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**To What Electricity Price Do Consumers Respond?  
Residential Demand Elasticity Under Increasing-Block  
Pricing**

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# To What Electricity Price Do Consumers Respond? Residential Demand Elasticity Under Increasing-Block Pricing

Severin Borenstein<sup>1</sup>

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**Abstract:** It is straightforward to evaluate how a perfectly-optimizing, perfectly-informed customer will respond to a non-linear price schedule, but such a customer is rare. In the common case of increasing-block pricing of water and electricity, consumers do not know what marginal price they face during a billing period, because they do not know what demand shocks will occur during the period. If consumers instead set optimal behavioral rules based on the distribution of possible marginal prices they will face (*e.g.*, turn off lights in unused rooms, set the A/C to 74 degrees, replace incandescent lights with CFLs), their consumption will not exhibit discrete responses to the discrete jumps in the price schedule. Using data from a large electricity utility, I show that the empirical distribution of consumption quantities is not consistent with consumers accurately knowing and responding to the marginal price they will face. I then estimate the price elasticity of demand using a panel of household observations at two-year intervals, identifying elasticity from the changes in the increasing-block price schedule. The results suggest that most consumers are probably responding to the *expected* marginal price or even less precise information about what marginal price they will face. The results are difficult to reconcile with the common approach of estimating demand elasticity as a function of the *ex post* marginal price that the consumer faces along an increasing-block price structure.

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## I. Introduction

Non-linear price schedules are probably as old as commerce. They can be as simple as an up-front fee before the first transaction and then a constant marginal price per unit bought, or they can be far more complex, with many changes in marginal price as quantity changes. For any schedule, it is generally straightforward to write down how the perfectly-optimizing, perfectly-informed consumer would respond, purchasing at a point at which the consumer's marginal value of the product is equal to (and dropping below) the marginal price she faces.

In reality, consumers make such decisions with limited information, attention and cognitive abilities. In such circumstances, they will engage in behavior that may depart significantly from the perfectly optimizing paradigm. The constrained optimizing behavior in which a consumer does engage may still be a fairly sophisticated response to the limited information environment, or it may be a very simple rule of thumb. Or the consumer's decision may be based on persistent misperceptions that lead to sub-optimal decisions.<sup>2</sup> The degree of attention invested in the decision probably also depends on the magnitude of its impact. Consumers are likely to put more effort into decisions when thousands of dollars of consumer surplus are at stake than when it is just a few dollars.

Since the early twentieth century, utilities have used non-linear prices in selling water, natural gas and electricity. For most of that time, the non-linear schedules have exhibited declining average, and in some cases marginal, price. In the last 30 years, increasing marginal price schedules have become more common in utility sales of water and electricity for residential use. Generally, these are "increasing-block" price schedules, so named because of their staircase nature, with one constant marginal price up to some quantity level and a higher marginal price for consumption above that quantity.<sup>3</sup> In some cases, the schedule has more than one "step" at which the marginal price increases. Figure 1 illustrates the electricity price schedule of Southern California Edison during the spring of

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<sup>2</sup> See, for instance, Stango and Zinman, forthcoming.

<sup>3</sup> Increasing block pricing is not used for commercial or industrial pricing in part, at least, because of the much larger range of electricity consumption among these customers than among residential.

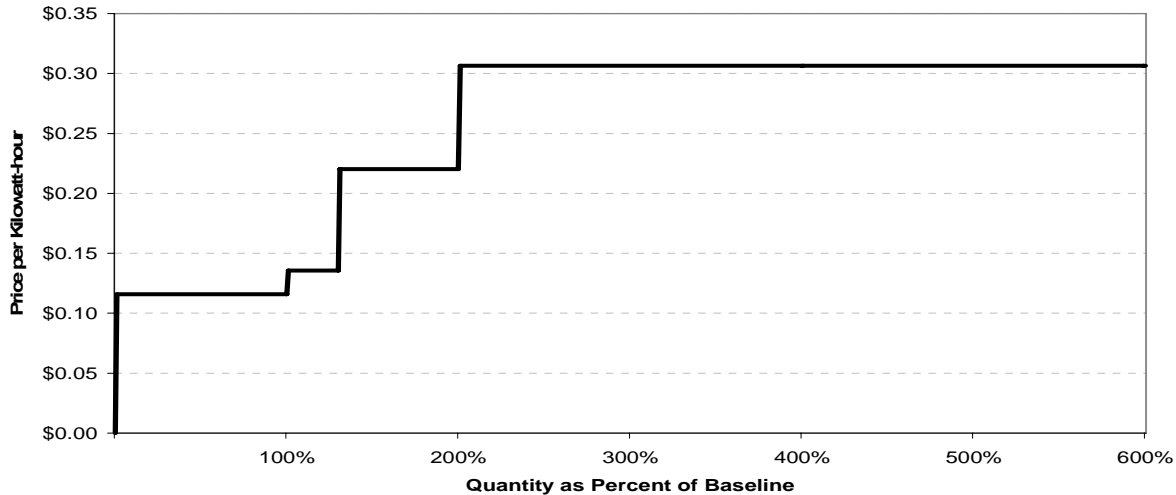


Figure 1: Increasing-Block Residential Electricity Tariff of Southern California Edison, 2006

2006 for sales to a residential customer.<sup>4</sup>

Whenever prices are not constant (and, occasionally, even when they are) economists are tempted to use the data to estimate demand elasticity. Such has been the case with non-linear price schedules for water and electricity, where a substantial literature has developed with the goal of estimating price elasticities from static, but non-linear, price schedules.<sup>5</sup> Most of this literature, however, has been based on the maintained assumption that customers are perfectly informed and perfectly optimizing on the margin at every moment. While internally consistent, such an assumption seems to be at odds with the way nearly everyone actually thinks about their residential water and electricity consumption. It seems safe to say that not only do most consumers not know how much power or water they have used since their current billing period began, most consumers don't know when their current billing period began.

Some of the previous research has recognized that customers may exhibit “optimization

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<sup>4</sup> Most residential electricity tariffs also include a daily service charge that is independent of usage, but this generally makes up a very small proportion of the bill.

<sup>5</sup> In electricity, see Taylor (1975), Henson (1984), Shin (1985), Herriges & King (1994), Reiss & White (2005) and Bushnell & Mansur (2005). Of these, Shin and Bushnell & Mansur consider in depth the possibility that customers cannot or do not optimize on the marginal price they face. A similar literature exists in water pricing. See Hewitt & Hanemann (1995) and Olmstead, Hanemann & Stavins (2007). Liebman and Zeckhauser (2004) treat directly the issue of sub-optimizing consumer behavior in the face of complex price schedules.

error,” the consumer failing to hit exactly the consumption quantity that she had intended within a billing period. These works take a step towards reality, but sacrifice some degree of internal consistency. They assume that consumers imperfectly hit the optimized consumption for which they have solved, but they assume that consumers themselves do not respond to the fact that they will hit their consumption target with error.

In this paper, I first present a model of consumers engaging in constrained consumption optimization when facing an increasing-block price schedule. The model is intended to better reflect how real-world residential electricity and water consumers are likely to behave. In it, consumers make “behavioral rule” decisions about their consumption patterns before the consumption period begins, then exogenous shocks to quantity demanded occur during the consumption period, but consumers do not change their behavior in response to the fact that the exogenous shocks change the marginal price they face. In setting their behavioral rules prior to the period, however, consumers are aware of the distribution of the potential shocks and optimize over that distribution. The model is an alternative to the perfectly-optimizing model, as well as to a simple rule-of-thumb model in which customers respond only to the average price of power.

In the remainder of the paper, I then explore the empirical relevance of all three models. Using household-level billing data from Southern California Edison, a utility with more than four million residential customers, I first compare some consumption patterns in the data with what one would expect to see under each model. I show that the cross-sectional distribution of quantity demanded in the data is not consistent with a perfect-optimization view of consumer behavior even when optimization error of up to 10% is incorporated. The finding is difficult to square with attempts to estimate the price elasticity of demand that rely heavily on the perfectly-optimizing model and are identified from consumer response to the abrupt changes in marginal price along the increasing-block price schedule.

Because the data include the years 2000 to 2006, I am then able to estimate demand for electricity identified by changes in the residential tariff that occurred over time. While a dataset that is a panel of household-level consumption and prices suggests that fixed-household-effect estimation might be revealing, I argue that short-run and long-run mean reversion in household consumption make this approach less robust than one might think. I propose an alternative estimation strategy, based on distributions of consumption in small

geographic areas, that is likely to be more robust.

Attempting to characterize any one of the three customer-behavior models as the single correct model would be obviously misguided. There is certainly a continuum of types of decision-making consumers, from those who pay little attention to their electricity bills and do not even know the pricing structure, to those who scrutinize their bills in detail and closely monitor their consumption in order to respond optimally to changes in marginal price. It is valuable, however, to develop an understanding of the distribution of the population across these types. Such information, for instance, would be quite helpful in forecasting the impact of a shift from a flatter price structure to a steeper increasing-block structure. The results of the demand estimation suggest that of the three customer-behavior models, both the average-price-response model and the constrained-optimization model have significant explanatory power, but the perfect-optimization model has comparatively little.

## II. Models of Customer Response to Increasing-Block Pricing

In the standard model of customer response to increasing-block pricing, the buyer has an inverse demand function that represents her marginal value of consumption during a billing period as a function of quantity,  $q$ , and other demand shifters,  $\mathbf{X}$ :  $P = P(q, \mathbf{X})$ , where demand is downward sloping,  $P_1 < 0$ .<sup>6</sup> The buyer faces a discontinuous marginal price schedule such as shown in figure 1. The buyer then optimizes through a series of inequality constraints. If the price schedule were a simple two-block structure –  $p_1$  for  $0 < q < \hat{q}$  and  $p_2$  for  $q > \hat{q}$  – then the optimal consumption would be

$$\begin{aligned} q &= P^{-1}(p_1, \mathbf{X}) && \text{if } P(\hat{q}, \mathbf{X}) \leq p_1 \\ q &= P^{-1}(p_2, \mathbf{X}) && \text{if } P(\hat{q}, \mathbf{X}) \geq p_2 \\ q &= \hat{q} && \text{if } p_2 > P(\hat{q}, \mathbf{X}) > p_1. \end{aligned}$$

From the fact that the customer faces a discrete marginal price shift at  $\hat{q}$  has emerged

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<sup>6</sup> A bit of attention to income effects is needed at this point, because a non-linear price schedule means that the usual relationship between substitution and income effects may not hold, depending on how the infra-marginal price changes relative to the marginal price a customer faces. In the case of electricity, however, income effects are likely to be extremely small. For a median customer in these data, with a \$50/month electricity bill, even a 50% change in *average* price would mean an income change of \$25/month, about 0.6% of monthly median household income. Typical estimates of the income elasticity of electricity demand is between 0.5 and 1.0. So, the income effect of this large price change would be a quantity change of less than 0.6%. The empirical work suggests that even with very price-inelastic demand, this is a small component of the effect.

the argument that price elasticity of demand may be estimated from a single static price schedule. Reiss & White (2005) explain the approach:

Intuitively, one can use the variation in consumption among all households on the same tariff segment to identify the non-price components of demand. Given that, the effect of price can be determined from the remaining difference in average consumption between households on different tariff segments, less the average difference in their unobserved characteristics. The latter is computable from the marginal distribution of  $\epsilon$  (*unobserved consumer characteristics*) and the price schedule. Researchers can therefore estimate demand without price schedule variation, provided one is willing to place some distributional restrictions on  $\epsilon$ .

