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Household Electricity Demand, Revisited

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Recent efforts to restructure electricity markets have renewed interest in assessing how consumers respond to price changes. This paper develops a model for evaluating the effects of alternative tariff designs on electricity use. The model concurrently addresses several interrelated difficulties posed by nonlinear pricing, heterogeneity in consumer price sensitivity, and consumption aggregation over appliances and time. We estimate the model using extensive data for a representative sample of 1300 California households. The results imply a strikingly skewed distribution of household electricity price elasticities in the population, with a small fraction of households accounting for most aggregate demand response. We then estimate the aggregate and distributional consequences of recent tariff structure changes in California, the consumption effects of which have been the subject of considerable debate.

1. INTRODUCTION

Recent efforts to restructure electricity markets have renewed interest in electricity demand and pricing. This interest reflects a broad desire to improve the efficiency of electricity markets, and policy-makers' concerns over the impact of price changes on consumers. How new pricing mechanisms would affect households' consumption and expenditures is a matter of considerable uncertainty, however. This uncertainty has provoked controversy and debate in the regulatory policy arena, hampering market reforms.

Using econometric methods to assess the effects of electricity price changes presents several challenges. These include the nonlinear structure of tariff schedules, aggregation of metered consumption behaviour over time and appliances, and the interdependence of energy use with longer-term household decisions over appliance ownership and dwelling characteristics. The first two issues introduce complex simultaneity problems between marginal prices and consumption. The third issue imposes high data requirements (information on household-specific appliance holdings and residence features), and creates heterogeneity in consumption responses related to the characteristics of these durable goods. When the researcher's objective is to develop a model for simulating the effects of prospective tariff changes, ignoring these issues will provide an incomplete assessment of demand responses and potentially misleading predictions of a new tariff's consumption and revenue consequences.

In this paper, we estimate a model of household electricity demand that can be used to evaluate alternative tariff designs. The model focuses on the heterogeneity in households' demand elasticities, their relation to appliance holdings and other household characteristics, and how they inform household consumption responses to complex (nonlinear) price schedule changes. Although these issues have received attention in the literature, few (if any) studies have addressed them in an integrated way.[1] This shortcoming is notable in that theory suggests that the effects of an alternative tariff design on a diverse population will depend on the heterogeneity in consumers' price elasticities as well as their consumption levels. We address these features using a model of endogenous sorting along a nonlinear price schedule, and a group-wise specification of price-sensitivity heterogeneity based on household appliance ownership. This model reveals a rich, highly asymmetric shape to the population distribution of households' price elasticities. It also indicates a larger aggregate price elasticity of residential electricity demand than prior studies that ignore these issues.

We estimate the model using data for a representative probability sample of California households from the *Residential Energy Consumption Survey* of the U.S. Department of Energy. The rich detail on appliance holdings and dwelling characteristics in these data allow us to model the considerable variation in households' electricity use and sensitivity. We have supplemented the *Survey* by matching each sample household with its complete, seasonally varying electric rate schedule. The use of precise rate schedule information is a central feature of the analysis, both to minimize specification error in estimation and to evaluate individual behavioural responses to alternative rate structures. To lend credence to the specifications and results, we conduct out-of-sample tests of the model that show how well it predicts consumption responses to new price changes.

We then use the model to study the effects of a controversial new tariff design in California. Following an electricity supply crisis in 2000–2001, regulatory authorities approved a novel, five-part tariff structure for residential electricity consumption. This design was intended to induce energy conservation, raise additional revenue for utilities, and minimize expenditure changes for lower-income households. Due to its unprecedented form, however, little was known about how well the new system would achieve these objectives prior to its adoption. We show how such uncertainties can be evaluated prospectively using the sample data, and contrast our estimates with methods employed by public agencies in California and elsewhere.

The next section lays the econometric groundwork for our empirical methods, and highlights how our approach differs from prior studies. Our treatment of the endogenous sorting problem that occurs with nonlinear prices builds upon Hanemann's (1984) and Hausman's (1985) choice models given nonlinear budget constraints. Our approach also handles two important aggregation-related problems common to electricity demand research. Section 3 then develops the empirical specification. Following prior work, this model explains heterogeneity in households' electricity price elasticities in terms of appliance holdings and use. Section 4 discusses estimation via an exact nonlinear method of moments, and Section 5 summarizes the data. Sections 6 and 7 present estimation results and elasticities, including out-of-sample validation tests of the model. In Section 8 we then illustrate how the model and methods lend themselves to analysing prospective tariff design changes, such as California's complex new tariff structures.

2. MODELLING DEMAND WITH NONLINEAR PRICES

Although economic theory offers considerable guidance on how consumers will respond to nonlinear prices, econometric treatments of estimation and identification in this setting remain

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[1] Taylor (1975) contains an early treatment of nonlinear tariffs in empirical work. More sophisticated methods followed Burtless and Hausman's (1978) work on closely related issues in the analysis of labour supply under nonlinear income taxation. Surprisingly little of these econometric techniques have permeated the (considerable) literature on electricity demand; notable exceptions are Maddock, Castano and Vella (1992) and Herriges and King (1994). A greater consensus has emerged on the importance of incorporating household-level appliance stock information into electricity demand analyses, as well as empirical methods for doing so; see Parti and Parti (1980), Dubin and McFadden (1984), Dubin (1985), and EPRI (1989).

incomplete. This section summarizes the problems inherent in prior estimation strategies, motivates and describes our econometric approach, and connects it to related econometric literatures.

2.1. Specification and identification

Most nonlinear price schedules take the form of multi-part tariffs. Since Gabor (1955), economists have realized that multi-part tariffs imply that the consumer faces a nonlinear (*i.e.* a kinked) budget constraint. The demand behaviour of a utility-maximizing consumer thus depends not on the average price, nor any single marginal price, but on the entire price schedule. The standard econometric approach to demand analysis in this setting, which traces to Hall (1973), is to "linearize" the budget constraint. This amounts to using the plane tangent to the consumer's nonlinear budget constraint at the optimal consumption bundle as its linear approximation. By doing so, one can express demand under nonlinear pricing in terms of the ordinary demand function of classical consumer theory, which assumes a linear budget constraint.

To be specific, let $x(p, y)$ be the ordinary demand function that indicates the consumer's desired quantity facing a constant (marginal and average) price p and income y. Suppose, however, that the consumer faces an increasing price schedule $s(p)$ of the form depicted in Figure 1. Here the consumer pays a low price p_1 for each unit up to the quantity $\bar{x}$, and a higher price p_2 thereafter. Then the optimal consumption level x^* satisfies

$$x^* = x(p^*, y^*) \tag{1}$$

where p^* is the slope of the approximating linear budget constraint and $y^* = y + \bar{x} \cdot (p^* - p_1)$. In economic terms, p^* is the consumer's equilibrium marginal willingness-to-pay and y^* is the income level that would induce consumption x^* at this (constant) price. With (1), the demand specification problem under nonlinear pricing can be recast in terms of the ordinary demand function familiar to applied work. Note that both p^* and x^* are endogenously determined, according to the three-equation system consisting of (1), the expression for y^*, and the nonlinear price schedule $s(p^*)$.[2]

Nearly all previous studies of household electricity demand have based estimation—either implicitly or explicitly—on a single-equation analogue of equation (1). Because the marginal price is simultaneously determined by a supply equation and a demand equation, standard econometric arguments imply that ordinary least squares estimation using p^* will yield biased and inconsistent estimates of demand parameters. Recognizing as much, most previous studies have used either an exogenous proxy for the marginal price or instrumental variables (IV) procedures in estimation. While either method can alleviate the endogeneity problem, both introduce biases of their own: the former due to mis-specification of the appropriate marginal price, and the latter because of the difficulty in finding good instruments (that do not *a priori* belong in the demand equation) in this setting.

To elaborate on the latter point, the natural set of instruments in this context are the components of the price schedule itself. This idea appears in early work by McFadden, Puig and Kirshner (1977) and others. An important shortcoming of this approach, however, is that there may be little or no price schedule variation in the data. This is a common situation in nonlinear pricing applications, as the data are often provided by a single firm that charges either one tariff,

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[2] The analysis with a decreasing price schedule is slightly more complex, because of the possibility that demand may have multiple crossings of the price (supply) schedule. In that event, these three equations have multiple solutions and a fourth equation (involving the indirect utility function) is needed to determine consumption. This analysis is feasible if the econometric demand specification admits a known indirect utility function; see, *e.g.* Hausman (1985).

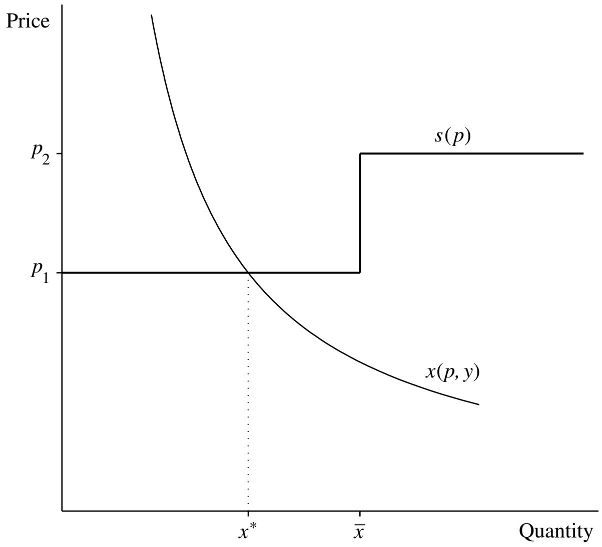

FIGURE 1
An increasing two-tier price schedule

or a few very similar ones, to all consumers. Researchers thus face a canonical weak instruments problem that can result in imprecise and misleading price-elasticity estimates.[3]

A second, and more general, concern arises when consumption decisions are aggregated over time or over distinct services. In the presence of nonlinear pricing, such aggregation often makes IV procedures infeasible.[4] For example, when the consumption data are aggregated over billing periods, the consumer's actual marginal prices are typically not observed. Thus there is no way to construct a proper IV estimator: the endogenous (sequence of) marginal prices are not available to project onto any instrument. Similar difficulties arise if consumption outcomes are aggregated over nonlinearly priced goods or services, rather than over time.[5]

Data aggregation problems of this sort are nearly universal in electricity demand studies. They occur both because a household's electricity meter aggregates consumption of numerous distinct appliance "services" (addressed further in Section 3), and because publicly available data often record consumption over annual (or other) intervals covering multiple billing periods. The predominant treatment of this latter issue in the literature has simply been to ignore it, proceeding as if the household faced a constant (marginal) price over the course of the year. This not only mis-specifies the prices consumers face, it assumes away the economic effects of interest.

