal Price versus Average Price

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| $\Delta \ln(\textit{expected marginal price}_t)$ | −0.036 | 0.004 | | |
| | (0.004) | (0.012) | | |
| $\Delta \ln(\textit{average price}_t)$ | | −0.056 | | |
| | | (0.015) | | |
| $\Delta \ln(\textit{expected marginal price}_{t-1})$ | | | −0.053 | 0.009 |
| | | | (0.004) | (0.012) |
| $\Delta \ln(\textit{average price}_{t-1})$ | | | | −0.086 |
| | | | | (0.015) |

*Notes:* See notes in Table 3. This table shows the results of the IV regression in equation (3) with expected marginal price instead of marginal price. The dependent variable is the log change in electricity consumption in billing period $t$ from billing period $t-12$. The data include monthly bills from January 1999 to December 2007. The sample size is 3,752,378. Standard errors in parentheses are clustered at the household level to adjust for serial correlation.

I consider that consumers construct their perceived price by deciding relative weights $w_k$ on $p_{k,it}$. Suppose that there is price variation in $p_{k,it}$ over time. Using the price variation, I estimate $w_k$ by observing how consumers respond to changes in $p_{k,it}$. Then, I can use the estimates of $w_k$ to recover the shape of consumers' perceived price. Suppose that consumers may care about the surrounding marginal prices up to a range of 100 percent from $x_{it}$. That is, $-100 \leq k \leq 100$. I model the density function of $w_k$ with the following asymmetric exponential functional form:

$$(4) \qquad w_k(\alpha, \boldsymbol{\theta}) = \begin{cases} \alpha \cdot \dfrac{\exp(-k \cdot \theta_l)}{\sum_{k \leq 0} \exp(-k \cdot \theta_l)} & \text{for } k \leq 0 \\[2ex] (1-\alpha) \cdot \dfrac{\exp(k \cdot \theta_r)}{\sum_{k > 0} \exp(k \cdot \theta_r)} & \text{for } k > 0. \end{cases}$$

This density function can characterize various forms of perceived price. First, parameter $\alpha$ describes the relative weight on $p_{k,it}$ between the left- and right-hand sides of $x_{it}$. For example, $\alpha = 1$ implies that consumers do not care about the price on the right-hand side of $x_{it}$ in the price schedule. Second, parameters $\theta_l$ and $\theta_r$ describe the slopes of the density function. The exponential form is useful because it can capture nonlinear upward and downward slopes with one parameter. The dashed lines in Figure 7 illustrate two examples of weighting functions. The first example shows the case with $\alpha = 0.5$ and $\theta_l = \theta_r = -0.1$, where consumers care about the price to the left and right of $x_{it}$ equally but put larger weights on the price close to $x_{it}$. The second example shows a similar case, but consumers care about the price further away from $x_{it}$. Using the weighing function, I estimate:

$$(5) \qquad \Delta \ln x_{it} = \beta \sum_{k=-100}^{100} w_k(\alpha, \boldsymbol{\theta}) \cdot \Delta \ln p_{k,it} + f_t(x_{it_m}) + \gamma_{ct} + \delta_{bt} + u_{it}.$$

This estimation is nonlinear in parameters only and linear in variables. I can thus run nonlinear IV estimation assuming the same identifying assumptions for the linear