Econometrically, estimation of this model has been done in a linear regression by instrumental variables<sup>7</sup> or with a mixed discrete/continuous choice (DCC) model estimated by maximum likelihood or with a method of moments estimator.<sup>8</sup> In the DCC models, consumers are assumed to calculate their preferred consumption if they were to face each of the possible marginal prices on the different steps and then choose on which of the steps to consume. These approaches, however, rely on discrete price changes at identifiable points and on the assumption that consumers respond to those abrupt price changes. That is, these papers assume that consumers chose their consumption quantity based on the marginal price that they are observed to have faced. Some research recognizes that consumers do not exactly hit their consumption target in every billing period due to variations in daily activities, weather, and other factors. This optimization error is argued to be part of the error term.

In practice, this view of consumer behavior is quite demanding. First, it has the obvious information requirements that the customer knows the date his current billing period began and will end, and the prices and quantity break points in the increasing-block schedule. More importantly, if there are any exogenous shocks to his demand, this approach requires that the consumer knows (or, at least thinks he knows) those shocks with certainty for the entire billing period at the time the period begins. Otherwise, when the consumer is choosing consumption on day 1 of the billing period he will not know the marginal price on which he should base his decision.

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<sup>7</sup> See Henson (1984), Shin (1985), Herriges & King (1994) and many of the papers reviewed in Taylor (1975).

<sup>8</sup> See Hewitt & Hanemann (1995), Reiss & White (2005), Olmstead et al (2007), and Olmstead (2008).

Consumers, of course, don't know exactly how their lives and electricity demand will evolve over the next month, so even if they were as compulsive as the model suggests, they would still have to make guesses throughout the period about the marginal price they will face for consumption.<sup>9</sup> Furthermore, it seems realistic to say that consumers know that they don't know the future and, as a result, rather than responding to the actual marginal price that results at the end of the period, they would be optimizing based on an expected marginal price. If there is much uncertainty about consumption over the entire billing period, this means that much of the consumption will be based on a guess of the ultimate marginal price that is a probability-weighted average of prices on the different steps. Those probabilities, and the expected marginal price, change smoothly with the expected consumption level. Thus, a customer whose final consumption ends up being five percent less than  $\hat{q}$  may have made most of his consumption decisions based on an expected price that differs only slightly from the expected price of a consumer whose final consumption ends up being five percent more than  $\hat{q}$ .

More realistically still, it seems likely that the vast majority of customers do not monitor their consumption relative to the price schedule during a billing period. Even that level of monitoring would require knowledge of the beginning and end dates of the billing period and frequent visits to the meter (as well as knowledge of how to read the meter) and record-keeping during the billing period. Such behavior is, to say the least, rare.

I propose an alternative model in which the consumer sets behavioral consumption rules – *e.g.*, turn off the computer at night, buy a more energy efficient refrigerator, replace some incandescent bulbs with compact fluorescents, set the A/C at 76 degrees – prior to the period based on an expectation of marginal price and does not update the rules until he receives feedback in the form of an electricity bill for the period. To be concrete, assume that the consumer has quasi-linear utility

$$U = V(q(r, X), X) + (I - B(q(r, X))) \quad [1]$$

where  $V(\cdot)$  is the utility derived from electricity consumption, which is a direct function of the quantity consumed and demand shocks, and the quantity consumed is a function of the consumption rules,  $r$ , adopted and demand shocks. The consumer controls  $q$  only

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<sup>9</sup> Albeit, these would be increasingly well-informed guesses as the end of the period approaches.



through adjustments to  $r$ , which must be set before knowing  $X$ . The second term is the residual income, total income minus the electricity bill, which is a non-linear function of electricity consumption.<sup>10</sup>

The consumer chooses  $r$  to maximize expected utility over the distribution of possible  $X$  values. Expected utility is

$$E[U] = \int [V(q(r, X), X) + (I - B(q(r, X)))] f(X) dX \quad [2]$$

Setting the derivative of  $E[U]$  with respect to  $r$  equal to zero gives

$$\int \frac{dV(q(r, X), X)}{dq(r, X)} \frac{dq(r, X)}{dr} f(X) dX = \int \frac{dB(q(r, X))}{dq(r, X)} \frac{dq(r, X)}{dr} f(X) dX \quad [3]$$

Equation [3] shows that the consumer will set  $r$  so that the expected marginal value from changing  $r$  slightly, taken over the distribution of  $X$ , is equal to the expected marginal change in his electricity bill from that change in  $r$ , taken over the same distribution.

A similar issue of constrained optimization has arisen in the study of labor supply response to increasing marginal tax rates.<sup>11</sup> Saez (2002) proposes a similar model in which the worker must choose effort before knowing an exogenous shock to his income. The variation here is that both the benefit and cost of the activity are potentially affected by the shock. That is, the marginal value of electricity is also dependent on the exogenous shock, not just the marginal cost of electricity, and the choice variable is therefore a consumption rule, rather than the target consumption quantity itself, that must be set before knowing the shock. For example, the typical consumer's marginal value of electricity is dependent in part on the weather, so even with price certainty it is more likely that she would decide *ex ante* on a given thermostat setting (a behavioral rule) rather than a target consumption level.

If the distribution of  $X$  is massed as a point, then  $r$  is just the deterministic optimal response to that  $X$  and the  $B(\cdot)$  function, and [3] simplifies to the standard marginal price optimization that many earlier papers have assumed. Some papers have recognized that

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<sup>10</sup> This quasi-linear utility function eliminates income effects, which I argued in footnote 6 is a reasonable approximation over the relevant price schedules.

<sup>11</sup> See Hausman (1981), Hausman (1983), Heckman (1983) and Saez (2002).

$X$  has a non-degenerate distribution, but within this formulation, they have assumed that customers ignore uncertainty in  $X$  when choosing  $r$ . Instead, consumers are assumed to base their decision on expected  $X$ , and are then consistently surprised that their quantity consumed is not what they had planned, resulting in the previously-mentioned optimization error:<sup>12</sup>

$$\frac{dV(q(r, \bar{X}), \bar{X})}{dq(r, \bar{X})} \frac{dq(r, \bar{X})}{dr} = \frac{dB(q(r, \bar{X}))}{dq(r, \bar{X})} \frac{dq(r, \bar{X})}{dr}. \quad [4]$$

Even the constrained optimization model I propose assumes what may seem to most people an unusual degree of involvement with one’s electricity consumption. Many people are unaware of the existence of an increasing-block price schedule or where the jump points are in the schedule relative to their consumption.<sup>13</sup> Many people also are unaware of the amount of electricity they consume (or even the units in which it is measured). These people might still respond to changes in their bills, but they might, for instance, not distinguish between a change in the marginal price they face on a given schedule and an overall change in the price schedule. For such people, the constrained optimization model might far exceed their sophistication of decision making. Therefore, a third model that I consider is that consumers respond to the average price of electricity they are charged. These consumers are assumed to have a rough idea of their consumption and to be able to infer roughly their average price, but they cannot or do not infer their expected marginal price of consumption.<sup>14</sup>

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<sup>12</sup> A model of “perfect optimization under uncertainty” is also possible in which the customer starts the billing period with a believed distribution of the marginal price he will face and constantly updates (and narrows) that distribution, and changes  $r$  in response, as  $X$  is revealed over the billing period. While this is technically plausible, it still requires much more attention to optimization in electricity consumption than one generally observes. This behavior would manifest, for instance, as the customer setting his air conditioning to a higher temperature near the end of the billing period – controlling for current weather conditions – if previous days had been unusually hot because he is more likely to face a higher marginal price in that billing period. I do not model this behavior explicitly, but it is clear that the implications would lie “between” the perfect optimization model and the constrained optimization model.

<sup>13</sup> Until a redesign of utility bills in 2008, SCE residential bills did not give a customer information about the marginal price of consumption above the tiers on which he is consuming. Even calculating it from their website required merging of data from different web pages.

<sup>14</sup> Evidence in support of this model comes from at least two common practices. First, energy efficiency tags on refrigerators and other appliances give a range of price impact comparisons based on the average

Intuitively, it is clear that both the constrained optimization model and the average-price optimization model will not yield the sort of customer behavior that is assumed for the marginal-price optimization approaches to elasticity estimation from increasing-block pricing. The price schedules that consumers optimize against will not exhibit discrete jumps. I examine these implications empirically in section IV after introducing the data in the next section.

### III. Data and Sources

The primary data for this analysis come from residential billing records of Southern California Edison, which were made available to the U.C. Energy Institute under a confidentiality agreement. The dataset used in this analysis includes virtually all residential bills for 1999-2006. Customers who were not individually metered, but instead are part of a “master-metered” building or other location, were not included in the data. In aggregate, such accounts constitute less than 3% of residential consumption at SCE.

The increasing-block tariff structure implies an increasing *marginal* price for electricity. A SCE customer whose consumption level puts him or her on the highest tier, for instance, still pays the lower-tier rates for consumption up to the highest tier.

The marginal rate that a residential customer pays increases as consumption increases relative to a “baseline” consumption level. A household’s baseline allocation is supposed to correspond to a minimal basic electricity usage. The baseline, however, is the same for all residential customers in a region regardless of the size of the residence or the number of people who live there. Within the region, a studio apartment receives the same baseline allocation as a four-bedroom house.<sup>15</sup> Baseline allocations do differ by geographic regions within the utility area: SCE’s service territory is divided into 6 different baseline regions. This is argued to reflect variation in basic electricity need due to climate differences, but in practice baselines are set based on different average usage across regions. As a

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price of electricity in different areas of the country, and the range does not include the prices on the upper tiers of California rates. More surprisingly, many vendors of residential solar photovoltaic systems in California advertise bill savings from such systems that are calculated based on the average price of electricity rather than the marginal price of replaced kilowatt-hours. The latter is likely to be much higher for customers that the solar PV vendors are targeting in California.