In this paper we handle these difficulties in an integrated way. The starting point is the true reduced form of the "supply equals demand" equilibrium condition in (1); that is, solving the three-equation system above for x^* as a function of the price schedule. We do so here assuming the consumer's ordinary demand function (demand at a constant price p) takes the

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[3] Dubin (1985) shows that ignoring simultaneity problems can produce substantially biased electricity demand elasticities. Maddock *et al.* (1992) show that one common IV approach fails to correct well for the simultaneity bias, resulting in estimated price elasticities that are biased toward the slope of the supply curve.

[4] We thank an anonymous referee for emphasizing this point.

[5] This problem also arises in other econometric applications. An example is the analysis of aggregated retail scanner data for consumption goods, which are often sold using nonlinear forms of pricing (volume discounts, limited-quantity coupons, 2-for-1 offers, etc.). Policy-makers that use such data are now evidently aware of these aggregation biases; see FTC (2002).

econometric form

$$x(p, y, z, \varepsilon; \beta) \tag{2}$$

where z represents observed consumer characteristics, ε unobserved consumer characteristics, and β a set of parameters to be estimated. To avoid unnecessary technicalities, assume demand is strictly increasing in ε and strictly decreasing in p.

Facing an increasing two-tier price schedule, the reduced form for the household's consumption level x^* as a function of the price schedule is

$$x^* = \begin{cases} x(p_1, y, z, \varepsilon; \beta) & \text{if } \varepsilon < c_1 \\ \bar{x} & \text{if } c_1 < \varepsilon < c_2 \\ x(p_2, y_2, z, \varepsilon; \beta) & \text{if } \varepsilon > c_2 \end{cases} \tag{3}$$

where $y_2 = y + \bar{x} \cdot (p_2 - p_1)$ and c_j is the solution to $x(p_j, y_j, z, c_j; \beta) = \bar{x}$ with $y_1 = y$ (that is, c_j is the maximum (for $j = 1$) or minimum (for $j = 2$) value of ε for which consumption occurs on tier j). Equation (3) states that consumption is given by demand at the low price if the first tier is on the margin, by demand at the high price plus an income effect if the second tier is on the margin, and by the quantity $\bar{x}$ when demand crosses supply in the "gap" between the two tiers of the price schedule.[6] The lower and upper cut-off values c_1 and c_2 satisfy $c_1 < c_2$ for any downward-sloping demand function, provided that income effects are not too large.[7]

It is useful to be clear about why estimating the single reduced-form equation (3) can separately identify the effect of price on demand and supply (*e.g.* β in (2)). Intuition from classical supply-and-demand simultaneity in linear econometric models suggests that additional exclusion restrictions are necessary—tantamount to assuming that viable instruments are available. With nonlinear pricing problems, however, this is not the case. Demand is identifiable here because (i) the supply schedule has constant-price segments, and (ii) the conditional distribution of ε (given the marginal price) is computable. Intuitively, one can use the variation in consumption among all households on the *same* tariff segment to identify the non-price components of demand.[8] 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 ε and the price schedule. Researchers can therefore estimate demand without price schedule variation, provided one is willing to place some distributional restrictions on ε. Of course, when there is price schedule variation in the data, this will provide a second "source of identification" for the demand specification (2).

In sum, by solving-out the marginal price to obtain (3), the simultaneity problems arising in econometric analyses using (1) can be avoided. In addition, if one proceeds from an empirical specification of the ordinary demand function that is consistent with (or perhaps derived from) a utility specification, then (3) indicates precisely how the individual terms of a nonlinear price

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[6] The term $\bar{x} \cdot (p_2 - p_1)$ that is added to income in the third case in (3) is the infra-marginal price discount: the difference between the expenditure necessary to purchase the higher quantities $x^* > \bar{x}$ under nonlinear pricing, and that necessary to purchase x^* at a constant price of p_2.

[7] Technically, the case conditions in (3) are correct only if certain restrictions on preferences hold. For a normal good (one whose consumption rises with income), these amount to assuming that the income effect is not "too large"; or, more specifically, that the income effect of the infra-marginal discount does not dominate the substitution effect of the higher marginal price. If this fails, the conditioning-event inequalities on the R.H.S. of (3) are more complex.

[8] This argument ignores income effects (cf. note 7) and confounding due to aggregation over time (more about which further below).

schedule enter the demand decision. This provides a framework for predicting how consumption would change under an entirely different price schedule.

2.2. Estimation issues

From an econometric perspective, equation (3) is a nonlinear censored regression model in which the censoring occurs in the interior of the distribution of outcomes rather than the tails. Such models are generally estimated by maximum likelihood methods, using the discrete structure in (3) to derive the change-of-variables from an (assumed) marginal distribution of ε to the distribution of x^*. Burtless and Hausman (1978), with later extensions by Hausman (1985), Moffitt (1986), and others, develop likelihood functions for models with this structure. Unfortunately, maximum likelihood estimation quickly becomes computationally intractable when the consumption outcomes from a mixed discrete/continuous model are aggregated over time. This problem renders likelihood methods infeasible for our application.[9] Consequently, we pursue a moment-based approach to estimation.

Conditional on the observables, (3) can be integrated piecewise to obtain

$$E(x^* \mid \cdot) = E_\varepsilon[x(p_2, y_2, z, \varepsilon; \beta)] + h(p_1, p_2, \bar{x}, y, z; \beta) \tag{4}$$

where $h(\cdot) \equiv \tau_2 - \tau_1$ is a sorting correction function defined by the truncated moments

$$\tau_j = \int_{-\infty}^{c_j(\beta)} [\bar{x} - x(p_j, y_j, z, \varepsilon; \beta)]\, dF_\varepsilon, \qquad j = 1, 2, \tag{5}$$

with c_1, c_2 defined in (3) and $y_1 = y$. These expressions do not place restrictions on $x(\cdot)$ or how ε enters it (beyond integrability of demand and monotonicity in ε). Although complex in the general form, the moments in (5) that correct for the nonlinearity of the price schedule are straightforward to evaluate for most error specifications in applied work. For example, if F_ε is $N(0, \sigma^2)$ and ε enters demand (2) additively, then expected consumption simplifies to

$$\begin{aligned} E(x^* \mid \cdot) = {} & [x(p_1, y, z; \beta) - \sigma\lambda_1]\Phi_1 + \bar{x} \cdot (\Phi_2 - \Phi_1) \\ & + [x(p_2, y_2, z; \beta) + \sigma\lambda_2]\,(1 - \Phi_2) \end{aligned} \tag{6}$$

where Φ_j is the standard normal distribution evaluated at $c_j(\beta)/\sigma$, ϕ_j the normal density at $c_j(\beta)/\sigma$, $\lambda_1 = \phi_1/\Phi_1$, and $\lambda_2 = \phi_2/(1 - \Phi_2)$.

Equation (6) highlights a useful parallel to more familiar econometric selection models. The terms in square brackets in (6) correct for the fact that, given the observables, consumers that sort onto the lower marginal price are different in their unobservable characteristics from those who choose the higher-tier price. This parallels conventional sample-selectivity problems inasmuch as the econometric complications in both settings stem from endogenous sorting along a budget constraint. Unlike traditional models of labour supply (such as Heckman, 1974), however, here the sorting occurs between segments of a nonlinear budget constraint. This situation generates greater information about the distribution of consumer preferences than sorting between interior and boundary solutions along a linear constraint, which makes (4) more complex than standard selection–correction models.[10]

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[9] To illustrate, the likelihood function for a single (monthly) consumption outcome x^* of the model (3) is a mixed continuous/discrete function with three discrete segments (one for each case in (3)). The likelihood function for the sum of 12 months' consumption outcomes therefore involves 3^{12}, or 531,441 distinct segments. While there is some redundancy involved, the task of evaluating such a likelihood function (for use in either direct or simulated likelihood methods) appears quite burdensome.

[10] At the risk of confusing matters, there is one other difference between the present analysis and traditional models of labour market supply. The analysis here is more complicated because the supply and demand system is non-

The moment expressions in equations (4) and (5), and its interpretation as a selection problem, suggest that it might be possible to take a semi-parametric approach to estimating this model (following Ichimura (1993) or Das, Newey and Vella (2003)). Such methods are not designed to handle situations, such as ours, where there is no ancillary selection information about which segment of the budget constraint is marginal. That is, there are no covariates that predict a household's tariff tier that can be *a priori* excluded from the demand specification. One paper that appears to have made progress in this area is Blomquist and Newey (2002), in the context of modelling labour supply decisions subject to nonlinear income taxation. Their non-parametric approach does not appear adaptable to the present setting, unfortunately, for two reasons. First, identification appears to require considerable cross-sectional variation in price schedules across sample observations. While not a problem for the labour supply context (due to wide wage dispersion), this is a significant limitation in nonlinear pricing applications. The second, and more subtle, issue is that the non-parametric literature cannot yet handle cases where the observed outcome is the aggregation of several distinct consumption decisions that are interdependent. Demand is then implicitly defined by an equilibrium relation for which the marginal effects (of price schedule changes) may not be non-parametrically identified. Such a structure is inherent in electricity demand analyses, due to the aggregation of consumption across appliances.[11]

These considerations necessitate a parametric approach to modelling F_ε in nonlinear pricing problems, at least in our context. In estimation we use (6), which fits our data well. In general, restrictions on F_ε sufficient to evaluate the truncated moments in (5) are necessary to estimate demand elasticities and other quantities dependent on (2), in the absence of considerable (and exogenous) variation in price schedules. This, of course, raises the issue of whether such restrictions are valid for the particular application at hand. We take a formal approach to validating our model using out-of-sample testing in Section 7.

2.3. *Aggregation over time*

A method of moments framework also allows us to handle complications posed by data aggregation over time. In practice, electricity tariffs apply to households' consumption on a monthly basis. In contrast, the data available to us provide only *annual* household electricity consumption. This temporal mismatch is a potential source of bias, as the effects of prices and other time-varying covariates will tend to be confounded in the data. For example, a decrease in a household's cumulative demand over a period of several cooler-than-usual summer months could be due solely to the effect of weather, or due to an increase in seasonal electricity tariffs during the summer, or due to a composition of these two simultaneous effects. With only annual data, it is difficult to disentangle and separately identify the direct effect of marginal price changes. Yet estimating this effect is precisely what is required if we are to measure the effects of changing (monthly) tariff schedules.[12]

recursive. That is, in traditional labour supply models, the individual's labour supply function depends on the market wage, but the market wage is constant irrespective of the labour hours supplied. The slope of the budget constraint is therefore exogenous. In the present analysis, the quantity demanded depends on the marginal price (through substitution behaviour) and the marginal price depends on the quantity consumed (through the price schedule). This feature eliminates triangular-system approaches to estimation (*e.g.* Newey, Powell and Vella, 1999).

[11] To elaborate, aggregation across appliances implies that a household's electricity demand x^* takes the implicit form $x^* = \sum_k f_k(p(x^*), z)$, where $p(x^*) \in \{p_1, p_2\}$ is the marginal price (which depends on total consumption) and f_k is the demand for the k-th appliance's services. Projecting observed values of x^* onto $\{p_1, p_2, z\}$ non-parametrically describes the equilibrium relation between these variables, not the marginal effect of changing the price schedule on demand. The latter is the effect of empirical interest.