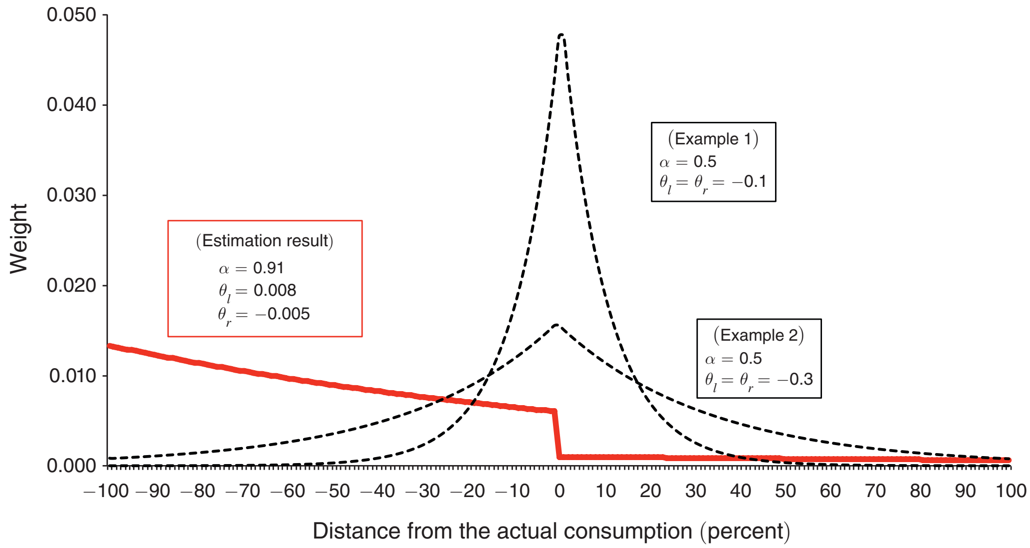



Figure 7. Shape of Weighting Functions: Examples and Estimation Results

*Notes:* The dashed lines illustrate two examples of the weighting functions of equation (5). The first example shows the case with $\alpha = 0.5$ and $\theta_l = \theta_r = -0.1$, in which consumers care about the price to the left and right of $x_{it}$ equally but put larger weights on the price close to $x_{it}$. The second example shows a similar case but consumers care about the price further away from $x_{it}$ The solid line shows the estimation result of $w(\alpha, \theta)$, which is shown in Table 5.

IV estimation conducted in the previous section (Amemiya 1983).[19] For the endogenous variable $\Delta \ln p_{k,it}$, I use the same form of the instrument used in the previous section, $\Delta \ln p^{PI}_{k,it} = \ln p_t(x_{k,it_m}) - \ln p_{t0}(x_{k,it_m})$.

The primary interests are the three weighing parameters, $\alpha$, $\theta_l$, and $\theta_r$. If consumers respond to expected marginal price, I expect that $\alpha = 0.5$ and $\theta_l = \theta_r$ regardless of the actual degree of uncertainty in consumption that consumers face. If consumers respond to marginal price, I expect steep slopes in $\theta_l$ and $\theta_r$. Finally, if consumers respond only to average price, I expect that $\alpha = 1$ because they would not care about the price above $x_{it}$. Elasticity parameter $\beta$ is the overall price elasticity and $\beta \cdot w_k(\alpha, \boldsymbol{\theta})$ shows the price elasticity with respect to the change in each $p_{k,it}$.

*Perceived Price Estimation Results*.—Table 5 shows the estimation results. Column 1 uses contemporaneous price as the price variable. The estimated $\alpha$ is 0.911, and I reject $\alpha = 0.5$ at the 1 percent significance level. That is, I reject the null hypothesis that consumers have equal weights on the left- and right-hand sides of $x_{it}$. Moreover, the estimated $\alpha$ is not statistically different from one. The point estimates of $\theta_l$ and $\theta_r$ imply the possibility that the slopes are asymmetric, and thus, consumers may have a higher weight on prices at very low consumption levels. However, both estimates are not statistically different from zero. Thus, I cannot reject the hypothesis that the slopes are flat. The solid line in Figure 7 plots the estimated weighting function.

[19] An alternative approach is to use a continuous density function for $w$. It makes the estimating equation nonlinear in both parameters and variables, requiring stronger identifying assumptions for nonlinear IV estimation. Because the marginal price $p_{k,it}$ is flat in most parts of the five-tier price schedule and does not change with a slight change in $k$, the discrete approximation in equation (5) would not deviate significantly from the continuous form of $w$.