<sup>15</sup> The baseline allocation is higher for customers who have electric heating systems and some other electrical appliances.

result, variation is driven not only by climate differences, but also by wealth levels, average residence size, and choices to install air-conditioning.<sup>16</sup>

Prior to the California electricity crisis in 2000-01, SCE had a two-tier rate structure with an 18% price difference between the steps. All consumption above the baseline level was charged at the second-tier rate. After the electricity crisis, a 5-tier tariff was implemented with marginal price changing at 100%, 130%, 200% and 300% of baseline. Prices were virtually frozen for consumption up to 130% of baseline, the bottom two tiers, but were increased substantially for higher tiers. In later periods, the fourth and fifth tiers have sometimes been assigned the same marginal rate.<sup>17</sup>

Not all of SCE's residential customers are on the standard tariff. The largest exception from the standard tariff is customers who are on the CARE (California Alternate Rates for Energy) program, which is an income-based program that offers lower rates to low-income customers.<sup>18</sup> About 27% of SCE's customers were on CARE in 2006, up from 11% in 2000. The CARE program is advertised as offering "a 20% discount" off the standard residential rates, but not all components of the bill are included in the discount and some fees are excluded entirely for CARE customers. In practice, the discount is 20%-30% on the lowest two tiers of consumption and greater than that for higher tiers. I exclude CARE customers from the price elasticity analysis, as explained in more detail below.

A small number of customers are on special tariffs that incorporate time-of-use electric-

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<sup>16</sup> I drop bills with outlier quantities, which were defined as less than 2 kWh/day or more than 8 times baseline consumption. A refrigerator typically uses at least 1-2 kWh/day, so it is implausible that an occupied primary residence would fall below 2 kWh/day. The 8 times baseline upper bound is over 120 kWh/day per day for a typical house in the summer. This translates to a constant consumption of 5 kW at all time which would require a large central air conditioning unit to be running (not just turned on, but never cycling off) practically continuously. A small share of bills are based on estimated usage because meter readers are unable to access the meters. SCE reported during the sample period that about 0.4% of residential bills were based on estimated usage. These are not identifiable in the dataset, so no attempt to adjust for estimation is made.

<sup>17</sup> Under SCE's standard residential rate during March-May 2006, a customer with a baseline consumption allocation of 300 kWh during a given billing period who actually consumes 1100 kWh would pay 11.58¢ for each of the first 300 kWh, 13.55¢ for each of the next 90 kWh, 22.03¢ for each of the next 210 kWh, 30.65¢ for each of the next 300 kWh, and 30.65¢ for each of the last 200 kWh (tiers 4 and 5 had the same marginal rate in 2006).

<sup>18</sup> For June 2008 through May 2009, a residence with one or two occupants must have a household income no higher than \$30,500 in order to qualify for CARE, with the threshold increasing by \$5,300 for a third occupant, and by \$7,400 for each additional occupant.

	<b>Tier 1</b>	<b>Tier 2</b>	<b>Tier 3</b>	<b>Tier 4</b>	<b>Tier 5</b>
<b>Range of Tier (as a percentage of baseline)</b>	<b>0% -100%</b>	<b>100%-130%</b>	<b>130%-200%</b>	<b>200%-300%</b>	<b>300% and up</b>
Percentage of Total Residential Usage	55.2%	11.1%	16.9%	10.8%	6.0%
Percentage of Customers on Tier for Marginal Consumption	32.0%	14.5%	25.5%	17.5%	10.4%
Marginal Electricity Price (\$/kWh)	0.1158	0.1355	0.2203	0.3065	0.3065

Table 1: Percentage of kWh sold and Percentage with Marginal kWh on Each Tier in 2006 (non-CARE customers only)

ity pricing, special rates for SCE employees, for people with electric vehicles, and other idiosyncratic rate structures. In aggregate, these nonstandard tariffs cover less than 1% of residential customers and residential consumption.<sup>19</sup> Most of these customers still face a five-tier tariff with the same baseline allocation and breakpoints between the tiers as if they were on the standard residential tariff, but with somewhat different rates. I exclude these customers as well from elasticity analysis.

Regardless of the tariff that a customer is on, the customer has an assigned baseline consumption and his or her monthly consumption can be allocated across the tiers shown in table 1. For customers not on the CARE program, the top row of table 1 shows the total quantity of residential consumption that was billed on each of the tiers during 2006, the last year included in this analysis. The second row of table 1 shows the proportion of households whose average daily consumption puts them on each of the five tiers for their marginal consumption. Among SCE’s non-CARE customers, 32% consume less than the baseline and therefore face the tier 1 price for their marginal consumption, while 10.4% consume more than 300% of baseline so face the tier 5 price for their marginal consumption.

Typically, a residence receives a bill about every 30-33 days, but the number of days

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<sup>19</sup> One larger program is the “automated power shift” (APS) program that allows SCE to cycle off residential air-conditioning units for short periods of time. This program, however, operates only during the summer and impacts only summer rates.

varies over time even for a given premises. The customer’s baseline consumption for the billing period is his *daily* assigned baseline multiplied by the number of days in the billing period. With that baseline consumption figure for the period, total consumption can be allocated across the tiers. Combining these data with historical residential tariff information and matching the consumption across tiers to the contemporaneous residential tariff then yields the customer’s total bill for electricity (before any daily connection charge, bill adjustments, or other fees that are independent of the level of consumption), as well as the marginal price that the customer faced.

The data do not include the address or the name of the customer. They do, however, include the nine-digit ZIP code, which allows a fairly precise neighborhood matching with census data. Summary household demographic data are available from the U.S. Census at the level of census block group (CBG), a geographic designation that on average includes about 600 households in SCE territory. Census block groups are considerably larger than the areas associated with nine-digit ZIP codes. Each nine-digit ZIP code is assigned to the CBG in which it was located.<sup>20</sup>

#### IV. Evidence About Customer Optimization

As described earlier, nearly all of the literature that has estimated customer price elasticity in response to increasing block pricing has assumed that customers optimize on the *ex post* observed marginal price that they face.<sup>21</sup> Some have assumed that customers implement this strategy with some error. If this were the case, one would expect to see customers “bunched” around the points where the marginal price increases. This is the standard result of a kinked budget constraint. Saez (2002) examines a similar phenomenon regarding labor supply decisions around income levels at which marginal income tax rates change, an issue that was discussed two decades earlier by Heckman (1983) and Hausman

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<sup>20</sup> A small number of customer records did not include a nine-digit ZIP code, or did not match to a nine-digit ZIP code in the census data. In the case of nine-digit ZIP codes that did not match to the census data, I used the numerically closest nine-digit ZIP code. In the case of having only a five-digit ZIP code, those customers were allocated probabilistically among all of the nine-digit ZIP codes within the five-digit ZIP code based on the share of households that were in each of the nine-digit ZIP codes.

<sup>21</sup> Assuming that customers optimize on the *ex post* marginal price is not equivalent to ignoring endogeneity, nor is the problem alleviated by correcting for the endogeneity of price.

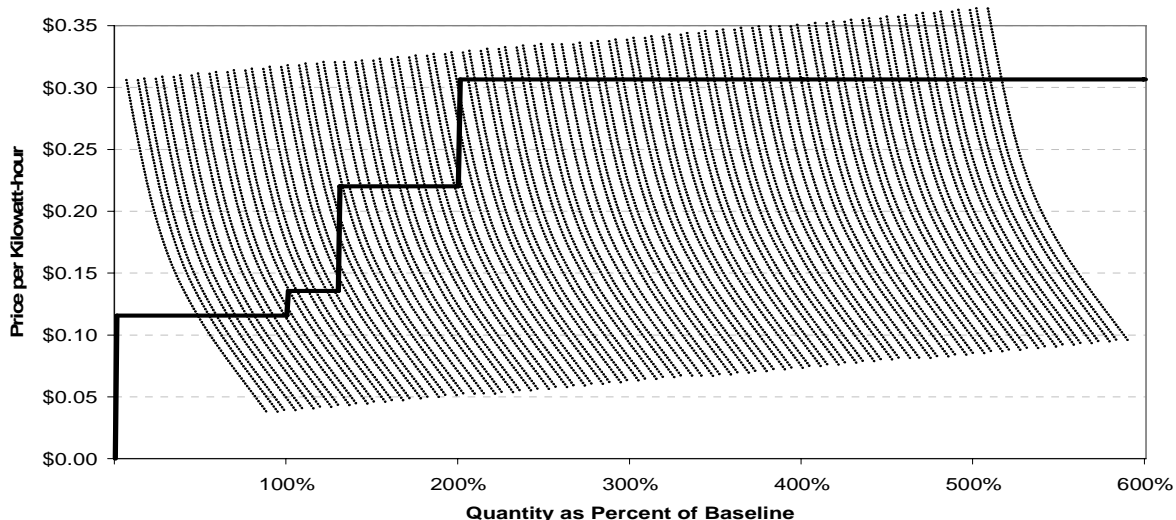


Figure 2: Uniform Distribution of Demand Functions and Bunched Quantities Demanded (1981, 1983). Saez finds evidence of much less bunching than optimizing behavior would suggest. I find a similar result for changes in marginal electricity rates.

Figure 2 illustrates why one would expect to find bunching at the quantities where marginal electricity price increases. If the distribution of customer demand functions is smooth around these marginal price changes, then a disproportionate share of customers should be observed choosing consumption that is exactly at the point of price increase.<sup>22</sup> While in practice customers are not likely to target their consumption down to the last kilowatt-hour, one would expect to see a tendency to be much more careful about further consumption increases at the points where the marginal price increases, and that would result in bunching. If customers try to optimize, but have very large optimization error, then there would be little or no bunching, but there would also be less hope of identifying demand elasticity based on responses to the jumps in the *ex post* observed marginal price.

The potential magnitude of the bunching effect is illustrated in figures 3 and 4. Figure 3 shows a fairly typical distribution of customer demand quantities under a flat-rate tariff.<sup>23</sup>

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<sup>22</sup> In the absence of uncertainty, the conditions for finding this bunching for optimizing consumers are quite weak. It requires only that demand has elasticity less than zero and the distribution of demand functions does not happen to have large troughs right around the quantities where the steps in the tariff occur. The normal unobserved (to the econometrician) customer heterogeneity that justifies the usual regression error would not reduce the level of bunching one should observe in the data. Optimization error does reduce bunching, as discussed below.