[12] Similar temporal aggregation problems occur in other contexts, such as when workers' wages are determined weekly (including overtime), but only monthly or annual data are available.

Addressing this problem constructively requires modelling each monthly consumption outcome, in order to avoid mis-specifying the prices consumers actually face. It also requires information on how demand conditions changed during the year. To be precise, let w_t denote the observable variables affecting consumption in month t, including the applicable price schedule and that month's weather conditions. Let x_t^* denote the household's electricity consumption in month t, and $x^a = \sum_{t=1}^{12} x_t^*$ the household's annual electricity consumption. The value of x_t^* for month t is determined by (3), using the R.H.S. covariates for that month.

To estimate the model we require an expression for the expected value of annual demand, $E[x^a \mid w_1, w_2, \ldots, w_{12}]$. Exploiting linearity of expectations, we assume

$$E[x^a \mid w_1, w_2, \ldots, w_{12}] = \sum_{t=1}^{12} E[x_t^* \mid w_t], \tag{7}$$

where $E[x_t^* \mid w_t]$ is as defined in (6).[13] That is, we evaluate the (conditional) expectation of annual demand by evaluating the monthly consumption equation 12 times, using the appropriate covariates for each month. There is no simple form for otherwise calculating the expected value of annual demand.

In the empirical analysis of demand behaviour, the expected consumption equations (6) and (7) serve two roles. They can be used to estimate a model of demand that avoids aggregation biases when consumers face nonlinear tariffs of the form in Figure 1; and, given the estimated demand model, they can be used to predict how consumption would differ under an alternative tariff structure. Proceeding to the first of these objectives next, we now consider the specification of a household electricity demand function, $x(p, y, z, \varepsilon; \beta)$.

3. HOUSEHOLD ELECTRICITY DEMAND

Like many household services, electricity is not consumed directly. Rather, electricity demand is derived from the flow of services provided by a household's energy-using appliances. The durability of these appliances creates a distinction between short-run and long-run demand elasticities. The "short-run" refers to demand behaviour taking a household's existing appliance stock as given. For example, in response to an increase in the price of electricity, a household might tolerate a warmer air conditioner setting or reduce the number of hours a pool filter operates. In contrast, long-run elasticities incorporate both changes in utilization behaviour and any adjustments to the stock of appliances owned by the household.

This distinction has important consequences for modelling demand behaviour. The long-run effects of electricity price changes are an equilibrium outcome of households' appliance replacement decisions (on the demand side) and appliance manufacturers' choices of technological characteristics and prices for new appliances (on the supply side). Like most prior studies, however, our (cross-sectional survey) data do not contain the longitudinal information necessary to estimate how these replacement decisions are prompted by changing energy prices. Thus, we focus on analysing short-run demand elasticities, and leave appliance replacement decisions for subsequent research. Our results therefore describe changes in demand

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[13] Equation (7) makes a subtle separability assumption about the conditioning sets, which affects household substitution behaviour over time. If we assume that households consume electricity out of permanent rather than contemporaneous (*i.e.* monthly) income, the only time-varying elements in w_t are the monthly weather-related covariates and the price schedules (being seasonal). Equation (7) makes the implicit assumption that, conditional on a household's existing appliance stock, knowledge of the electricity price schedules and weather patterns for past and future months this year has no effect on the current month's consumption. While untestable directly, this is a plausible assumption since households cannot store electricity.

due to changes in appliance utilization behaviour, rather than equilibrium appliance stock adjustments.[14]

This approach to modelling electricity demand amounts to conditioning on households' existing appliance stocks. Since households vary markedly in the set of appliances they own, however, the factors influencing electricity demand in one household may differ significantly from those in the next. We address such heterogeneity by specifying electricity demand functions at the level of the individual appliance.[15] Because we do not observe the electricity consumption of individual appliances, but rather total household electricity consumption, we treat the electricity used by each of a household's individual appliances as a latent outcome. We then aggregate these appliance-level demand specifications to model household electricity demand.

Specifically, we treat total household demand as the sum of electricity used by K distinct appliance categories. These categories include space heating, water heating, air conditioning, refrigeration, pools, and the like. If a household owns an appliance of type $k = 1, 2, \ldots, K$, we assume that electricity consumption (per billing period) for the category, x_k, takes the linear form

$$x_k = \alpha_k p + \gamma_k y + z_k' \delta_k + \varepsilon_k \tag{8}$$

where p is the price of electricity, y household income, z_k a vector of observable household characteristics, and ε_k unobservable household characteristics. The unknown demand parameters α_k, γ_k, and δ_k are assumed constant across households. Depending on the appliance, the category-specific vector z_k may include household demographic information, dwelling structure characteristics, appliance attributes, and (contemporaneous billing-period) weather data. We interpret equation (8) as household demand when it faces a constant (marginal and average) price, p.

Since a household's total electricity demand is the sum of its appliances', we can aggregate (8) to obtain

$$x = \sum\nolimits_k d_k \alpha_k p + \sum\nolimits_k d_k \gamma_k y + \sum\nolimits_k d_k z_k' \delta_k + \sum\nolimits_k d_k \varepsilon_k, \tag{9}$$

where x is total household electricity consumption, $d_k = 1$ if the household owns appliance type k, and $d_k = 0$ if otherwise. This is conveniently rewritten as

$$x = \alpha p + \gamma y + z' \delta + \varepsilon \tag{10}$$

by setting $\alpha = \sum_k d_k \alpha_k$, $\gamma = \sum_k d_k \gamma_k$, and so on. Although equation (10) looks like a conventional linear demand function, the price, income, and other slope coefficients depend upon the household's appliance portfolio. Notice that we are not estimating α directly, but rather the parameters $\alpha_1, \alpha_2, \ldots, \alpha_K$ that characterize the price-sensitivity of each appliance category (and similarly for γ, δ). Thus, this specification allows households with numerous electricity-intensive appliances, such as air conditioners, swimming pools, or electric space heating systems, to exhibit different price and income elasticities than households without such appliances.[16]

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[14] The element of technological change in appliance manufacturers' choices makes estimating the long-run effects of electricity price changes particularly complex. One effort to do so is the EPRI Residential End-Use Energy Planning System (REEPS) micro-simulation models; see Goett and McFadden (1984). These models build on Dubin and McFadden's (1984) model of contemporaneous appliance choice and utilization decisions.

[15] This latent-variables approach to modelling electricity consumption is implicit in Fisher and Kaysen's (1962) pioneering work on aggregate electricity demand. Later studies using related approaches include Parti and Parti (1980), Barnes, Gillingham and Hagemann (1981), and Dubin (1985). The present approach is sometimes termed "conditional demand analysis" in the literature (see especially EPRI, 1989 and references therein); we avoid this usage because it conflicts with similar terminology in econometric multi-level budgeting models.

[16] A separate issue not examined here is that the choice of major appliances in a residence is ultimately endogenous, and may be statistically endogenous to a model of utilization behaviour. Dubin and McFadden (1984)

Equation (10) corresponds to the conventional demand function $x(p, y)$ of classical consumer theory. That is, it specifies the amount of electricity the household would consume *if* it faced income level y and a constant price p for electricity. Since the sample households face nonlinear price schedules, the optimal consumption level is given by evaluating demand using equation (3). The expected value of demand is similarly determined, by appropriately inserting the demand specification (10) into the expected consumption equation (6).

Variances. An important aspect of this model is that the household-level demand error, ε, is heteroscedastic. This occurs because the stochastic term in the household-level demand specification is the sum of the stochastic terms associated with the K appliance utilization equations (8). Specifically, from equations (8) to (10), the variance of the household-level stochastic term is a function of the appliances owned:

$$\begin{aligned}\operatorname{var}(\varepsilon) &= \sum\nolimits_{j=1}^{K} \sum\nolimits_{k=1}^{K} d_j d_k \operatorname{cov}(\varepsilon_j, \varepsilon_k) \\ &\equiv \sigma(d_1, d_2, \ldots, d_K)^2.\end{aligned} \tag{11}$$

We think of the appliance-level stochastic terms as reflecting households' idiosyncratic tastes for utilizing appliances. A variety of behavioural considerations then suggest that the covariance terms entering (11) will tend to be positive, so that the variance of the household-level stochastic term will increase with the number of appliances owned.

From an econometric perspective, equation (11) is a simple model of group-wise heteroscedasticity in which the "group" is a specific portfolio of household appliances. Normally, this would not be a major concern for estimating the parameters of a linear demand specification such as (10). When consumers face nonlinear prices, however, the variance of the household-level stochastic term affects the likelihood that a consumer will fall on one tariff segment or another. This can be seen immediately from equation (6), where (the root of) the variance term, σ, enters the conditional expectation function and the tariff segment probabilities. The heteroscedastic variance of unobserved tastes thus affects expected consumption calculations and estimation of all the demand parameters.

4. ESTIMATION DETAILS

The foregoing discussion suggests a straightforward, albeit nonlinear, least-squares procedure for estimation. This is to choose as estimates the values of the unknown parameters that minimize the difference between the observed and expected annual consumption outcomes. Unfortunately, for some realizations of the data (including ours), the conditional expectation function (6) may be nearly flat with respect to σ near its true value. In essence, the first moments of the sample may contain too little information to estimate the variance components in (11) accurately. To resolve this problem, it is necessary to incorporate additional information into estimation.

We employ a generalized method of moments (GMM) procedure based on first- and second-moment differences between observed and expected annual consumption:

$$\begin{aligned}u_1 &= x^a - h_1(\mathcal{W}, \theta) \\ u_2 &= (x^a)^2 - h_2(\mathcal{W}, \theta) - 2\, h_1(\mathcal{W}, \theta)\, (x^a - h_1(\mathcal{W}, \theta)),\end{aligned}$$

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present some evidence on this issue for gas vs. electric home heating systems. In earlier work we attempted to account for this possible endogeneity in a homoscedastic model (where the household-level error did not depend on the appliances owned; cf. equation (11)). For appliance instruments we used 30-year averages of local weather data. The results from this model did not differ noticeably from an un-instrumented homoscedastic model.

where $h_r(\mathcal{W}, \theta) = E[(x^a)^r \,|\, \mathcal{W}]$ denotes the r-th conditional moment of annual consumption, θ the unknown parameters to be estimated, and $\mathcal{W}$ all observable variables influencing the household's annual consumption. The second equation bases inference on the centred second moment of annual consumption.[17] Let β denote the demand parameters from (10) and ξ a vector of variance terms from (11), so $\theta = (\beta, \xi)$. Since optimal instruments in this setting involve (covariance-weighted) derivatives of the conditional moments h_1 and h_2, we set

$$z_1(\mathcal{W}, \theta)' = \nabla_\beta \; h_1(\mathcal{W}, \theta) \qquad \text{and} \qquad z_2(\mathcal{W}, \theta)' = \begin{bmatrix} \nabla_\beta \; h_2(\mathcal{W}, \theta) \\ \nabla_\xi \; h_2(\mathcal{W}, \theta) \end{bmatrix},$$

and base estimation on the orthogonality conditions $E[z_r' u_r] = 0$, $r = 1, 2$.[18] Note that the gradient of h_1 with respect to the variance parameters is excluded from the instruments, for the sample analogue contains no useful information (it is essentially singular—this is the reason the variance parameters are not identified by (6) alone).[19]

The functional form of $h_1(\mathcal{W}, \theta)$ is given by (6) and (7). The functional form of $h_2(\mathcal{W}, \theta)$ is derived similarly, and involves the second moment of the truncated normal distribution. In doing so, an additional complication arises due to temporal aggregation of consumption. While computing h_1 involves only the mean and variance of the stochastic term ε in the underlying monthly demand specification, evaluating h_2 requires an assumption about the correlation of ε over time. We assume that the value of ε in the household's demand specification (10) is independent from month to month. Jointly estimating an autocorrelation structure for the 12 monthly unobservables appears impractical with annual consumption data.