Table 5—Estimation of the Shape of Perceived Price

| | Price variable | | |
|---|---|---|---|
| | Current month (1) | One-month lag (2) | Four-month average (3) |
| Weighting parameter $\alpha$ | 0.911 | 0.896 | 0.883 |
| | (0.082) | (0.083) | (0.087) |
| Slope parameter $\theta_l$ | 0.008 | 0.013 | 0.015 |
| | (0.013) | (0.014) | (0.014) |
| Slope parameter $\theta_r$ | −0.005 | −0.009 | 0.001 |
| | (0.015) | (0.015) | (0.017) |
| Elasticity parameter $\beta$ | −0.059 | −0.086 | −0.094 |
| | (0.005) | (0.006) | (0.006) |
| $p$-value for $H_0$: $\alpha = 0.5$ | 0.00 | 0.00 | 0.00 |
| $p$-value for $H_0$: $\alpha = 1$ | 0.28 | 0.21 | 0.18 |

*Notes:* See notes in Table 3. This table shows the results of the nonlinear IV regression in equation (5). Standard errors in parentheses are clustered at the household level to adjust for serial correlation. Column 1 uses the contemporaneous price; column 2, the one-month lagged price; and column 3, the average of one-, two-, three-, and four-month lagged prices, as a price variables in the regression.

The shape is close to a uniform distribution. In fact, it is not statistically different from the uniform distribution $\mathcal{U}[0, x_{it}]$. Columns 2 and 3 present similar findings for one-month lag price and the average of four-month lag prices.

The results provide several implications. First, the estimates of $\alpha$ imply that consumers are unlikely to respond to expected marginal price. Second, the estimated shape of the weighing function is consistent with the results in the previous section, and both strategies find that consumers respond to average price rather than marginal or expected marginal price.[20] The next section examines the welfare and policy implications of this finding.

## IV. Welfare Analysis

### A. *Nonlinear Pricing and Energy Conservation*

Many electric, natural gas, and water utilities in the United States have adopted nonlinear pricing similar to California's residential electricity pricing. Policy makers often claim that higher marginal prices for excessive consumption can create an incentive for conservation. Note that the retail price of utility companies is usually regulated and has a zero profit condition with a rate of return. When utility companies switch from a flat marginal rate to multi-tier pricing, they need to lower the marginal price for some tiers so as to raise the marginal price for other tiers. Thus, the effect on aggregate consumption is ambiguous because some customers see an increase in price while others see a decrease in price. I use the data in my sample to examine how nonlinear pricing changes consumption compared to a counterfactual

[20] My results are consistent with evidence from laboratory experiments such as those conducted by de Bartolome (1995). In a laboratory experiment, he examines the tax rate used by individuals. He finds that many subjects use their average tax rate as if it is their marginal tax rate.

flat marginal rate for two scenarios: (i) customers respond to average price, and (ii) they respond to marginal price.

I calculate counterfactual consumption by making the following assumptions. First, I assume that consumers have a demand function $x_i = \lambda_i \cdot {p_i}^{\beta}$ with a price elasticity $\beta$ and fixed effects $\lambda_i$. Second, based on my empirical findings, I assume that consumers are currently responding to average price. This assumption implies that the observed consumption in the data equals $\lambda_i \cdot {AP_i}^{\beta}$. When consumers face a counterfactual flat marginal rate, their counterfactual consumption equals $\lambda_i \cdot flat^{\beta}$. Finally, I calculate counterfactual consumption $\lambda_i \cdot {MP_i}^{\beta}$ by assuming that when consumers correctly perceive their true marginal price, they respond to marginal price with price elasticity $\beta$.[21]

When aggregate consumption changes in the counterfactual scenarios, the total revenue and cost also change. To keep total consumption comparable between the observed and two counterfactual cases, I assume that the utility company maintains a profit neutrality condition by adjusting the tariff in the following way. First, I assume that the long-run marginal cost equals the average cost of electricity under the existing nonlinear tariff. For example, for SCE's tariff in 2007, the marginal cost based on this assumption equals 16.73 cents/kWh. Then, the alternative flat marginal rate tariff is simply a marginal rate of 16.73 cents/kWh, which produces the same profit as the existing five-tier tariff. Second, I assume that the company adjusts each five-tier rate by the same proportion to keep profit neutrality when aggregate consumption changes.