<sup>23</sup> This is actually taken from the distribution of SCE customer quantities demanded in 1999 when there

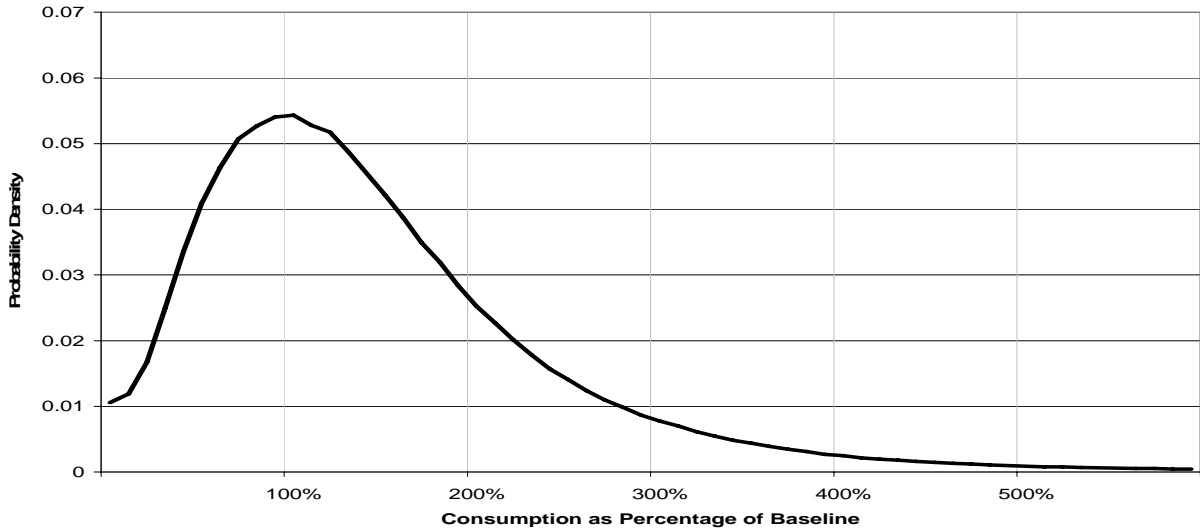


Figure 3: Distribution of Quantity Without Retail Bill Tiering

If this distribution were the result of a population of customers each with a demand function  $q_i = a_i p^\epsilon$ , then one can determine the distribution of the  $a_i$ ,  $h(a_i)$ , for any  $p$ ,  $\epsilon$ , and population of  $q_i$ . With that empirical distribution of  $a_i$ , it is straightforward to calculate the share of customers that should be observed consuming in any quantity interval. Figure 4 illustrates this exercise using the distribution from figure 3, assuming a demand elasticity of -0.1 and SCE’s standard residential 4-tier price schedule that was presented in figure 1. The figure is constructed using quantity intervals of 10% of the baseline consumption quantity for the frequency calculations. Customers who would, theoretically, consume exactly at the quantity at which a price change occurs are allocated equally to the two adjoining intervals. This allows for optimization error – the failure of a household to hit exactly the consumption level that it targets – uniformly distributed across plus or minus 10% of baseline quantity or about 7% of the average household’s consumption.

The calculation suggests that for the largest step in SCE’s tariff, which occurs at 130% of baseline, there should be bunching in the adjoining 10 percentage point intervals that creates about a 35% bump in the population of those intervals compared to linear interpolation between adjoining intervals. For the second largest step in SCE’s tariff, at 200% of baseline, the bump should be about 30%. If one assumes instead that optimization error spreads actual consumption uniformly around the desired quantity by 20% of baseline,

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were only two-steps to the tariff with a 18% price increase.



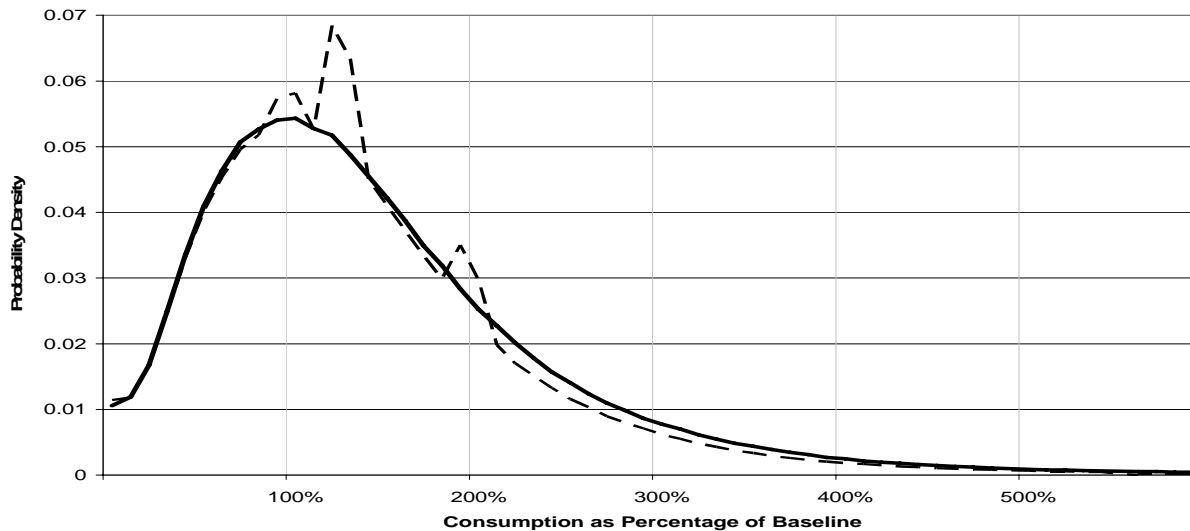


Figure 4: Simulated Distribution of Quantity Demanded Under SCE's 2006 Four-Tier Tariff instead of 10% of baseline, that cuts the size of these peaks in the distribution by half, but still leaves them quite large. On the other hand, if one assumes a long-run demand elasticity of -0.2 or larger that makes the peaks more pronounced.<sup>24</sup>

Figure 5 presents the actual observed effect of the increasing marginal prices for SCE customers for all bills in March, April and May 2006 or, more accurately, the absence of such an effect. Similar non-effects are evident for other years.<sup>25</sup> The hypothesis that the actual distributions could be a random outcome of draws from the theoretical distribution that would result from marginal price optimization with optimization error up to plus or minus 10% of baseline is clearly rejected.<sup>26</sup> This seems to be inconsistent with estimates of demand elasticity based on optimized customer response to changes in marginal prices along the schedule, though a sufficiently large optimization error would, of course, eliminate the bunching, which I discuss further below.

This is not to say that consumers never respond to marginal prices for electricity, nor

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<sup>24</sup> Reiss & White (2005) report an elasticity of -0.39. Theirs is a medium-run estimate of sorts because it is based on cross-sectional consumption variation, but holds constant appliance ownership. Their estimate would imply very significant bunching.

<sup>25</sup> Likewise, 2006 data for the other two investor-owned utilities in California – Pacific Gas & Electric and San Diego Gas & Electric – also show no bunching.

<sup>26</sup> Figure 5 is based on about 12 million billing observations over more than four million households.

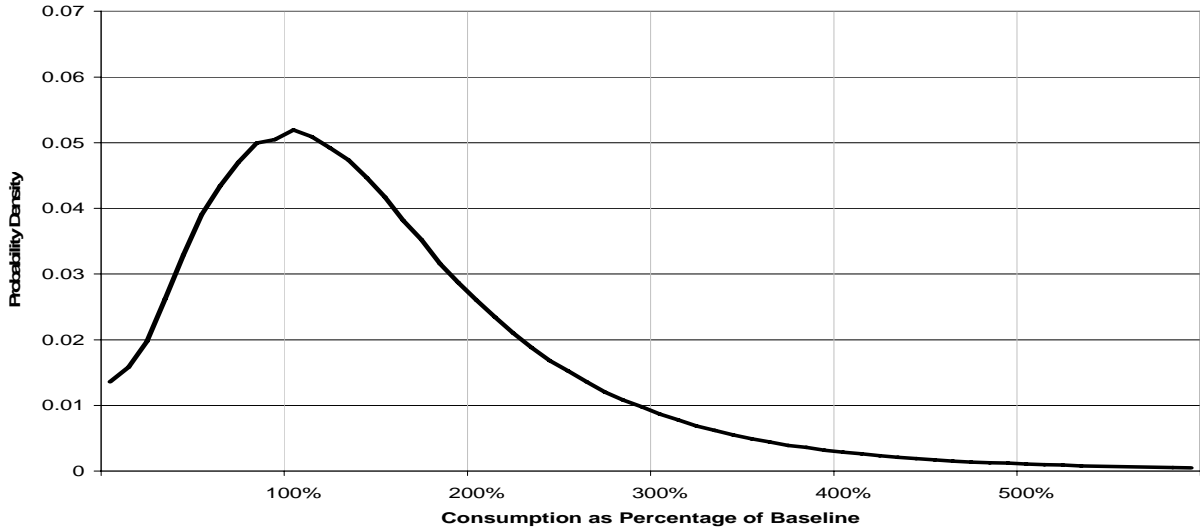


Figure 5: Actual Distribution of Quantity Demanded Under SCE’s 2006 Four-Tier Tariff

that they would fail to show additional response if they were given more information in a sufficiently clear format. In the case of SCE, however, the evidence is quite strong that consumers are not responding to marginal prices in the way that the simplest consumer theory would predict. This leaves the questions of what, if any, notion of price customers do respond to, and how sensitive this is to the amount and type of information the utility gives the customer. The data available for this study do not allow analysis of the second question, but time series of data from SCE do allow a broader analysis of customer price response.

*How Predictable is Customer Usage and Marginal Price?*

As illustrated in section II, the degree to which the standard estimation of residential electricity demand – based on marginal-price response to increasing-block pricing – captures consumer behavior depends in part on the consumer’s predictability of his own demand and the amount of “optimization error.” Such uncertainty also affects how a constrained-optimizing consumer will respond to an increasing-block schedule. Studying time series data on customer usage gives an idea of the size of the uncertainty.

To explore this issue, I selected from the SCE dataset a random sample of 10,000 customers with at least 60 bills, or about 5 years, in the dataset. For each customer separately,

the following regression was estimated:

$$\ln(\text{Daily\_Use})_t = \sum_{j=1}^{12} \alpha_j \cdot \text{Month}_j + \beta \cdot \ln(\text{Daily\_Use})_{t-1} + \gamma_1 \cdot t + \gamma_2 \cdot t^2 + \gamma_3 \cdot t^3 + \epsilon, \quad [5]$$

where  $\text{Month}_j$  are twelve month-of-year dummy variables. The standard error of this regression, the root mean squared error corrected for degrees of freedom (RMSE), is an indication of how well consumers are likely to be able to predict their consumption in a period. This RMSE could be an upward biased estimate of consumer uncertainty if consumers have better information about this month’s consumption than is revealed by their typical seasonal pattern, last month’s consumption, and a cubic function in time. It could be biased down both because some consumers pay far less attention to consumption than this regression suggests and because most customers have lived in their current location less than 8 years – 8 years is the median length of time that the customers in this subsample were at their location during the sample period – and are working with much less data than is in these regression.<sup>27</sup>

The results from the sample of 10,000 customers indicates an average RMSE of 0.186 and a median of 0.159, suggesting that with this information the average consumer will be able to predict his consumption with a standard error of about 20% (median 17%), or a 95% confidence interval of plus or minus 40% (median 34%).<sup>28</sup> That degree of noise in consumption choice seems likely to make it quite difficult to infer price responsiveness of demand from changes around discontinuities in the marginal price even if customers did not account for the marginal price uncertainty when choosing their behavioral rules.