Estimation sequentially minimizes the metric $||A\,u(\theta)||^2$, where A is a weighting matrix held fixed during each minimization, and $u(\theta)' = [u_1(\theta)' \; u_2(\theta)']$ is the $2n$-vector of "stacked" first and second conditional moment differences for all n households. The matrix $A = \tilde{R}\,\tilde{Z}'D$, where D is a diagonal matrix containing the survey sampling weight for each observation, $\tilde{Z}$ the matrix of instruments evaluated at an initial (consistent) estimate of θ, and $\tilde{R}$ the (Cholesky) root such that $\tilde{R}'\tilde{R} = [D\tilde{Z}'\tilde{\Omega}\tilde{Z}D]^{-1}$. Here $\tilde{\Omega}$ is the true covariance function matrix $E[u(\theta)u(\theta)' \,|\, \mathcal{W}]$, evaluated at the initial estimate of θ. These covariance functions are directly computable (the non-zero elements being the second through fourth conditional moments of annual consumption), and we use their analytic expressions in estimation.

To obtain final parameter estimates, we iterated minimization of the GMM distance metric six times using successive updates of the matrix A. Full optimization required approximately three minutes on a 2·0 GHz computer, with 270 moment equations and 212 estimated parameters. Numerical optimization was performed using an efficient trust-region subspace minimization algorithm (Nocedal and Wright, 1999) and implemented in Matlab.

5. DATA AND EMPIRICAL SPECIFICATIONS

We estimate the model using data from the *Residential Energy Consumption Survey* (RECS). The RECS is conducted every three to four years by the U.S. Department of Energy to collect information on household appliances and energy use. The survey is a nationally representative

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[17] Centring (via the cross-product term $-2h_1(x^a - h_1)$) considerably improves sampling precision: if $(x^a)^2 > h_2$ then the cross-product term tends to be negative, and conversely if $(x^a)^2 < h_2$, which reduces the sampling variance of u_2.

[18] It may be verified by direct analysis that these instruments preserve a unique solution for θ to equations $E[z_r' u_r] = 0$, $r = 1, 2$, provided that the variance function $\sigma(d_1, d_2, \ldots, d_K)^2$ is bounded away from zero.

[19] In estimation we use a re-parameterization of the variance function (11) that facilitates estimation but at the cost of increasing the number of parameters. Estimation is easier because the re-parameterized GMM objective function is orthogonal in each of the 154 variance parameters. This re-parameterization imposes positive definiteness but otherwise places no restrictions on the covariance matrix in (11).

probability sample of households, with representative subsamples for several large states. We use the California subsamples of the 1993 and 1997 survey waves. Together they provide information on 1307 California households.

The survey is conducted through in-home interviews. Interviewers inventory the household’s appliances, assess physical characteristics of the residence, and collect demographic information. The survey also includes weather data (heating and cooling degree-days) for each household, which are obtained from the nearest National Weather Service (NWS) station during the survey year. Each household’s metered energy consumption data are collected by the survey directly from its electric utility. Further details about the RECS data and survey design are available in EIA (1994, 1996).

The appliance information, representativeness, and quality of the consumption data make the RECS particularly valuable for analysing household electricity demand. There are, however, two noteworthy shortcomings of the RECS data. The first is that the RECS public-use files only provide *annual* household electricity consumption and expenditures, as noted in Section 2. The second shortcoming pertains to the limited electricity tariff information available in the survey. Inadequate pricing data are a first-order problem for many previous studies of electricity demand and for other researchers using the RECS. Our considerable efforts to rectify this problem merit a brief digression here.

5.1. Prices

During the sample period most California households faced an increasing two-tier electricity price schedule each month, such as the one depicted in Figure 1. These schedules vary by service provider, climate zone, household heating system, household income, and season. For example, the state’s largest utility, Pacific Gas and Electric (PG&E), had 72 variants of its standard residential rate schedule in effect during 1993 and 1997. A similar structure applies to the state’s other major utilities.

The RECS data provide two summary price measures for each household. The first is the household’s annual average electricity price, in cents per kilowatt-hour. The second is the local electric utility’s annual average revenue per kilowatt-hour sold to all its residential customers. Either of these price measures unfortunately presents problems for modelling electricity demand at a disaggregate (household) level. As noted in Section 2, the first of these two price measures is endogenous (it rises with consumption) and bears a complex relation to the household’s monthly use. The second, utility-level average price, while putatively exogenous, will typically mis-measure the actual marginal price faced by a household. Either summary price measure could therefore be expected to provide poor information regarding the marginal price facing the household each month, and thus biased price elasticity estimates.

To address these shortcomings, we developed a procedure for matching each observation in the RECS with the complete rate schedule facing the household. The data this requires that are not provided in the RECS are each household’s utility and its utility-designated climate zone. To determine these, we exploit three types of information in the RECS about the household: the local utility’s average electricity price, the availability and price of natural gas, and the weather information. The weather data provide considerable information regarding where in California’s diverse climate zones each household is located. The utility-level electricity and natural gas price data then help pinpoint the household’s service provider.

To match each RECS household to its utility and climate zone, we first used maps of utility service areas to assign each of the approximately 240 NWS stations in California to one (or two adjacent) utility service territories. We then collected the local average electricity and gas prices for each service territory in the state. These weather and price data are the same primary data series used by the RECS and included with each household in the survey. We then determine each household's utility and climate zone by matching the household's information in the RECS with the known average price and weather data for each utility and NWS station in California.

The remaining information necessary to determine a household's specific rate schedule (namely, the household's income and its home heating system) are directly available in the survey. We also used the RECS's electricity expenditure data to determine which eligible low-income households are actually participating in their utilities' low-income electricity tariff programmes. To complete the procedure, we manually compiled the complete 1993 and 1997 electricity tariff books for each California utility, from filings archived at the California Public Utilities Commission public records library and direct contact with municipal utilities' tariff departments. In the end, the 1307 California households in the RECS sample were matched to 189 distinct rate schedules.

Table 1 provides some information on how well this matching procedure performs. As the survey is a stratified probability sample of California households, we expect (and find) reasonable agreement between what the utilities report as their number of residential accounts and the number of households implied by the survey. For the five largest utilities (which serve 93% of California households), the implied geographic distribution of RECS households by utility is quite close to that reported in the utilities' regulatory accounting data. The most notable deviations occur for the two smallest investor-owned utilities, Sierra Pacific and PacifiCorp, which serve sparsely populated mountainous northern and eastern areas of the state. We believe that the stratification design and a special segment of the RECS that oversamples low-income households may account for their overrepresentation.[20]

5.2. Appliance demand specifications

Our monthly appliance demand specifications are based on prior empirical research that has studied households' appliance use decisions. Principal sources are the EPRI/REEPS model described in LBL (1995) and the EIA Residential End-Use Model, EIA (1995). We model end-use electricity demand using eight distinct appliance categories: (1) baseline electricity use; (2) electric space heating; (3) central air conditioning; (4) room air conditioning; (5) electric water heating; (6) swimming pools; (7) additional refrigerators and freezers; and (8) other appliances. The baseline category accounts for the electricity consumption of appliances that are universally owned, such as the (first) refrigerator and lights. This category also implicitly includes consumption attributable to any unspecified electrical appliances below the resolution of the RECS survey (such as electric clocks, irons, hair dryers, and the like). Appliance categories two through six are energy-intensive end uses that previous research indicates exhibit some utilization price elasticity (EPRI, 1989). The final category includes less energy-intensive household appliances. A description of all appliances entering the model is provided in Table A1.

Different factors influence appliance-level electricity demand in each category. In particular, we estimate separate price and income effects for each of the first six categories. The remaining appliances are assumed to have a common price effect, as previous studies indicate most of these (refrigeration, cooking, clothes dryers, etc.) exhibit no significant electricity price elasticity. Demographic and other explanatory variables entering the model are defined in Table A2. Demographic characteristics of households are assumed constant during the survey year; the

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[20] We are grateful to U.S. Energy Information Administration analysts for lengthy discussions on these RECS sampling issues. One unresolved issue is the RECS sampling weights imply 350,000 more California households with electricity service than comparable figures in California utilities' regulatory accounting data (this is evident in the bottom line of Table 1). In addition, the survey's cluster sampling procedure will generally yield uneven coverage of smaller utility service areas.

TABLE 1

Average price and number of households for California electric utilities

	Average residential rate in 1993[a] (cents per kWh)	*Number of households* Actual[a]	*Number of households* Estimate[b]	*Per cent of households* Actual[a]	*Per cent of households* Estimate[b]
Investor-owned utilities					
Pacific Gas & Elec.	12·25	3,748,831	4,069,268	34·8	36·6
Southern Calif. Edison	12·10	3,636,295	3,655,184	33·8	32·9
San Diego Gas & Elec.	10·81	1,005,257	1,020,010	9·3	9·2
PacifiCorp (Calif.)	6·94	31,872	351,053	0·3	3·2
Sierra Pacific Pwr. (Calif.)	8·79	36,581	169,317	0·3	1·5
Investor-owned subtotal		8,458,836	9,264,832	78·5	83·3
Municipal/public utilities					
Los Angeles	9·85	1,168,229	1,169,431	10·8	10·5
Sacramento	7·65	416,364	377,054	3·9	3·4
Riverside	10·57	80,828	35,510	0·8	0·3
Imperial	8·36	67,021	7592	0·6	0·1
Santa Clara	7·30	38,129	126,735	0·4	1·1
Lompoc	9·21	12,729	61,569	0·1	0·6
Plumas-Sierra	7·70	4674	82,557	0·0	0·7
Subtotal		1,787,974	1,860,448	16·6	16·7
Other municipal/public utilities[c]		526,480	0	4·9	0·0
State total		10,773,290	11,125,280	100·0	100·0

[a] Sources: U.S. Dept. of Energy Form EIA-861 (1993), FERC Form 1 (1993).
[b] Estimate based on the 1993 RECS survey data (see text).
[c] Households served by other small municipalities, rural electric cooperatives, and public power districts.

monthly varying covariates in our specifications are the price schedules and the weather data.[21] All monetary variables are normalized to real (June 1993) prices, using the CPI-U series for California's three consolidated metropolitan statistical areas.