Table 6 presents how nonlinear pricing changes aggregate consumption compared to a counterfactual flat marginal rate. I use the SCE data for 2007, where consumers had one of the steepest five-tier price schedules.[22] I include all SCE customers with the standard five-tier tariff. I compute counterfactual consumption using the medium-long run price elasticity estimate $-0.088$. The aggregate consumption *increases* by 0.27 percent if consumers respond to average price. The intuition behind this result is as follows. When the price schedule is switched from a flat marginal rate to nonlinear pricing, lower-usage consumers increase their consumption because they have a lower price. Higher-usage consumers decrease their consumption, but only slightly, because their average price does not increase much. In contrast, the marginal price increases substantially. This is why aggregate consumption *decreases* by 2.33 percent if consumers respond to marginal price. The results suggest that if consumers respond to marginal price, nonlinear pricing would be effective in reducing aggregate consumption. However, if consumers respond to average price, nonlinear pricing may not reduce aggregate consumption compared with the counterfactual flat marginal rate pricing.[23]

[21] This assumption is plausible if consumers currently use average price as an approximation of marginal price so that when they are informed about marginal price, they would respond to it with price elasticity $\beta$. However, there is a possibility that their fundamental elasticity can be different for marginal price, which cannot be tested in my data.

[22] I calculate the same statistics for other years and also for data from the San Diego Gas & Electric. The results are similar to the case for SCE in 2007.

[23] This analysis uses the same price elasticity for lower- and higher-usage consumers. The increase in aggregate consumption can be even higher when lower-usage consumers are more price sensitive or less informed about their marginal price than higher-usage consumers.

Table 6—Effect of Nonlinear Pricing on Energy Conservation

| | Assumption on consumers' perceived price | |
|---|---|---|
| | Average price | Marginal price |
| (A) Consumption under five-tier nonlinear pricing | 20,526 | 19,993 |
| (B) Consumption under counterfactual flat rate | 20,471 | 20,471 |
| Percent change from (B) to (A) | 0.27<br>(0.02) | −2.33<br>(0.05) |

*Notes:* The table shows how nonlinear pricing changes aggregate consumption compared to the counterfactual flat marginal rate for two scenarios: (i) customers respond to average price and (ii) customers respond to marginal price. This table uses data for SCE in 2007, where consumers had one of the steepest five-tier price schedules in the sample period. The results do not change when I use the data for other years or for SDG&E. Asymptotic standard errors are calculated by the delta method based on the standard errors of the estimated price elasticity.

## B. *Efficiency Costs of Nonlinear Pricing*

Multi-tier electricity pricing creates efficiency costs because it does not reflect the marginal cost of electricity (Faruqui 2008).[24] While the marginal cost of electricity generally depends on the timing of consumption, there is no evidence that the marginal cost depends on the level of a customer's monthly consumption. Among time-invariant electricity pricing, therefore, the most efficient pricing is likely to be the flat marginal rate that equals the marginal cost of electricity.[25] In multi-tier pricing, compared to the efficient flat marginal rate, the marginal prices for lower tiers are too low and those for higher tiers are too high. The deadweight loss of price schedule $p(x)$ for a consumer whose consumption equals $x^*$ can be calculated by the integral between the efficient price and the price schedule, $dwl(p(x)) = \int_0^{x^*} |p(x) - mc|\, dx$.