The implications of that noise are still greater in the context of the constrained-optimization model of consumer behavior. That is, if consumers actually optimize against the fact that there will be very considerable unpredictable variation in their consumption after they set their behavioral rules – and therefore very considerable unpredictable variation in the marginal price they face – then behavior is less likely to exhibit much response to the discontinuities in the price schedule.

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<sup>27</sup> I also omit prices from this regression, though given the inelasticity of demand that is a very small effect relative to the RMSE found. I also don’t explicitly control for the California electricity crisis in 2000-01 and the public appeals for conservation that accompanied it.

<sup>28</sup> The number is higher in the summer months due to air conditioning, but even in the March-May period on which I focus it is only 1-3 percentage points lower than the overall mean and median.

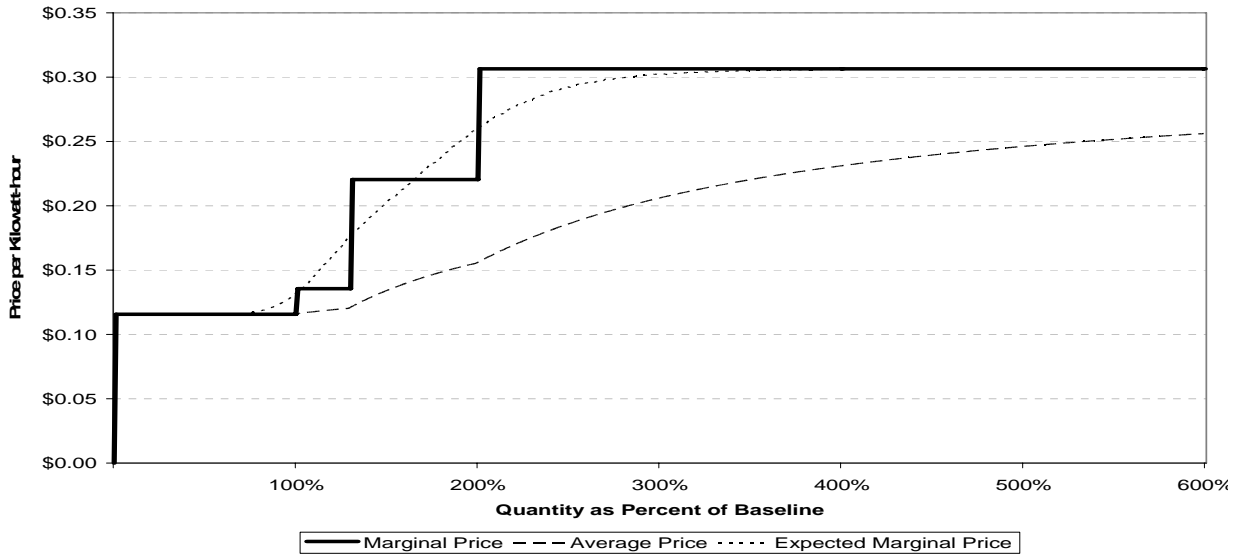


Figure 6: Marginal, Expected Marginal and Average Price Under SCE’s 2006 Four-Tier Tariff

A straightforward application of this empirical finding illustrates its implications. In order to focus on the effect of uncertainty over marginal price, assume that the behavioral rules adopted are such that the derivative of utility with respect to the choice of  $r$  will be invariant to the demand shock  $X$ . This would be the case, for instance, if the rule is “always have  $W$  watts of lighting on when I am at home in the evening,” and the variation is due to the unpredictability of how often I am at home in the evening.<sup>29</sup> The impact of the demand shock is then only on the marginal price of consumption, the right-hand side of the equation [3]. That is, the consumer will set the behavioral rule in order to equalize the (deterministic) marginal value of changing  $r$  with the expected marginal cost of changing  $r$ .

Figure 6 shows the SCE price schedule from figure 1 along with the expected marginal price a consumer would face for each possible expected level of consumption, assuming that his actual level of consumption is the expected plus a normally distributed random variable with mean zero and standard error equal to 20% of the expected consumption. As one would expect, the expected marginal price is quite a bit smoother than the underlying

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<sup>29</sup> More precisely, the shocks that determine how much time I spend at home in the evening do not affect the marginal value I get from additional lighting when I am at home, so the shocks will not change the optimal  $r$  for a given marginal price. This isn’t as likely to hold precisely in terms of heating and cooling. The value of lowering the thermostat to 74 degrees from 78 degrees may be different when the outdoor temperature is 80 degrees than when it is 95 degrees.

price schedule. Figure 6 also shows the average price of consumption, which could be relevant for the reasons discussed earlier.<sup>30</sup>

But the impact on the *ex post* observed quantity is even more substantial, because it is equal to the constrained-optimized target quantity plus optimization error caused by a random draw on  $X$ . Assuming an error with a standard deviation equal to 20% of the target quantity, Figure 7 presents the *ex post* distribution of quantity that one would expect to observe when the underlying distribution of expected demand is as shown in figure 3 and the elasticity of demand is -0.1. Besides the underlying quantity distribution (under a flat tariff), figure 7 presents the simulated resulting quantity distribution under marginal price optimization with optimization error and expected marginal price optimization with optimization error. Either one is clearly much more consistent with the observed demand quantity presented in figure 5 than is the simulated distribution of quantity demanded under (nearly) perfect optimization in figure 4. The optimization error alone is so large that it would wipe out any noticeable bunching in the data even if consumers were myopically optimizing on marginal price. The same is not true if one assumes 10% standard deviation optimization error or if the long-run demand elasticity were -0.3; in either of those case, simulated marginal price optimization with optimization error still produces noticeable bunching that is not present in the actual data, while expected marginal price optimization with optimization error produces a smooth distribution of quantity demanded.

Thus, if consumers attempt to respond strictly to marginal price, but have large demand shocks that they ignore in their economic decision making, then their resulting distribution of consumption could possibly be consistent with marginal price optimization. This explanation only fits the data if consumers have quite inelastic demand. The behavior still would be internally somewhat inconsistent, a combination of careful marginal optimization on a target marginal price while ignoring the probability distribution of marginal price. A consumer who accounts for the exogenous demand shock in planning consumption – a constrained-optimizing view – would face a much smoother expected marginal price function. The resulting patterns of quantity demanded would be very similar if optimization error is sufficiently large and demand is sufficiently inelastic, but myopic behavior would

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<sup>30</sup> Average price excludes the 17¢/day connection charge that is independent of consumption.

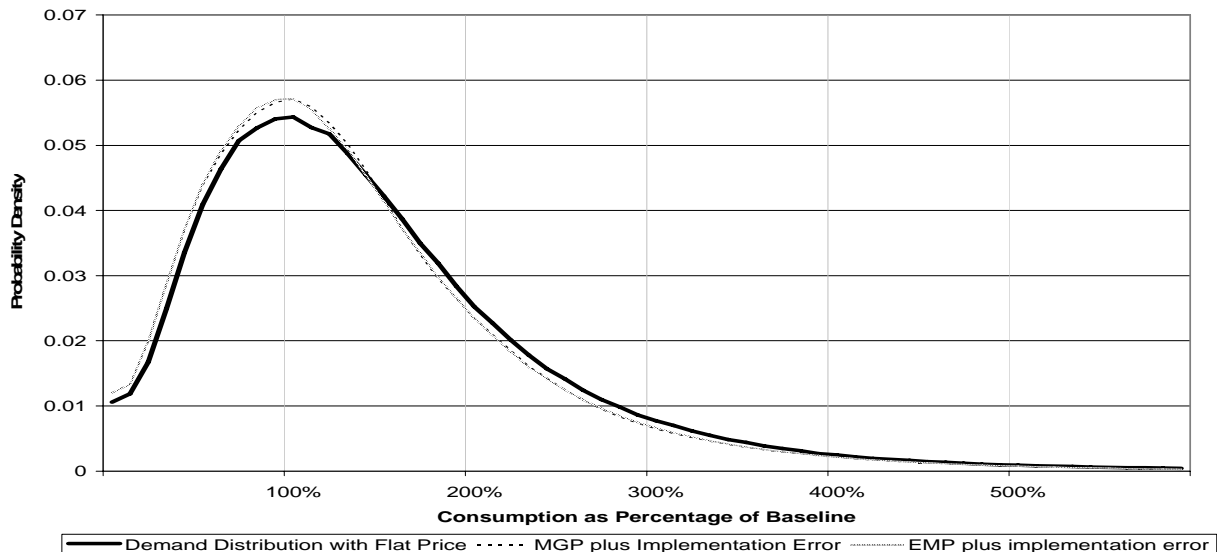


Figure 7: Simulated Demand Distributions with optimization Error

result in more bunching than constrained optimization if optimization error is sufficiently small or demand is more elastic.

Still, as figure 6 suggests, the price against which consumers would respond differs substantially between the theories. Thus, examining the consumption response to changes in price might allow one to distinguish between the theories.

#### *Evidence of Customer Response to Increasing-Block Pricing*

While it is clear that consumer response to increasing-block pricing does not reflect precise optimization on marginal price, constrained optimizing behavior would still result in different consumption changes for consumers at different points along the price schedule as the steepness of the price schedule changes. If the price schedule became steeper, one would still expect to see the consumption of heavier users decline relative to the consumption of lighter users.

The data that SCE made available to UCEI go back to 1999, before the California electricity crisis and before the implementation of the five-tier rate structure. In 1999, SCE had a simple two-tier structure with a price of \$0.1081 up to baseline consumption and \$0.1274 on all consumption above baseline. By late 2001, a five tier structure had been implemented with a top price of \$0.2262. Unfortunately for this analysis, many other events

had occurred that could confound the time-series comparison. California's electricity crisis from June 2000 to May 2001 brought public conservation campaigns, threats of blackouts, and explicit conservation rebates during the ensuing summers for households that reduced consumption by at least 20% compared to summer 2000. The rebates were distributed through a lump sum bill credit at the end of the summer, further muddying the analysis.