6. RESULTS AND IMPLICATIONS

6.1. Estimates and marginal effects

Table 2 presents the model's estimated marginal effects for the principal variables of interest. Table entries show the effect of a one unit increase in each explanatory factor on monthly kilowatt-hour consumption of each specified appliance. We compute marginal effects separately for each household (using the gradient of its conditional expectation function (6)), and then average across households using the RECS sampling weights. These are interpretable as the mean marginal effects in the population, conditional on ownership of the indicated appliance. Raw demand parameter estimates are reported in Table A3. The fitted model has a mean square error of (2352 kWh/year)^2, which is approximately one-third of the sample variance of consumption.[22]

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[21] In addition to the specifications evident in Table A3, we imposed a constraint that electricity consumption for space heating and cooling is zero during the summer and winter months, respectively. To accommodate the varied heating and cooling season lengths for different regions and elevations in California, this was implemented via a minimum (one per day) degree-day threshold for the use of these appliances.

[22] Hansen's over-identification test statistic is 76·9, which under simple random sampling has $p = 0{\cdot}05$ (df $= 58$) asymptotically. The RECS is not based on simple random sampling, however. Its multi-stage sampling design implies the actual critical value of this test statistic will be larger (possibly much larger) than its nominal counterpart. We take an alternative formal approach to testing model fit in Section 7, using standard errors adjusted by the survey's design

TABLE 2

Estimated marginal effects (asymptotic standard errors in parentheses)

Explanatory variable	*Effect on kWh consumed per month for:* [a]					
	Baseline use	*Elec. space heating* [b]	*Central air cond.* [c]	*Room air cond.* [c]	*Elec. water heating*	*Swimming pool*
Price (cents/kWh)	0·4	−37·8	−22·5	−63·4	−34·0	−27·5
	(3·7)	(14·8)	(21·3)	(31·1)	(9·5)	(18·4)
Income ('000 $)	0·4	16·2	9·1	21·6	−32·8	6·3
	(2·3)	(13·0)	(10·6)	(20·8)	(7·5)	(9·8)
No. of members	18·0	−7·9	−38·6	−52·1	47·5	
	(3·3)	(20·3)	(16·3)	(19·9)	(10·6)	
No. of rooms	12·9	20·4	9·8	29·2	−35·3	
	(4·5)	(22·0)	(17·4)	(23·4)	(15·2)	
No. of bathrooms	27·0				119·0	
	(9·8)				(40·1)	
Heating deg.-days ('00 °F, base 60)	−10·6	43·3				
	(6·3)	(21·9)				
Cooling deg.-days ('00 °F, base 70)	−59·5		233·0	45·1		
	(22·5)		(57·0)	(123·0)		
Dummy variables						
Apt. building	−48·4					
	(14·1)					
Housing project	−78·9					
	(24·6)					
At home during day	15·8					
	(10·0)					
Urban location	−35·5					
	(11·9)					
Rural location	31·4					
	(25·1)					

(Effects of additional appliances are shown in Table A4*)*

[a] Estimated change in monthly appliance electricity consumption associated with a unit increase in the explanatory variable, *ceteris paribus*. The marginal effects shown are estimated population means, conditional on appliance ownership.

[b] Heating-season months only.

[c] Cooling-season months only.

The signs and magnitudes of the estimates in Table 2 generally agree with prior studies, although there are a few exceptions.[23] The estimated price effects vary substantially across appliances. The smallest effect is associated with baseline use, and is effectively zero. All other appliance price sensitivities are of considerable practical significance. For example, the −27·5 estimate for price and swimming pools in Table 2 implies that a one cent per kilowatt-hour (kWh) increase in the marginal price would reduce a household's annual utilization of pool pumps and motors by approximately 330 kWh per year, which is 15% of a pool's typical electricity use. The

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efficiency ratios to account for its complex sampling design.

[23] For example, the negative coefficients on income and on the number of rooms in the water heating specification. We suspect this may be due to confounding from unobserved variation in water heater energy efficiency, which is likely to be considerably higher in newer (larger) homes in California. The negative coefficients on the number of household members and space cooling are also of unexpected sign, and may be attributable to an omitted (positive) influence of householder age on space cooling demand.

TABLE 3

Price and income elasticities for California households

Mean elasticities of electricity demand[a]	*Price* GMM method	*Price* OLS method	*Income* GMM method	*Income* OLS method
All households	−0·39	+0·16	−0·00	+0·00
Households with:				
Electric space heating	−1·02	−0·46	−0·00	+0·01
No electric space heating	−0·20	+0·35	−0·00	−0·00
Central or room air conditioning	−0·64	+0·05	+0·02	+0·02
No air conditioning	−0·20	+0·24	−0·01	−0·01
No electric space heating nor air conditioning	−0·08	+0·39	−0·01	−0·01

[a] Annual elasticities (see text and Appendix B).

price effects for major appliances providing space heating, cooling, and water heating services differ from one another considerably, both in absolute terms and relative to typical consumption for each appliance (see Table A4).

By contrast, the income effects are mostly statistically insignificant and negligible as a practical matter. This is not entirely surprising, given that our analysis is conditional on households' appliance stocks. To the extent that income affects electricity consumption, it is evidently manifest through households' choices of appliances rather than through utilization behaviour. These results are consistent with prior studies' findings of low-to-negligible appliance utilization income elasticities at the household level (*e.g.* Parti and Parti (1980) and Dubin and McFadden (1984)).

Details on specific appliance-level consumption estimates are provided in Appendix A and Table A4.

6.2. Price elasticities

Table 3 presents estimated average annual household price and income elasticities. These elasticity estimates correspond to the percentage change in a household's annual electricity consumption resulting from a 1% increase in the marginal price (or household income) in each month of the year, holding the appliance stock fixed. We calculate demand elasticities separately for each of the 1307 households in the sample, and then average using the survey sampling weights. The elasticities shown in Table 3 are estimated population means for California households.

Before interpreting these numbers, it is important to note that with nonlinear tariffs there is more than one "price" involved in measuring the elasticity of demand. For example, one can calculate the elasticity of demand with respect to an increase in the intercept of the price schedule, with respect to the price of a specific tariff tier, or with respect to the consumer's marginal price. We present elasticity estimates based on the third of these interpretations, so as to reflect households' demand sensitivity on the margin. In doing so we recognize the fact that with multi-part tariffs, changing a consumer's marginal price may alter consumption within the current tariff segment or induce a discrete jump to a different price tier. Our elasticity calculations explicitly account for this possibility, using methods described in Appendix B.

We estimate the mean annual electricity price elasticity for California households to be −0·39. Previous studies of residential electricity demand data have estimated widely varying utilization price elasticities, ranging from nearly zero to about −0·6. These estimates reflect differences in the geographic regions examined, as well as considerable variation in data quality and statistical techniques. Studies conducted by electric utilities, which often have higher-quality data, tend to obtain price elasticities within a narrower range of −0·15 to −0·35 (EPRI, 1989). Our results with the California RECS data fall at this set's upper end, but are close to the −0·35 estimate contained in a much earlier Rand Corporation study of Los Angeles-area households by Acton, Mitchell and Mowill (1976).

It is useful to compare our estimates to those using more traditional estimation methods. The second column in Table 3 shows the elasticities obtained if we ignore the simultaneity of price and quantity under nonlinear pricing and simply perform OLS using the household's average price. The resulting mean price elasticity estimate is +0·16, which has the wrong sign. Such large biases are typical when simultaneity is ignored in electricity demand studies, for the simple reason that there is wide (cross-sectional) variation in demand but relatively limited variation in the price schedules. OLS techniques using the consumer's average or marginal price therefore tend (in essence) to fit the average slope of the price schedule. Similar biases are noted in Dubin (1985) and Maddock *et al*. (1992).

Additional regressions that use other summary price measures appearing in the literature (*e.g.* the midpoint of the two tiers or utility-level average prices) yield elasticity estimates of the correct sign, but much smaller in magnitude than the GMM results using the complete rate schedule. For example, estimates obtained using OLS with the (statistically exogenous) utility-level average price measure in the RECS yield a mean household price elasticity of −0·28.[24] This estimate is consistent with the bias toward zero that one would expect due to this proxy's mis-measurement of the consumer's actual marginal price. It also suggests an explanation for why our GMM estimates imply somewhat more price-elastic behaviour than many earlier studies' (particularly the utility-conducted studies noted above), in that most prior work treats tariff structure information in either an *ad hoc* manner or not at all.

Heterogeneity in price sensitivity. The disaggregate data also reveal considerable and meaningful heterogeneity in households' price and income elasticities. As noted previously, the model permits households' price and income elasticities to vary across households not just with their consumption level, but also with their appliance holdings. Table 3 illustrates the marked differences in demand elasticities for households with different heating and cooling systems. Households with electric space heating or air conditioning exhibit a much higher electricity price elasticity than households without such systems. Households that do not use electricity for either of these purposes have an estimated mean price elasticity very close to zero. This heterogeneity is consistent with the limited prior evidence on electricity price elasticity variation across households (*e.g.* Dubin, 1985). As a practical matter, it suggests that there are effectively two "types" of households with respect to electricity demand behaviour: those who use electricity for space heating or air conditioning and exhibit some electricity price elasticity, and those who do not and are price insensitive.

Further information about the heterogeneity in households' demand elasticities is provided in Figure 2. This histogram of the sample households' price elasticities is constructed (using the survey weights) to represent the distribution for the California population. The point-mass at zero

[24] Price elasticity differences of seemingly small amounts (*e.g.* −0·28 vs. −0·39) are economically quite important in electricity markets. Assuming residential demand is too inelastic by this difference of −0·1 when increasing the marginal rate by (say) three cents per kWh would overestimate annual revenue for California's larger utilities by approximately 75 million dollars.