I start with the assumption that the long-run marginal cost of electricity equals the average cost of electricity under the existing five-tier tariff, which is 16.73 cents/kWh for SCE in 2007. This marginal cost can be higher or lower than the social marginal cost depending on the assumptions on environmental externalities from power generation. I thus calculate the deadweight loss for a wide range of the possible social marginal costs of electricity.

Figure 8 shows the aggregate deadweight loss for various values of the social marginal cost of electricity with the price elasticity of −0.088. For a social marginal cost less than 21 cents/kWh, $dwl(MP)$ is larger than $dwl(AP)$. This is because when consumers respond to marginal price, they consume less on average compared to the efficient level. However, when the social marginal cost exceeds this value because of large environmental externalities from electricity generation, $dwl(AP)$ is larger than $dwl(MP)$. This is because in the presence of the negative externalities, the optimal consumption level approaches the quantity obtained with the marginal price response.

[24] See Borenstein (2012) for the redistribution effect of nonlinear electricity pricing.

[25] Time-variant electricity pricing generally improves efficiency substantially. Such pricing is not applicable for customers in my sample because their meters are read monthly.

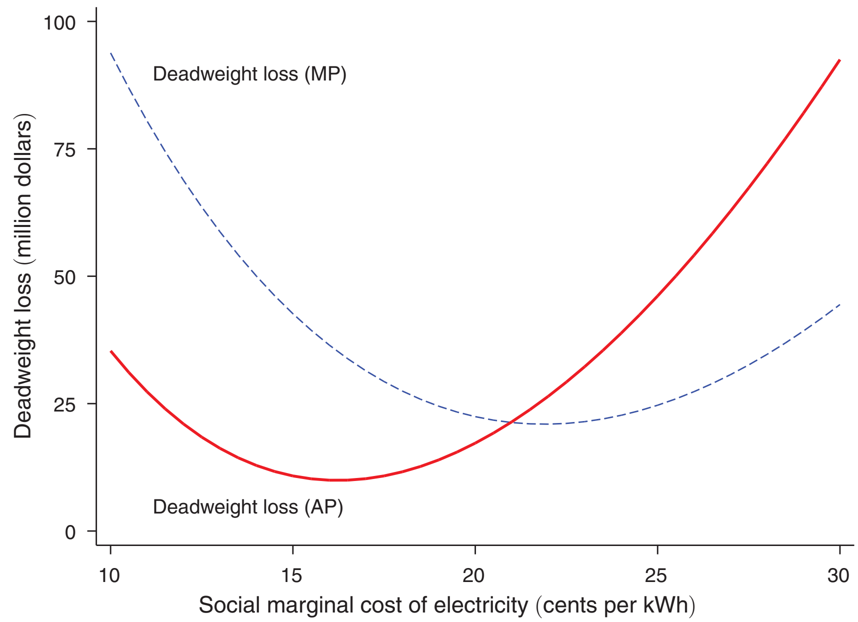



Figure 8. Efficiency Costs of Nonlinear Pricing

*Notes:* This figure presents the deadweight loss (DWL) from the five-tier tariffs for SCE in 2007, for different assumptions on the social marginal cost of electricity as well as on how consumers respond to nonlinear pricing. The DWL is calculated with the price elasticity of −0.088. The solid line shows the DWL when consumers respond to their average price. The dashed line displays a counterfactual DWL when consumers respond to their marginal price. The DWL is larger for the marginal price response when the social marginal cost is less than 21 cents/kWh and becomes smaller when the social marginal cost exceeds the cutoff value.

The welfare impact of the suboptimizing behavior in the case of electricity consumption thus depends on the social marginal cost of electricity. This result contrasts with the welfare implication for the labor supply response to a nonlinear income tax schedule (Liebman and Zeckhauser 2004), where the suboptimal response always produces smaller deadweight loss, because workers are less discouraged to work when they misperceive their average tax rate as the true rate.