For these reasons, I focus on a relatively clean comparison of the March through May periods at two-year intervals: customer billing periods that ended in March, April and May of 2000, 2002, 2004 and 2006. Figure 8 shows the retail rates that were in effect during each of these periods. These are the rates for each tier averaged over each 3-month period, but there was very minor variation across months within each 3-month interval. There was also very little tariff variation for the prior two months (with the exception of 2006, when a significant rate increase occurred in January) so customers had already received at least one bill at these rates prior to March. Besides the rate stability and absence of distorting events during these periods, these months also have the advantage of falling entirely within the winter baseline period, so there is no confusion within the data – and, one hopes, relatively little confusion on the part of consumers – that would result from changes in customer baseline quantities during the month. Figure 8 shows that rates increased and steepened substantially between spring 2000 and 2002, rising about 17% in the lowest tier to about 76% in the highest tier. They then fell and flattened between 2002 and 2004, offsetting about half to three-quarters of the increase in the prior two years. But rates again increased and steepened substantially again between 2004 and 2006 by about 3% in the lowest two tiers to about 83% in the highest two tiers. Thus, these four time periods offer three substantial rate changes for examination, two significant increases and one moderate decrease.<sup>31</sup>

It would be tempting to compare changes in the tariff structure with changes in same-household consumption to see if high-consuming households were responsive to the changes in marginal and average rates, while low consuming households that faced much smaller rate changes exhibit smaller variation in consumption. One would then expect to see a pattern of the higher consuming households cutting consumption more when the rates on

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<sup>31</sup> Customer baselines also changed slightly between 2002 and 2004. I account for these changes in the price schedules used in the analysis.

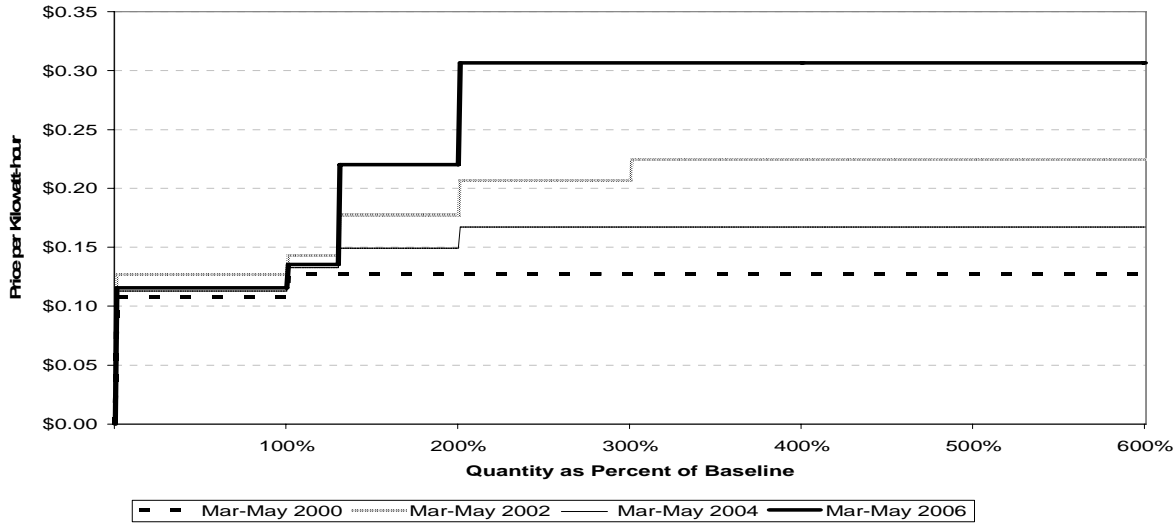


Figure 8: SCE Residential Tariff for March-May at Two-Year Intervals

higher tiers increase more (2000-2002 and 2004-2006) and increasing consumption more when the rates on higher tiers decline by more than on lower tiers (2002-2004). The difficulty with this approach to identifying elasticity is that there is natural mean reversion in household consumption over time. This occurs for at least two reasons. First, if households experience transitory consumption shocks – such as positive shocks from having visitors or negative shocks from being away from home – then any household observed at a more extreme part of the distribution will be likely to migrate back towards the center over time. Second, families that have children go through natural stages of consumption levels as they expand from no children to small children to teenagers, and (in most cases) back to no children at home. In fact, in these monthly time series consumption data, the household-level mean reversion is quite strong in all periods including those with no tariff change.<sup>32</sup> Separating the household mean reversion effect from the effect of rate changes is possible in theory, but fairly challenging in practice.

It seems quite likely, however, that neighborhoods experience much less fluctuation over time in the *distribution* of underlying demand functions across households living in the

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<sup>32</sup> A (preliminary) regression at the premises level of change in consumption percentile within CBG consumption percentile in the previous period shows a strong tendency towards mean reversion, indicating for instance, that a household at the 95th percentile in one month would be expected to be slightly below the 85th percentile just one month later.



neighborhood. That is, the share of households in a neighborhood whose occupants are on vacation or hosting visitors in a given month – after controlling for seasonality – is not nearly as subject to the stochastic variation that leads to mean reversion in any one household. Likewise, over time neighborhoods are not nearly as subject to fluctuations in power consumption due to demographic changes as is any one household. Thus, one would expect the factors that cause mean reversion at the household level to have little effect on the *distribution* of usage across households in a neighborhood. On the assumption that the distribution of demand functions is constant over time – adjusting for overall shifts as described below – one could look for indication of price elasticity by examining how the distribution of quantity demanded across households in a neighborhood varies with the retail electricity tariff.

In particular, under much weaker conditions of consumer understanding of and response to prices than strict marginal price optimization, one would expect that price increases in tiers 3, 4 and 5 relative to tiers 1 and 2 would cause the variation in consumption across households in a neighborhood to narrow. For instance, even if consumers respond to average price or expected marginal price rather than marginal price, a change in the price perceived by heavier users relative to light users would still tend to change the consumption of heavier users relative to light users and narrow or widen the distributions of use. Because distributions of demand vary across areas, variation in this narrowing and its relationship to variation in changes in price may allow effective identification of price elasticity.

This argument about the distribution of consumption only applies if the neighborhood observed is stable. If there were a significant expansion or contraction of the housing stock within the sample in a neighborhood, then it would be much more difficult to infer the implication of the tariff change for the distribution of consumption quantities. To control for this, one could either examine only consumption on premises that existed at both the beginning and end of a 2-year period, or one could examine only neighborhoods with relatively little change in the housing stock. The results are quite consistent between these two approaches. I present here results based on comparisons of the same premises at the

beginning and end of the two-year period.<sup>33</sup> For premises to be included in the calculation of the consumption distribution parameters, they not only had to exist at the beginning and end of a two-year interval, but the customer at the address had to be on the standard residential tariff in both periods.<sup>34</sup>

To examine the properties of the distribution, it is also necessary to have sufficient premises to estimate those properties. I present here analysis where neighborhood designations are based on census block group (CBG) areas. An average CBG contains about 600 households in SCE's service territory. I include in the analysis only CBGs with at least 100 premises.<sup>35</sup>

Of course, factors other than tariff changes affect the distribution of electricity consumption across households in a CBG. Perhaps of most concern is income distribution changes. If the distribution of income is widening within CBGs, then a positive income elasticity of demand for electricity would be likely to widen the distribution of electricity consumption. While a snapshot of census data on income distribution is available, no reliable time series of income distribution changes at the CBG level is yet available for this time period.<sup>36</sup>

Under certain assumptions, the impact of tariff changes on the distribution of customer consumption can be used to estimate directly the price elasticity of demand. Again, a central underlying assumption is that while the demands of individual consumers are subject to shocks and lifecycle effects that lead to mean reversion at the customer level, the distribution of demand functions across a set of premises in a neighborhood is not subject to these systematic effects. Thus, the quantity demanded by the customer at

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<sup>33</sup> Premises are identified based on SCE's reported "premises number," which is unique to a building.

<sup>34</sup> This excluded not only premises that house customers on the CARE program (by far the largest component of the excluded premises), but also premises at which the customer was on some other special tariff, such as for electric heat or water heating, special medical equipment, or time-of-use pricing.

<sup>35</sup> I have also done this analysis at the zip code level, which reduces the number of observations by slightly more than 90%, and found very consistent results, though with larger standard errors.

<sup>36</sup> Even if such data were available, correcting for income distribution changes and their impact on the relative consumptions of different households within the distribution would require fairly strong structural assumptions (or estimates) about the income elasticity of electricity demand and how it varies across consumption levels. Even single point estimates of the income elasticity of demand vary by more than a factor of two in the literature, so the inference from such an approach would not be very reliable.

percentile  $n$  of the quantity distribution in CBG  $g$  at time  $t$  can be written:

$$\ln Q_{ngt} = \alpha_0 + \alpha_1 \cdot \ln P_{ngt}(Q_{ngt}) + \Omega X + \epsilon_{ngt}$$

where  $P$  is the relevant price to which the consumer is responding (marginal, expected marginal or average), which is a function of  $Q$  and is discussed further below, and  $X$  is a vector of the other factors that would shift the entire distribution of demand, including income, weather, and technology, as well as time and CBG fixed effects. Differencing this equation over  $t$  for a given  $n$  and  $g$  gives:

$$\begin{aligned} [\ln Q_{ngt_2} - \ln Q_{ngt_1}] &= \alpha_{0'} + \alpha_1 \cdot [\ln P_{ngt_2}(Q_{ngt_2}) - \ln P_{ngt_1}(Q_{ngt_1})] \\ &+ \Omega[X_{ngt_2} - X_{ngt_1}] + [\epsilon_{ngt_2} - \epsilon_{ngt_1}] \end{aligned} \quad [5]$$

For example, the dependent variable might be the quantity change from 2000 to 2002 at the 75th percentile of the distribution. In differencing the equation, the time-invariant CBG fixed effect is eliminated. Any change in the time fixed effects is absorbed by retaining the constant term, which is now called  $\alpha_{0'}$ . Any factor in  $X$ , however, that changes between the two time periods will remain.

The data provide multiple observations in a time period within the same CBG during a month: the different points along the distribution of quantity demanded. For this analysis I use five observations, at the 10th, 25th, 50th, 75th, and 90th percentiles, in each CBG-month. These observations have different price changes due to the changes in the increasing-block structure, but they likely have similar changes in  $X$  variables, such as weather or technology. Estimation with multiple observations for each CBG and CBG-month fixed effects *in the differenced equation* would then eliminate  $X$  factors that changed between  $t = 1$  and  $t = 2$ , but experienced the same change for all customers in the CBG.

Other factors in  $\Omega X$  will remain, however, if changes in a variable that is part of  $X$  are different at different points in the distribution or if  $\Omega$  varies along the distribution. For instance, if income grew between 2000 and 2002, but it systematically grew by more for households at the upper end of the electricity distribution, then the differencing would not cause the bracketed  $X$  term in [5] to be zero. Alternatively, even if income grew at the same rate at all points of the distribution, if the income elasticity of demand differs

systematically along the distribution, then the  $\Omega$  would need a  $n$  subscript and differencing would not eliminate the term because the uniform growth in income would have differential impacts on the 75th than on the 25th percentile consumption level.