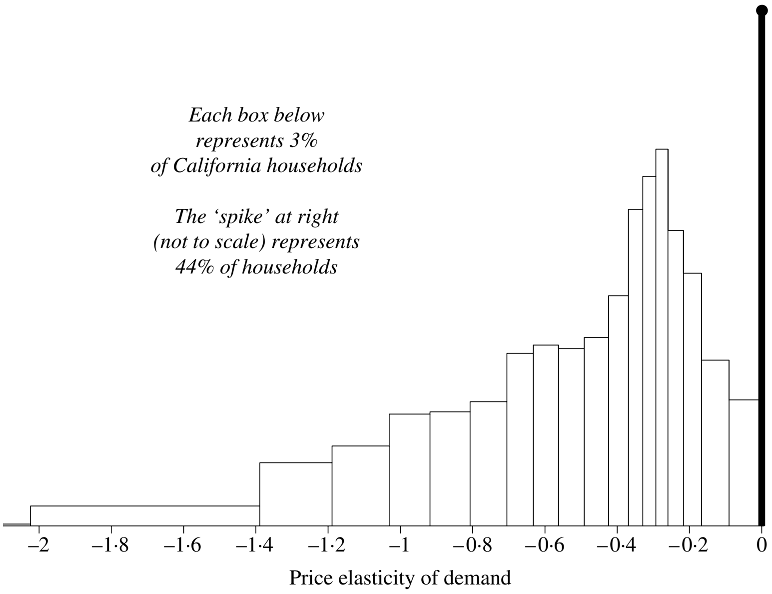

FIGURE 2

Estimated distribution of California households' electricity price elasticities

indicates that 44% of California households exhibit no short-run demand sensitivity to changes in the marginal price of electricity. This segment of the population is primarily households that own no major electric appliances other than a refrigerator, and whose minor appliances fall within the inelastic "baseline use" category of the model. The expected fraction of households whose demand curves cross their price schedules in the "gap" between the two price tiers is 1–2% each month. Thus, very few households have a locally zero estimated price elasticity due only to the discontinuity in the price schedule.

The striking feature of Figure 2 is its highly asymmetric, negatively skewed shape. This pattern indicates that most households will alter their electricity consumption very little in response to a price change. A small fraction of households, however, are actually elastic demanders (roughly 1 in every 8 families) and would react with large changes in their electricity use. This has noteworthy implications for the welfare effects of electricity price changes, inasmuch as most of the dead-weight welfare losses from a price increase would evidently be borne by a fairly small share of the consumer population.

Where a household is located in this distribution is related to its income and other demographic characteristics. Table 4 summarizes household electricity price elasticities by income and consumption levels. How price elasticities vary with household income (in the cross section) is of interest because regulatory commissions provide subsidized tariffs to low-income households, and are at times concerned with the consumption incentives of these subsidies. The conventional wisdom is that households with lower incomes are more sensitive to energy prices than households with medium-to-high incomes. The results in the top half of Table 4 are consistent with this view, although the magnitudes of these differences are not dramatic.

The lower half of Table 4 indicates how household price elasticities vary with the amount of electricity the household consumes. This relationship is of interest because the aggregate consumption and revenue effects of a tariff change depend upon how elasticities vary across the different tiers of the price schedule. Somewhat surprisingly, we find that elasticities are lower

TABLE 4

Price elasticities by household income and electricity consumption

Quartile	Quartile range	*Price elasticity*[a] GMM method	 OLS method
By household annual income level:[b]			
1-st	Less than \$18,000	−0·49	+0·15
2-nd	\$18,000 to \$37,000	−0·34	+0·17
3-rd	\$37,000 to \$60,000	−0·37	+0·14
4-th	More than \$60,000	−0·29	+0·17
By household annual electricity consumption:			
1-st	Less than 4450 kWh	−0·46	+0·37
2-nd	4450 to 6580 kWh	−0·35	+0·04
3-rd	6580 to 9700 kWh	−0·32	−0·00
4-th	More than 9700 kWh	−0·33	−0·08

[a] Mean annual electricity price elasticity for households within each quartile.
[b] Approximate California household income quartiles, in 1998 dollars.

for households that use high amounts of electricity, despite the fact that households with energy-intensive electric space heating/cooling systems have much greater electricity price sensitivity *ceteris paribus*. This inverse relationship reflects both a weak correlation between household income and ownership of electric space heating/cooling systems, and the fact that households tend to substitute toward more price-inelastic electricity uses as income rises. Thus, from an economic efficiency standpoint, the welfare cost of raising a given amount of revenue will be minimized if the marginal price changes are disproportionately larger for the highest-demand consumers.

Further results along these lines using different data are examined in Reiss and White (2003).

7. VALIDATION: THE 1998 PRICE CHANGES

Our empirical results rest in part on the appliance demand specifications and error distribution assumptions of the model. Because we must aggregate over appliances and over time to match the consumption level of the data, these appliance demand specifications are not testable directly. In this section we examine the model's validity using both within- and out-of-sample tests.

7.1. *Within-sample fit*

For purposes of interpreting the out-of-sample test below, it is useful to first examine the representativeness of the RECS consumption data and in-sample model predictions. Because electric utilities are subject to extensive regulatory reporting requirements, there exist comprehensive aggregate data on utilities' actual sales and number of customers. In principle, averages from these data will differ from their counterparts for the RECS households by amounts attributable to the survey's sampling error.

Some evidence on this issue is provided in Table 5. The first numerical column in Table 5 presents actual electricity consumption per household for California and its four largest utilities. The second column presents the corresponding mean electricity consumption for the RECS

TABLE 5

Within-sample predicted and actual consumption

Electricity consumption per household, in kWh	Actual[a]	*Sample data* Sample mean	Standard error[b]	Actual error	*Estimated model* Predicted mean	Average within-sample error
Pacific Gas & Elec.	6531	5796	258	+735	5899	+103
Southern Calif. Edison	6238	6063	291	+175	5961	−102
San Diego Gas & Elec.	5706	4627	514	+1079	4775	+148
Los Angeles Wtr. & Power	5261	5113	454	+148	4867	−246
All California	6355	6007	157	+348	6010	+3

[a] Weighted average of the total residential sales (in kWh) divided by the number of residential accounts in each of 1993 and 1997, as reported by each utility. Source: U.S. Dept. of Energy Form EIA-861 (1993, 1997).
[b] Standards errors shown account for the multi-stage sample design of the RECS (see EIA, 1994).

sample households along with the standard error of the survey. For the state as a whole, Table 5 implies that the RECS sample under-represents actual household electricity consumption by slightly more than two standard errors. We also find that the RECS data understate average household consumption for each of the state's four largest utilities, although by sometimes less than two standard errors.[25]

The final columns compare the model's predictions to these actual and sample consumption averages. Since the model is fitted to the RECS data, the difference between the observed and predicted averages represents within-sample error. Although our model is nonlinear, the average within-sample error for the full sample is essentially zero. As with the raw sample data, however, the estimated model under-predicts actual consumption for each utility and the state overall. This is not entirely surprising, given that the model can at best capture the behaviour of the sample to which it is fitted. We conclude that while the RECS sample appears to understate actual household consumption in California, the model does reasonably well (*i.e.* within a few per cent) at fitting the sample data for each utility.

7.2. *Out-of-sample tests*

In January 1998, shortly after the end of our sample data, California's three largest investor-owned utilities reduced the price of residential electric service by 10%. This price change, by virtue of its magnitude and exogeneity to the household, provides a unique opportunity to evaluate the model's out-of-sample accuracy. We also account for the El Niño Pacific weather disturbance that occurred in 1998 and 1999, which changed California's weather patterns substantially.

Ideally, we would prefer to evaluate the model using within-household differences in predicted and actual consumption between 1997 and 1998 (*i.e.* a matched-pair test). Unfortunately, due to the triennial (and non-longitudinal) nature of the RECS, we do not have data on actual consumption after 1997 for the sample households. Instead, we base inference on

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[25] There are other reasons why the *utility-specific* averages might differ between the RECS and the actual (regulatory accounting) data. First, while the RECS is designed to generate a representative sample of households at the state level, the sampling scheme is not designed to produce representative samples within each utility's service territory. Second, the household-utility matching procedure we use to obtain rate schedules (in Section 5) introduces potential misclassification error. The difference in state-level average consumption between the RECS and the regulatory accounting data is not subject to these caveats, however.

TABLE 6

Out-of-sample prediction tests for 1998 and 1999

Utility electricity sales per household, in kWh	Actual[a]	Predicted	Difference	Std. error	Prob.[b]
Panel A: 1998					
Pacific Gas & Elec.	6775	6198	+578	252	0·02
Southern Calif. Edison	6455	6233	+223	280	0·43
San Diego Gas & Elec.	5935	5005	+930	580	0·11
Los Angeles Wtr. & Power	5438	4885	+554	498	0·27
Panel B: 1999					
Pacific Gas & Elec.	6905	6187	+718	267	0·01
Southern Calif. Edison	6423	6257	+136	292	0·64
San Diego Gas & Elec.	5964	5078	+886	647	0·17
Los Angeles Wtr. & Power	4866	4826	+40	496	0·94

[a] Total residential sales (in kWh) divided by the number of residential accounts, as reported by each utility. Source: U.S. Dept. of Energy Form EIA-861 (1998, 1999).

[b] Approximate probability of a difference between actual and predicted at least as large (in magnitude) as observed, under the model.

comparisons to the average household consumption reported in California utilities' regulatory accounting data for 1998 and 1999.

To implement a formal test we first extended the actual weather series used in the model through 1998 and 1999. We also collected the exact form of the tariff changes implemented in 1998 and 1999 for each RECS household.[26] We then use the model to predict what the RECS households would have done in 1998 and 1999, given the price change and weather conditions that occurred, and aggregate these responses to the utility level.

Table 6 compares these out-of-sample predictions to actual residential electricity consumption for California's four largest utilities in 1998 and 1999. The second-to-last column provides estimated standard errors for the difference between the actual and predicted consumption averages. These standard errors account for both the non-sampling variance in future consumption outcomes under the model, and the sampling error associated with the RECS multi-stage design.[27] The final column reports the (two-sided) probability of observing a difference at least as large as that shown, under the maintained assumptions of the model. Small p-values constitute evidence against the validity of the model.

As the within-sample results foreshadowed, the model continues to under-predict average consumption in 1998 and 1999. For three of the four utilities in each panel, however, the observed differences from the model's predictions are within the bounds of what may be ascribed to chance by conventional standards of statistical significance. The smallest p-values, for Pacific Gas and Electric in 1998 and 1999, are attributable to the particularly acute under-representativeness (relative to sampling error) of the RECS households' consumption data for

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[26] The January 1998 price decrease amounted to lowering each tier of the household's price schedule by 10%. The actual marginal price change thus depends upon the household's particular rate schedule. There was also a separate price increase for households served by the Los Angeles Department of Water and Power in 1999, which shows up as a notable decline in consumption for Los Angeles households between 1998 and 1999.

[27] Since we have a nonlinear model and the RECS uses a multi-stage sampling design, the standard errors for this test are approximate. We use a linear approximation (delta) method to estimate the variance of average predicted consumption under simple $(1/n)$ random sampling, and then inflate the result by the design efficiency ratio of the RECS consumption series (about 1·4) to get the standard errors in Table 6. This method and related techniques are discussed in Skinner, Holt and Smith (1989).

this utility. Interestingly, for three of the four utilities in each panel, the model's average error (relative to actual) is smaller for the out-of-sample years of 1998 and 1999 than it is for the within-sample years reported in Table 5. On that basis, the model appears to deliver reasonable predictions for how California households respond to electricity price changes.