## V. Conclusion and Discussion

This paper exploits price variation at spatial discontinuities in electricity service areas to examine whether consumers respond to marginal price or alternative forms of price in response to nonlinear pricing. The evidence strongly suggests that consumers respond to average price and do not respond to marginal or expected marginal price. I show that this suboptimizing behavior makes nonlinear pricing unsuccessful in achieving its policy goal of energy conservation and substantially changes the efficiency cost of nonlinear pricing.

Why do consumers respond to average price rather than marginal price? Given the information available to most residential electricity customers in my sample period, the information cost of understanding the marginal price of electricity is likely to be substantial. First, monthly utility bills are often complex and make it harder for consumers to understand the nonlinear structure of their pricing.

Second, it is difficult for most consumers to monitor cumulative electricity consumption during a billing month without having an in-home display that provides the information about their consumption. In contrast, such information is not required to respond to average price. Consumers can simply use the total payment and consumption on their monthly bill and do not have to understand the actual shape of their price schedule. It can, therefore, be rational for most consumers to use average price as an approximation of their true marginal price.

The discussion about the information cost raises an important question for future research: Does information provision help consumers respond to their true marginal price? Chetty and Saez (2013) find that information provision of nonlinear income tax schedules indeed changes labor supply responses in their randomized controlled trial. For electricity pricing, Wolak (2011) and Jessoe and Rapson (forthcoming) find that information provision changes the price elasticity of electricity demand. With the recent technological developments in energy markets, a growing number of consumers in the United States and many other countries now have access to real-time feedback on their price and consumption. Providing such information has the potential to improve market efficiency, provided it can help consumers to correctly perceive and respond to their actual marginal price.

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# Online Appendix for
# Do Consumers Respond to Marginal or Average Price? Evidence from Nonlinear Electricity Pricing

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April 13, 2013

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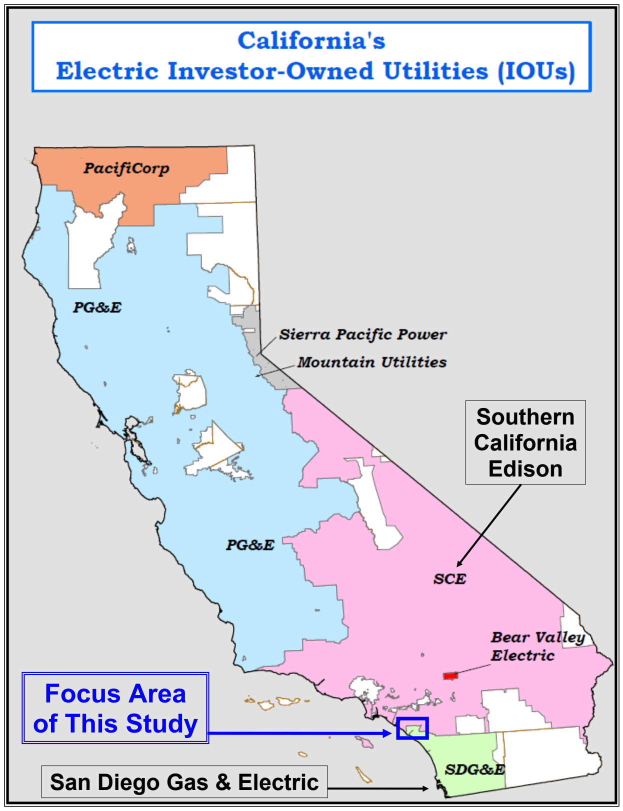
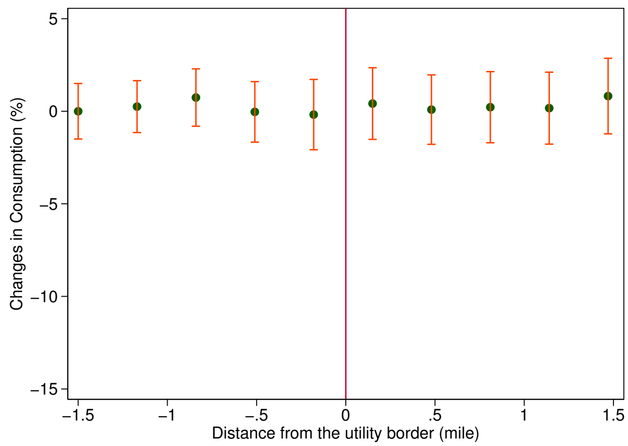
Figure A.1: Service Territories of California's Investor-Owned Electric Utilities