For now, I assume that all factors not eliminated by the time differencing or absorbed by the CBG-month fixed effects are captured by month-percentile fixed effects. For instance, if the weather in March 2002 was substantially colder than in March 2000 that might increase all customer demand, but might do so more (proportionally) for the 90th percentile of the demand distribution than the 10th percentile. As long as the proportional difference in the effect of this weather change on the 90th versus 10th percentile is uniform across all CBGs within a month it will be absorbed by a month-percentile fixed effect.

Still, a bias will remain if the relative shift of 90th versus 10th percentile change in demand differs across CBGs and that difference is correlated with the relative price change faced by customers in the 90th versus 10th percentile demand across CBGs. One possible way this could happen is if, for instance, the level of consumption at different percentiles (which is clearly correlated with the change in price) differs across CBGs in a way that is correlated with income *and* differences in income changes at different income levels (a widening of the income distribution, for example) are changing the relative electricity demand of 90th versus 10th percentile consumers. To address this possible bias, I also estimate demand allowing the month-percentile effects to vary with income levels across the CBGs.<sup>37</sup>

Equation [5] has price on the right-hand side, but the earlier analysis of consumer demand bunching suggests that a strict implementation of consumer optimization on marginal price would be difficult to justify. I pursue each of the theories discussed earlier. The first is to follow the literature, despite the evidence from the previous section, and assume that consumers were responding to the *ex post* observed marginal price. The second approach is to assume that consumers respond to the average price associated with the *ex post* observed consumption quantity. The third is to assume that consumers plan their consumption based on expected marginal price as described earlier and that the *ex post* observed con-

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<sup>37</sup> Finally, of course, the linear in logs (constant elasticity) functional form is an important maintained assumption in the statistical inference.

sumption quantity is the mean of the distribution plus a mean-zero orthogonal error.

Regardless of which price measure is used, it is endogenous. Price changes with consumption, so failure to account for the endogeneity will impart a positive bias to price elasticity estimates, because a customer with a positive demand shock will also face a higher price. In addition, the price to which the consumer is responding is likely measured with error even under the maintained hypothesis that the form of the price I am assuming is correct. This is because price (in any of the hypothesized forms) is a function of quantity and quantity is uncertain.<sup>38</sup>

To address these issues in the differenced equation, I create an instrument that is the difference in price at the quantity consumed by the observed percentile in the distribution in the earlier period. For instance, for the 75th percentile observation in a given CBG, the price change would be the  $[\ln P_{ngt_2}(Q_{ngt_2}) - \ln P_{ngt_1}(Q_{ngt_1})]$ , so the price change would be positively correlated with any quantity shock due to the upward slope of the price schedule. But taking the price change at a fixed quantity,  $[\ln P_{ngt_2}(Q_{ngt_1}) - \ln P_{ngt_1}(Q_{ngt_1})]$  would not exhibit that correlation, because both price observations are based on the same quantity, which is drawn from the pre-change period, so this is likely to be a valid instrument.<sup>39</sup>

Thus, the equation I estimate is

$$\begin{aligned} [\ln Q_{ngt_2} - \ln Q_{ngt_1}] &= \alpha_0 + \alpha_1 \cdot [\ln P_{ngt_2}(Q_{ngt_2}) - \ln P_{ngt_1}(Q_{ngt_1})] \\ &+ \sum_{g=1}^G \gamma_{1g} CBG_g Mar + \gamma_{2g} CBG_g Apr + \gamma_{3g} CBG_g May \\ &+ \sum_{n=25,50,75,90} \delta_{1n} Mar_n + \delta_{2n} Apr_n + \delta_{3n} May_n + \epsilon_{ng} \end{aligned} \quad [6]$$

where  $CBG_g$  is an indicator variable for an observation in census block group  $g$ ,  $Mar$ ,  $Apr$  and  $May$  are indicator variables for observations in each month,  $n$  still indexes the different percentile observations, and  $Mar_n$  is an indicator variable for an observation on

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<sup>38</sup> I do assume that the changes in the price structure are exogenous. Regulators changed rates over the years to meet revenue shortfalls or surpluses that would be very hard to tie to demand fluctuations at all, let alone to fluctuations in the relative demand of different size consumers.

<sup>39</sup> Failure to instrument for price does indeed yield the expected endogeneity bias. All estimated price elasticities are positive and significant. This probably suggests that the endogeneity bias is more of an issue in practice than the attenuation bias that results from measuring  $P$  with error.

percentile  $n$  in March, and likewise for  $Apr_n$  and  $May_n$ . The fixed effects for the 10th percentile observations are absorbed by the CBG-month fixed effects.

The results are shown in the top of table 3 using expected marginal price as the explanatory price variable. The number of observations differs slightly across the three time periods as some CBGs have sufficient qualifying premises to be included in some of the two-year intervals but not others. The downward trend in the number of included CBGs is due to the growth in the CARE program. Standard errors are clustered at the CBG level so they are not artificially depressed by the correlation across March/April/May observations or use of multiple different percentile observations in the same CBG. These results do not account for spatial correlation across neighboring CBGs which is no doubt also present, but clustering on larger spatial groups of CBGs – reducing the number of clusters by a factor of 10 – increases the standards errors only slightly.

The results suggest that the elasticity of demand with respect to a change in the expected marginal price was about -0.17 between 2000 and 2002, about -0.15 between 2002 and 2004, and about -0.12 between 2004 and 2006. Recall the first and third of these periods saw substantial price increases and the second saw moderate price decreases. The standard errors are quite small. The comparable estimated elasticities using average price and marginal price as the explanatory price variable are in the two rows below the regression (with month-percentile fixed effects not reported). Estimated elasticity with respect to marginal price is substantially smaller and estimated elasticity with respect to average price is substantially larger. The latter result is not surprising because average price varies less than expected marginal price.

Nonetheless, the estimates may not be as stable as either the small range of elasticities or the small standard errors would suggest. Equation [6] constrains the elasticity to be the same across months. In the lower panel of the table, I present the unconstrained elasticity estimates. These alternative specifications suggest that the estimates for the middle period, 2002-2004, are not very stable, possibly due to the comparatively small change in prices that occurred over this period.

The monthly elasticity estimates for the 2000-2002 and 2004-2006 periods exhibit a fairly clear pattern of lower elasticity in March, increasing into April and May. In nearly all cases

Dependent Variable:  $\ln(Q_{ngt2}) - \ln(Q_{ngt1})$

Period	2000-2002 Change	2002-2004 Change	2004-2006 Change
$\ln(E[\text{MargP}_{ngt2}]) - \ln(E[\text{MargP}_{ngt1}])$	-0.1722 ( 0.0077 ) ***	-0.1489 ( 0.0276 ) ***	-0.1156 ( 0.0060 ) ***
Mar-25	-0.0056 ( 0.0008 ) ***	0.0098 ( 0.0009 ) ***	0.0254 ( 0.0010 ) ***
Mar-50	0.0023 ( 0.0012 ) *	0.0155 ( 0.0012 ) ***	0.0559 ( 0.0018 ) ***
Mar-75	0.0146 ( 0.0019 ) ***	0.0158 ( 0.0021 ) ***	0.0868 ( 0.0028 ) ***
Mar-90	0.0225 ( 0.0026 ) ***	0.0158 ( 0.0030 ) ***	0.1051 ( 0.0034 ) ***
Apr-25	0.0019 ( 0.0008 ) **	0.0069 ( 0.0009 ) ***	0.0240 ( 0.0010 ) ***
Apr-50	0.0116 ( 0.0011 ) ***	0.0128 ( 0.0014 ) ***	0.0497 ( 0.0017 ) ***
Apr-75	0.0259 ( 0.0018 ) ***	0.0135 ( 0.0022 ) ***	0.0762 ( 0.0027 ) ***
Apr-90	0.0345 ( 0.0025 ) ***	0.0141 ( 0.0031 ) ***	0.0928 ( 0.0034 ) ***
May-25	-0.0056 ( 0.0008 ) ***	0.0255 ( 0.0009 ) ***	0.0049 ( 0.0010 ) ***
May-50	-0.0015 ( 0.0011 )	0.0448 ( 0.0010 ) ***	0.0170 ( 0.0015 ) ***
May-75	0.0094 ( 0.0018 ) ***	0.0527 ( 0.0018 ) ***	0.0343 ( 0.0025 ) ***
May-90	0.0160 ( 0.0025 ) ***	0.0562 ( 0.0029 ) ***	0.0450 ( 0.0032 ) ***
Constant	-0.0243 ( 0.0013 ) ***	0.0486 ( 0.0032 ) ***	0.0055 ( 0.0007 ) ***
Number of Observations	103730	100180	96585
Number of CBGs	7022	6763	6574
<hr/>			
$\ln(\text{AvgP}_{ngt2}) - \ln(\text{AvgP}_{ngt1})$	-0.1990 ( 0.0131 ) ***	-0.4133 ( 0.0426 ) ***	-0.1835 ( 0.0091 ) ***
<hr/>			
$\ln(\text{MargP}_{ngt2}) - \ln(\text{MargP}_{ngt1})$	-0.0946 ( 0.0049 ) ***	-0.0382 ( 0.0074 ) ***	-0.0736 ( 0.0042 ) ***

#### Elasticity Estimates Unconstrained Across Months

Expected Marginal Price: $\ln(E[\text{MargP}_{ngt2}]) - \ln(E[\text{MargP}_{ngt1}])$			
March	-0.1126 ( 0.0102 ) ***	0.0878 ( 0.0283 ) ***	-0.0764 ( 0.0074 ) ***
April	-0.1876 ( 0.0101 ) ***	-0.4664 ( 0.0488 ) ***	-0.1123 ( 0.0080 ) ***
May	-0.2103 ( 0.0089 ) ***	-0.1615 ( 0.0324 ) ***	-0.1597 ( 0.0074 ) ***
Average Price: $\ln(\text{AvgP}_{ngt2}) - \ln(\text{AvgP}_{ngt1})$			
March	-0.0708 ( 0.0181 ) ***	0.0153 ( 0.0512 )	-0.1429 ( 0.0122 ) ***
April	-0.2566 ( 0.0166 ) ***	-0.9571 ( 0.0627 ) ***	-0.2169 ( 0.0116 ) ***
May	-0.2635 ( 0.0159 ) ***	-0.4065 ( 0.0572 ) ***	-0.1890 ( 0.0113 ) ***
Marginal Price: $\ln(\text{MargP}_{ngt2}) - \ln(\text{MargP}_{ngt1})$			
March	-0.0521 ( 0.0071 ) ***	0.0054 ( 0.0098 )	-0.0467 ( 0.0052 ) ***
April	-0.1008 ( 0.0064 ) ***	-0.0726 ( 0.0101 ) ***	-0.0724 ( 0.0058 ) ***
May	-0.1268 ( 0.0064 ) ***	-0.0434 ( 0.0104 ) ***	-0.1088 ( 0.0063 ) ***

Census Block Group fixed effects not reported

IV estimation with price variables endogenous. Standard errors in parentheses.