8. ANALYSING PROSPECTIVE TARIFF DESIGNS

An important feature of the model developed above is that it can be used to evaluate, on a prospective basis, the effects of complex price schedule changes. For a variety of practical reasons, regulatory agencies are often reluctant to authorize randomized-assignment pricing experiments as a means to evaluate major tariff changes. Thus, counter-factual simulations based on econometric models become the analytic method of choice. The accuracy of these simulations is a matter of considerable practical interest, inasmuch as tariff changes for electricity can affect billions of dollars in consumer expenditures.

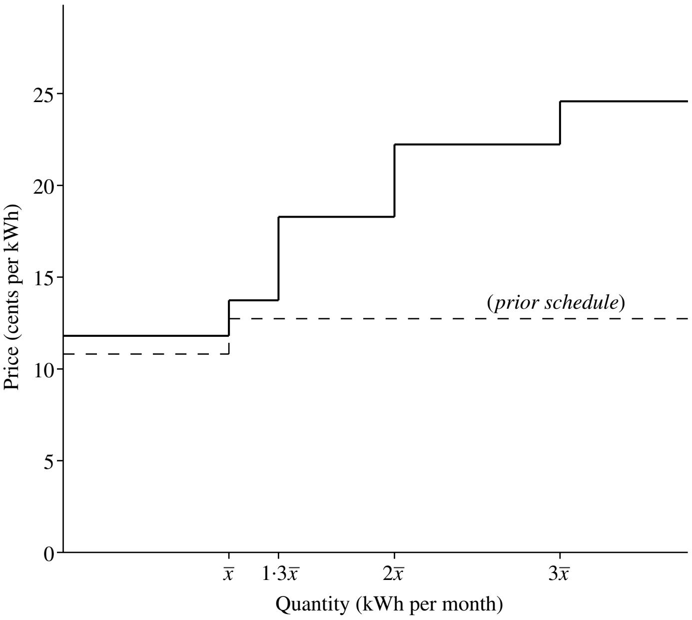
In this section, we provide consumption and expenditure estimates for a complex tariff design being implemented in California. Following a financial crisis facing that state's utilities in the spring of 2001, the California Public Utilities Commission approved new tariff structures for the state's two largest utilities. The new multi-part tariff structure for residential electric service is shown graphically in Figure 3. Under this five-tier design, the household inherits from its prior (two-tier) tariff a monthly reference quantity, $\bar{x}$. The first $\bar{x}$ kilowatt-hours of monthly electricity consumption are then billed at one price per kilowatt-hour, the next $30\% \times \bar{x}$ are billed at a higher price, and so forth as indicated in Figure 3. The reference quantity $\bar{x}$ and the specific tier prices vary based on the utility, the season, the household's climate zone and home heating system, and other factors.

This novel pricing system is intended to achieve several objectives. First and foremost is to raise additional revenue for the state's utilities. Second, the new tariff is intended to promote energy conservation, particularly among higher-demand consumers. Third, there is a distributive objective underlying this tariff design. Electricity is a necessary good (in the sense that its budget share declines as household income rises), so a uniform increase in the price of electricity can be quite regressive. By raising marginal prices more for higher levels of consumption, regulatory authorities hope to attenuate this regressivity and minimize expenditure changes for lower-income households.

Because the five-part tariff is unprecedented in historical consumption data, there is no way to extrapolate how well this new system would achieve these objectives using descriptive (*i.e.* reduced-form) econometric methods. Rather, predicting aggregate demand requires explicitly modelling consumer choice behaviour under the new tariffs. To do so, suppose j indexes the five tiers in Figure 3, p_j is the marginal price on tier j, and $\bar{x}_j$ is the j-th-tier upper boundary. Set $x_j = x(p_j, y_j, z, \varepsilon; \beta)$, where y_j denotes the household's income plus the cumulative infra-marginal price discount applicable in tier j. Conditional on observable household characteristics, the expected value of monthly household consumption is then

$$\begin{aligned} E(x^* \mid \cdot) = {} & \sum\nolimits_{j=1}^{5} P_\varepsilon(\bar{x}_{j-1} < x_j < \bar{x}_j) \cdot E_\varepsilon(x_j \mid \bar{x}_{j-1} < x_j < \bar{x}_j) \\ & + \sum\nolimits_{j=1}^{4} P(x_{j+1} < \bar{x}_j < x_j) \cdot \bar{x}_j \end{aligned} \tag{12}$$

using the conventions $\bar{x}_0 = 0$, $\bar{x}_5 = \infty$, and P_ε the distribution of ε given the observables. The first sum is the contribution to expected consumption conditional on demand crossing the price schedule on one of the five steps, and the second sum is the contribution conditional on demand crossing the price schedule in one of the "gaps" between the steps. As before, this



Notes: The reference quantity, $\bar{x}$, varies across households and seasons. The rates depicted above are for the most common residential tariff schedule for this utility. The prior schedule shown applied from 1998 through 2000.

Source: Southern California Edison PUC Advice Letter 1545E, Schedule D, Tariff Sheet 29197E (2001).

FIGURE 3

A five-tier price schedule Southern California Edison, Residential Electric Service

amounts to a probability-weighted average of expected demand within each segment of the new tariff schedule. Stated in behavioural terms, the consumer sorting-on-the-unobservables problem that occurs with multi-part tariffs must be addressed not only in demand estimation, but also when predicting consumption at new prices.[28] Such nonlinearities are why the aggregate impacts of a new tariff design depend, sometimes delicately, upon the heterogeneity in consumers' price elasticities across the population.

We use equation (12) and the estimated demand model to evaluate a five-tier tariff system adopted by the California Public Utilities Commission in May 2001. With little prior analysis, this system was implemented the following month for approximately 7·8 million households served by the Pacific Gas and Electric Company and the Southern California Edison Company. We use these utilities' tariff books to identify the terms of the new tariff applicable to each household in the RECS sample. We also evaluate these tariff changes for "normal" weather conditions, using 30-year average degree-days from the NWS station located nearest each household. The tier selection probabilities in (12), which depend upon both the household and its particular tariff schedule, are evaluated using the normality assumption and household-specific variance estimate from the econometric model. We evaluate the expected consumption equation

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[28] In particular, equation (12) differs from what one obtains by simply intersecting the household's estimated demand curve (assuming ε to be zero) and the new price schedule. That technique implicitly treats the tariff segment selection probabilities in (12) as either zero or one, and ignores the conditional expectation adjustment for ε in each tariff segment. Unless the variance in the household's future consumption (given the observables) is in fact zero—a highly unlikely circumstance—such a technique will systematically misestimate consumption under a new price schedule.

TABLE 7

Household consumption and expenditure changes with five-tier tariff schedules (all monetary amounts in constant 1998 *dollars)*

Means per household[a]	All households	*By income quartile* [b] 1-st	2-nd	3-rd	4-th
Consumption (kWh/year)					
With 2 tiers (1998)	6196	5524	6299	6330	7455
With 5 tiers	5578	4987	5677	5519	6637
Change (%)	−10·0	−9·7	−9·9	−9·7	−11·0
Expenditures ($/year)					
With 2 tiers (1998)	718	633	734	734	873
With 5 tiers	897	770	921	925	1120
Change (%)	24·8	21·6	25·4	25·9	28·3

[a] Estimated population means for the 7·8 million California households served by the Pacific Gas and Electric Corporation or the Southern California Edison Company. For calculation methods, see text.

[b] For income quartile breakpoints, see Table 4.

separately for each of the 1307 households in the RECS sample, and average these predictions using the survey sampling weights. A similar formula and procedure is used to estimate each household's (expected) expenditures under the new tariff.[29]

Table 7 provides estimates of average household electricity consumption and expenditures under the new five-tier tariffs. For comparison, we also show the values obtained using the prior two-tier tariff schedules in effect from 1998 through 2000. The first numerical column presents estimated population means for all the 7·8 million affected households. The results indicate their average (and aggregate) annual electricity consumption would be approximately 10% lower under the new five-tier tariff system than under the preceding tariffs over a normal weather year. The corresponding increase in annual household electricity expenditures is approximately 25%, or $179 per household (in 1998 dollars). To put this in some perspective, $179 is 8% of the average 1998 state personal income tax liability per household in California.

Our expenditure results are considerably lower than the official estimates of the California Public Utilities Commission. That agency predicted the increase in the two affected utilities' total residential electric revenues would be approximately $1·8 billion annually, or $228 per household. The difference between these two estimates can be explained largely by differences in the treatment of demand elasticities. In particular, the Commission uses a "static scoring" method for predicting the revenue change associated with a new rate schedule design. This amounts to assuming that each consumer's annual demand is completely price-inelastic, so that expenditure changes can be predicted by applying the old and new tariff schedules to the same consumption data. Inasmuch as consumers do exhibit some demand elasticity, this method overestimates revenue associated with the higher tariff structure.

Since the model we employ is estimated with survey data, we have information on individual households' income levels that can be used to examine the distributional consequences of tariff changes. This issue has not been examined quantitatively in the state regulatory agency's tariff

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[29] Note that approximately 10% of households participate in a low-income tariff programme that is exempt from the new tariff designs. These households appear in our sample, and our predictions for them use their (unchanged) tariffs. The predictions do not account for changes in an eligible non-participating household's incentive to apply for this programme, however.

models, as their analyses rely upon utilities' billing data that do not include income information. The additional columns in Table 7 report the model's predictions for average consumption and expenditures by household income quartile. Not surprisingly, under either tariff electricity consumption and electricity expenditures increase with household income. What is interesting to note, however, is that in percentage terms the change in household electricity consumption between the new and old tariff systems is nearly constant across income quartiles. That is, the larger marginal price increases paid by households consuming higher quantities more or less exactly offsets the increasingly inelastic demand behaviour of households with higher incomes (see again Table 4).

A similar phenomenon is evident in the estimated expenditures. In absolute terms, however, the increase in expenditures across income quantiles does not rise nearly as fast as income. This implies, and can be verified directly in the unsummarized data, that the new tariff is (slightly) more regressive than the system it replaces. It is, however, considerably less regressive than a revenue-equivalent traditional uniform rate increase, whose distributional impacts California policy-makers have sought to avoid.

9. CONCLUDING REMARKS

The practical motivation for this paper arose from an acrimonious—and, we believe, poorly informed—debate over the consequences of major electricity price changes in California. Our objective is not to impugn the decisions ultimately made and examined here, however; rather, it is to show how more sophisticated empirical methods, in conjunction with detailed micro-survey data now available, can be productively harnessed to resolve *ex ante* the policy-making uncertainties that fuel such debates.

It is worth noting that substantively similar methodological issues arise in a variety of other markets. Regulatory pricing of local telephone service (a perennially controversial matter) and residential water use are leading examples. In those markets nonlinear pricing is quite common, and formal demand analysis is a largely accepted part of the price-setting process. The econometric issues addressed in this paper would appear particularly germane to those contexts. In a substantively different setting, there are close parallels between the analytic methods used here and the micro-simulation procedures commonly used to evaluate tax code changes. Specifically, the methodological aspects of implementing "dynamic" vs. "static" scoring techniques for tax revenue changes are precisely analogous to the modelling of consumers' demand elasticities in the tariff design analysis presented here.