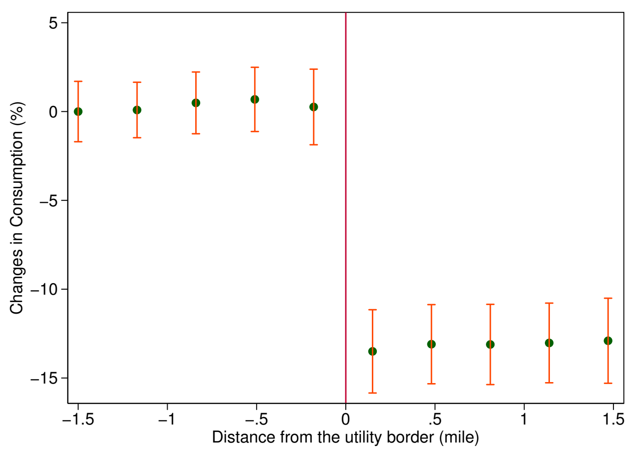

*Notes*: This figure shows a service territory map of California's investor-owned electric utilities. The original map is provided by the California Energy Commission. Blank areas indicate areas served by electric utilities that are not investor-owned. In this study, I use two electric utilities: Southern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

Figure A.2: Changes in Consumption from 1999 to 2000 by Distance from the Utility Border

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




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




*Notes*: The figure provides evidence of the validity of the spatial regression discontinuity design and suggests that using samples closer to the utility border does not affect my estimation results (shown in Table A.1). The horizontal axis shows miles from the border using negative values for SCE territory and positive values for SDG&E territory. The left-hand side of the vertical line represents the distance from the border for SCE customers and the right-hand side, the distance from the border for SDG&E customers. The dots show the mean percent change in consumption from a billing month in 1999 to the same billing month in 2000 in a 0.25 mile bandwidth. City-by-time fixed effects and billing-cycle-by-time fixed effects are subtracted to control for weather and other factors. The range bars show the 95% confidence intervals. Consumption is not statistically different between SCE and SDG&E customers before the utility companies had different price changes in the summer of 2000. However, it is systematically different after the price change.

Table A.1: Robustness Checks

| | Main Result | | Unbalanced Panel | | Samples in 1 mile of the border | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| $\Delta$ln(Marginal Price$_{t-1}$) | | 0.006 | | 0.006 | | -0.010 |
| | | (0.011) | | (0.009) | | (0.019) |
| $\Delta$ln(Average Price$_{t-1}$) | -0.075 | -0.082 | -0.077 | -0.086 | -0.076 | -0.064 |
| | (0.005) | (0.015) | (0.004) | (0.012) | (0.008) | (0.025) |
| N | 3,752,378 | 3,752,378 | 6,876,201 | 6,876,201 | 1,395,433 | 1,395,433 |

*Notes*: This table shows the results of the IV regression in equation (3) with fixed effects and control variables specified in the equation for different samples and alternative instruments. See notes in Table 2. Columns 1 to 2 show the main result that are presented in Table 2. Columns 3 to 4 use unbalanced panel data that include all households who opened and closed their electricity account during my sample period (from January 1999 to December 2007). Columns 5 to 6 limit the sample to households in 1 mile of the territory border of SCE and SDG&E. Standard errors in parentheses are clustered at the household level to adjust for serial correlation.