\*\*\*=significant at 1%    \*\*=significant at 5%    \*=significant at 10%

Table 3: Estimation of Demand Elasticity with Alternative Measures of Price (equation [6])

the results from using the expected marginal price are bracketed by elasticity estimates using marginal price and average price.

The percentile fixed effects are intended to capture systematic changes in the distribution due to factors in the  $\Omega X$  term that affect different parts of the distribution differently. Although it is not dictated by theory, one might expect that these effects would likely be monotonic along the distribution. For instance, if cold weather increased consumption, but did so proportionally more for heavy electricity users, then a change in weather between years would be reflected in a monotonic change in the month-percentile fixed effects as one looks at higher percentiles for a given month. So, it is reassuring that this monotonic pattern (with the 10th percentile effect omitted and implicitly equal to zero) is evident in nearly all of the month-percentile fixed effects.

The estimated equation [6] for which the results are presented in tables 2 and 3 is premised on the assumption that the exogenous relative shift of consumption at different percentiles in the CBGs does not differ across CBGs in a way that is correlated with price changes. The chief concern is that wealthier CBGs, or CBGs with wealthier upper percentiles in consumption, might see a larger (or smaller, but probably larger if income disparities are widening) relative shift out in the demand of those at the upper end of consumption distribution. To address this concern, I estimate an augmented version of equation [6]

$$\begin{aligned}
[\ln Q_{ngt_2} - \ln Q_{ngt_1}] &= \alpha_{0'} + \alpha_1 \cdot [\ln P_{ngt_2}(Q_{ngt_2}) - \ln P_{ngt_1}(Q_{ngt_1})] \\
&+ \sum_{g=1}^G \gamma_{1g} CBG_g Mar + \gamma_{2g} CBG_g Apr + \gamma_{3g} CBG_g May \\
&+ \sum_{n=25,50,75,90} \delta_{1n} Mar_n + \delta_{2n} Apr_n + \delta_{3n} May_n + \epsilon_{ng} \\
+ \sum_{n=25,50,75,90} \delta_{1n} Mar_n \cdot \ln medHHI_g &+ \delta_{2n} Apr_n \cdot \ln medHHI_g + \delta_{3n} May_n \cdot \ln medHHI_g + \epsilon_{ng}
\end{aligned} \tag{7}$$

where  $\ln medHHI_g$  is the 2000 median household income for that census block group. Though these terms are jointly highly significant, they do not qualitatively change the elasticity estimates.<sup>40</sup>

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<sup>40</sup> I also estimate [7] replacing median household income with the income for the corresponding percentile in the income distribution with the CBG, *e.g.*, the 25th percentile income for the 25th percentile fixed CBG-month effects. These also were highly significant, but do not change the elasticity results.



Dependent Variable:  $\ln(Q_{ngt2}) - \ln(Q_{ngt1})$

Period	2000-2002 Change	2002-2004 Change	2004-2006 Change
Pairwise Inclusion of Price Variables			
$\ln(\text{MargP}_{ngt2}) - \ln(\text{MargP}_{ngt1})$	0.0737 ( 0.0104 ) ***	-0.0085 ( 0.0061 )	0.0284 ( 0.0114 ) **
$\ln(E[\text{MargP}_{ngt2}]) - \ln(E[\text{MargP}_{ngt1}])$	-0.2629 ( 0.0162 ) ***	-0.1392 ( 0.0287 ) ***	-0.1504 ( 0.0158 ) ***
<hr/>			
$\ln(\text{MargP}_{ngt2}) - \ln(\text{MargP}_{ngt1})$	-0.0825 ( 0.0053 ) ***	-0.0071 ( 0.0069 )	-0.0396 ( 0.0043 ) ***
$\ln(\text{AvgP}_{ngt2}) - \ln(\text{AvgP}_{ngt1})$	-0.0659 ( 0.0138 ) ***	-0.3988 ( 0.0418 ) ***	-0.1434 ( 0.0095 ) ***
<hr/>			
$\ln(\text{AvgP}_{ngt2}) - \ln(\text{AvgP}_{ngt1})$	0.0455 ( 0.0143 ) ***	-0.4534 ( 0.0707 ) ***	-0.1211 ( 0.0089 ) ***
$\ln(E[\text{MargP}_{ngt2}]) - \ln(E[\text{MargP}_{ngt1}])$	-0.1865 ( 0.0089 ) ***	0.0251 ( 0.0448 )	-0.0830 ( 0.0059 ) ***
<hr/>			
Inclusion of All Three Price Variables			
$\ln(\text{MargP}_{ngt2}) - \ln(\text{MargP}_{ngt1})$	0.0778 ( 0.0104 ) ***	-0.0107 ( 0.0060 ) *	0.0694 ( 0.0116 ) ***
$\ln(\text{AvgP}_{ngt2}) - \ln(\text{AvgP}_{ngt1})$	0.0459 ( 0.0143 ) ***	-0.4468 ( 0.0705 ) ***	-0.1291 ( 0.0092 ) ***
$\ln(E[\text{MargP}_{ngt2}]) - \ln(E[\text{MargP}_{ngt1}])$	-0.2825 ( 0.0172 ) ***	0.0347 ( 0.0457 )	-0.1657 ( 0.0158 ) ***

Census Block Group and Month-Percentile fixed effects not reported  
 IV estimation with price variables endogenous. Standard errors in parentheses.  
 \*\*\*=significant at 1%    \*\*=significant at 5%    \*=significant at 10%

Table 4: Estimation of Demand Including Multiple Measures of Price

*To What Price Do Consumers Respond?*

With these somewhat different results using different measures of price, a natural question to ask is which better represents consumer behavior. The three measures are highly correlated with one another, but they do clearly differ substantially in the neighborhood of the jumps in the increasing-block price schedule.

Table 4 presents regressions in which multiple measures of price are included as explanatory variables. The results reinforce the impression that observed marginal price is not the best indicator of the effect of price on consumer demand. The top panel shows that when expected marginal price and observed marginal price are both included in the regression, expected marginal price is negative, significant and of plausible magnitude in all three periods while observed marginal price is estimated to have an incremental impact that is positive and significant in the first and last period, and insignificant in the middle period.

The second panel shows that observed marginal price has a more plausible negative incremental impact in a regression with *ex post* observed average price, at least in the first and last period. Average price, however, remains consistently negative and significant in all three periods. The third panel indicates that expected marginal price is less clearly dominant against average price in explaining consumer response. It is significant in the first and last period, but in the middle period quantity response seems to be better modeled – within this constant-elasticity functional form – as a function of average price. The bottom panel of table 4 shows the results from regressions with all three price measures. It reinforces the conclusion that observed marginal price is the least useful of the three measures in gauging consumer response. With all three regressors, observed marginal price is positive and significant in the first and last period, while it is negative, small and significant at the 8% level in the middle period.

Obviously, none of these is the single “correct” measure of price, and each is a slightly nonlinear function of the others. There is a range of ways in which consumers perceive and process price information given their constraints in information, cognition and attention. Furthermore, the constant elasticity functional form is in itself a significant restriction on the way in which price affects consumption quantity. Still, plausible modeling of consumer behavior suggests that consumers are likely to be responding to less-discrete perceived price schedules and empirical support for that conclusion is fairly robust.

## VIII. Conclusion

Over the last 40 years, as focus on U.S. energy policy has waxed and waned, there has been intermittently keen interest in the price elasticity of demand for electricity. With the controversies that have followed electric industry restructuring and rising concerns about climate change, attention to the issue has grown again recently. Unfortunately, limited data availability has forced some research to impose strong assumptions on consumer demand behavior, particularly in attempting to infer price elasticity from cross-sectional data under increasing-block pricing. A number of papers have assumed that consumers choose quantity demanded for a period based on the marginal price that they end up facing for the period.

I have argued that even under the most vigilant daily or hourly optimizing behavior,

consumers under increasing-block pricing would not choose consumption based on the *ex post* observed price for the billing period, because exogenous shocks to demand would make it impossible for a consumer to know throughout the period what that marginal price would be. In a more plausible view of behavior, customers do not monitor their consumption closely within billing periods, but instead respond to the price schedule and the possible distribution of their demand states by establishing rules about behavior. I show that this results in consumers equating their expected marginal value of consumption with a smoothly increasing expected marginal price function, one that would not be consistent with discrete-continuous choice modeling of demand. Of course, even the constrained-optimization behavior that I posit may go way beyond the typical customer's awareness of electricity price, in which case one might expect to observe consumers responding to overall changes in the average price they face, but nothing more sophisticated than that.

If consumers were able to optimize precisely against the end-of-period marginal price they face, a straightforward application of consumer theory suggests that one would expect to see a bunching of observed quantities around the steps in the increasing-block pricing schedule. I simulate the impact that the steps should have on the observed quantity distribution and show that they are quite large, even under fairly conservative assumptions. Actual empirical distributions of residential demand quantity, however, does not exhibit such bunching.

Attempts to estimate demand elasticity from a static price schedule are generally a response to the limited availability of data that include other price variation. Luckily, intertemporal price variation do exist in the billing data from Southern California Edison that I have been able to analyze. Substantial changes in the residential price schedule over the 2000-2006 time period enable me to estimate the response to price changes and to evaluate how well different measures of price perform in this estimation. All three measures of price that I investigate – observed marginal price, a measure of expected marginal price, and average price – are estimated to have a negative and significant impact on consumption. The estimated impact of observed marginal price is consistently between 0 and -0.12. These should be interpreted as medium to long run elasticities, responding to changes in the price schedule that occurred at least a few months earlier. As such, they are smaller than comparable elasticities than have been reported in previous studies

using the DCC approach. The size of the SCE dataset also permits me to compare the appropriateness of the price variables by estimating demand with more than one of the price variables even though they are highly co-linear. The results suggest that marginal price is a less revealing indicator of consumer response to changes than are either of the other two measures.

Overall, the results indicate that among the distribution of consumers there are many who likely respond to little more than average price information, while others either consciously or unconsciously are aware of – and show some response to – the expected marginal price that they are likely to face. The estimated level of response is not as robust over time as one might hope for, but it appears to be in the elasticity range of -0.1 to -0.2 for expected marginal price and somewhat higher for average price, a measure that itself varies less.

It is unclear how much one can generalize from this result to the use of increasing-block pricing in general. It is quite clear from studies of cellphone pricing and marginal income taxes that consumer understanding of non-linear price schedules varies widely. Such understanding seems amenable to education campaigns, though such approaches will still run up against attention and cognition constraints that are likely significant for the vast majority of consumers who don't think like economists, and even for many who do.

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