Last, an interesting and useful extension of this research is the normative empirical analysis of nonlinear tariff designs. The methods employed above would appear to lend themselves readily to development of more economically efficient tariffs. For example, if the new five-part tariffs in California are efficient (by almost any criterion), it is by fortuity rather than by design. Despite a great deal of work in the theoretical literature on efficient nonlinear pricing schemes, there are as yet few (if any) detailed empirical studies. We leave this interesting issue a matter for future research.

APPENDIX A. APPLIANCE-LEVEL SPECIFICATIONS

A.1. Specification and parameters

A complete list of the variables entering the demand model is shown in Tables A1 and A2. The complete set of coefficient estimates are listed in Table A3. This table is organized so that each column contains the parameter estimates associated with an appliance category's electricity demand. These raw parameters are used to obtain the marginal effects in Table 2, as described in Section 6.

TABLE A1

Appliances entering electricity demand model

Mnemonic	*Appliance*	*Description*
	Primary electric space heating	1 if household has permanently installed electric space heating (electric furnace, heat pump(s), or wall resistance units)
	Central air cond.	1 if household has a central air conditioning unit
	Room air cond.	1 if household has room window/wall air conditioning units
	Electric water heat.	1 if household has an electric water heater
ELECCOOK	Electric cooking	1 if household has an electric oven and/or stove
ELECDRYR	Electric dryer	1 if household has an electric clothes dryer
FREEZER1	Separate freezer	1 if household has a separate (stand-alone) freezer
FREEZER2	Second freezer	1 if household has two (stand-alone) freezers
FRIDGE2	Second refrigerator	1 if household has a second refrigerator
CLTHWASH	Clothes washer	1 if household has an automatic clothes washer
DISHWASH	Dishwasher	1 if household has an automatic dishwasher
PORTHEAT	Portable space heat	1 if household has one or more portable electric space heaters
HOTTUB	Hot tub	1 if household has a hot tub with electric heating
POOL	Swimming pool	1 if household has a swimming pool
H2OBEDHT	Waterbed heating	1 if household has a waterbed with electric heating
MICROWV	Microwave	1 if household has a microwave oven
NTV	Number of TVs	Number of televisions in household

TABLE A2

Additional explanatory variables entering demand model

Mnemonic	*Variable*	*Description*
PRICE	Electricity price	Monthly electricity price, in 1993 cents per kilowatt-hour
INCOME	Household income	Average monthly household income, in thousand 1993 dollars
HDD	Heating degree-days	Monthly heating degree-days base 60 °F, in hundreds
CDD	Cooling degree-days	Monthly cooling degree-days base 70 °F, in hundreds
NROOMS	Number of rooms	Number of rooms in home (excluding bathrooms)
NBATHRMS	Number of bathrooms	Number of bathrooms in home
NMEMBERS	Number of members	Number of people in household
FRSIZE	Fridge/freezer size	Size of appliance, in cubic feet
ATHOME	At home	1 if someone is normally at home during the day
HUPROJ	Housing project	1 if household resides in a public housing project
APTBLDG	Apartment building	1 if household resides in an apartment building
RURAL	Rural location	1 if household resides in a rural location
URBAN	Urban location	1 if household resides in an urban location
YEAR97	Survey year 1997	1 if household data from 1997 survey wave

The model also includes 154 variance and covariance parameters (from equation (11)) not reported here. These indicate that the variance of household-level unobservable characteristics increases with appliance holdings, although it depends (in a complicated fashion) on the types of appliances owned by the household. Overall, the heteroscedasticity patterns sensibly reflect the enormous differences in potential energy consumption associated with different appliance portfolios.

A.2. Appliance consumption estimates

A useful feature of the fitted model is that it provides estimates of electricity use for each appliance. These are reported in Table A4. In addition to being of direct interest to energy analysts, these appliance-level consumption estimates provide a useful check on the model since they can be compared to independent estimates.

The first numerical column is the estimated proportion of California households that own particular appliances, based on a weighted average of 1993 and 1997 sample ownership frequencies in the RECS. The second column reports the model's prediction for the average annual electricity consumption of each appliance. These estimates are obtained

TABLE A3

Electricity demand model coefficient estimates—GMM method (asymptotic standard errors in parentheses)

Explanatory variable[a]	*Baseline use*[b]	*Elec. space heating*	*Central air cond.*	*Room air cond.*	*Elec. water heating*	*Swimming pool*	*Second refrig.*	*Separate freezer*
CONST	−24·6	379·0	312·0	814·0	467·0	514·0	−23·5	−108·0
	(49·9)	(216·0)	(276·0)	(369·0)	(107·0)	(229·0)	(61·6)	(57·9)
PRICE	0·4	−38·2	−23·2	−65·3	−35·3	−28·2		
	(3·8)	(15·0)	(22·1)	(32·5)	(9·6)	(19·3)		
INCOME	0·4	16·3	9·3	22·3	−34·0	6·4		
	(2·4)	(13·1)	(11·0)	(21·5)	(7·7)	(10·1)		
NMEMBERS	18·1	−8·0	−39·8	−53·7	49·3			
	(3·4)	(20·5)	(16·8)	(20·5)	(11·1)			
NROOMS	13·0	20·6	10·1	30·1	−36·6			
	(4·5)	(22·3)	(17·9)	(24·1)	(15·8)			
NBATHRMS	27·3				123·0			
	(9·9)				(41·8)			
HDD	−10·7	43·8						
	(6·3)	(22·1)						
CDD	−60·0		240·0	46·5				
	(22·7)		(58·8)	(128·)				
FRSIZE	6·5						7·8	9·3
	(1·7)						(3·7)	(3·3)
DISHWASH	20·4				11·3			
	(11·5)				(37·3)			
CLTHWASH	18·8				71·3			
	(14·0)				(40·9)			
ELECDRYR	66·2							
	(13·1)							
FREEZER2	178·0							
	(55·7)							
ELECCOOK	21·5							
	(11·7)							
MICROWV	32·8							
	(12·1)							
HOTTUB	109·0							
	(32·2)							
PORTHEAT	108·0							
	(21·1)							
H20BEDHT	51·2							
	(23·7)							
NTVS	40·7							
	(5·8)							
ATHOME	16·0							
	(10·1)							
APTBLDG	−48·8							
	(14·2)							
HUPROJ	−79·6							
	(24·8)							
RURAL	31·7							
	(25·3)							
URBAN	−35·8							
	(12·0)							

Table continues on next page

TABLE A3

Continued

Explanatory variable[a]	*Baseline use*[b]	*Elec. space heating*	*Central air cond.*	*Room air cond.*	*Elec. water heating*	*Swimming pool*	*Second refrig.*	*Separate freezer*
YEAR97	2·0 (10·3)							
Model RMSE (kWh/year)	2352·0							

[a] Estimated on 1307 California households in the 1993 and 1997 Residential Energy Consumption Surveys. The dependent variable is electricity consumption, in kWh; parameter estimates are monthly demand coefficients from equation (8).

[b] This category includes all miscellaneous electrical appliances not explicitly modelled such as lights, household electronics, fans, and so forth. The first refrigerator is included in this category because ownership is nearly universal and its effect not separately identifiable from other universally owned appliances such as lights.

TABLE A4

Estimated electricity consumption by household appliance

	Present study		*Prior estimates*[a]	
Appliance type	Households with appliance, in per cent[b]	Avg. annual electricity use, in kWh[b]	Average annual use, in kWh: EIA (1995)[c]	LBL (1997)[c]
Elec. space heating	23·2	1131	1185[b]	2609–3481[d]
Central air cond.	30·3	1270	1283[b]	1306–1446[d]
Room air cond.[e]	13·7	619	n.a.	476[d]
Elec. water heating	15·6	2389	2835	3658
Refrigerator	99·8	1231[f]	1141	1144
Electric cooking	46·0	258	451	822
Separate freezer	16·7	582	1013	1026
Elec. clothes dryer	32·2	795	1090	1000
Clothes washer[g]	64·1	223	n.a.	100
Dishwasher[g]	48·3	241	n.a.	250
Swimming pool	5·6	2227	n.a.	1500[h]
Hot tub	3·5	1288	n.a.	2300
Waterbed heater	5·1	606	n.a.	900
Microwave	83·4	388	n.a.	132
Televisions[e]	98·3	482	n.a.	513

Notes:

[a] Sources: U.S. Energy Information Administration (1995), Table 3.1, and public-use micro files.

Lawrence Berkeley Laboratory (1997), Tables A6 and A7.

[b] Estimates for California households.

[c] Estimates for all U.S. households, except as indicated.

[d] Range of estimates for households in southwestern U.S. states (Calif., Nev., and Ariz.).

[e] Estimates are for all units in household combined.

[f] Estimate based on second refrigerator only.

[g] Excludes energy used to heat water entering washer.

[h] Estimate for pool pump motor only.

n.a. indicates an estimate is not available.

from the fitted appliance demand equations (8), then averaged across households (using the RECS sampling weights) so as to reflect typical values in the population of appliance owners.

The third column in Table A4 contains appliance energy consumption predictions from a model developed by the U.S. Energy Information Administration (EIA, 1995). The final column is from a Lawrence Berkeley Laboratory (LBL, 1997) meta-analysis of numerous residential appliance energy consumption estimates. These estimates are derived from a wide range of direct metering, engineering, and statistical studies of energy use in different areas of the U.S. Overall, there is general agreement between these prior studies and the model's results—perhaps surprisingly so, since the present model is not fit to utilization data for individual appliances. The principal difference occurs with heating, where the LBL survey reports a significantly higher number than we or the EIA do. This can in part be explained by the broader geographic coverage of the LBL analysis and the high sensitivity of heating energy use to climate differences.

APPENDIX B. ELASTICITY CALCULATIONS

This Appendix describes the method used to calculate the elasticity estimates reported in Tables 3 and 4. There are two complications that make calculating elasticity estimates more involved here than in conventional settings. The first is the temporal issue of how to calculate an annual elasticity of demand when the consumer may face varying (and unobserved) marginal prices over the course of the year. The second is the discontinuity problem—because the price schedule is discrete, a change in the consumer's marginal price can move consumption smoothly within a single tariff segment, shift the consumer off or onto the discontinuity between tariff segments, or yield no change in consumption at all.

Addressing the discontinuity problem first, write the optimal consumption for household i in month t using the equilibrium relation from equation (1):

$$x^*_{it} = x(p^*_{it}, y^*_{it}, z_{it}, \varepsilon_{it}),$$

where $y^*_{it} = y_{it} + \bar{x}_{it} \cdot (p^*_{it} - p_{1,it})$. In this equation, p^*_{it} is the household's marginal willingness to pay for the last unit consumed (which may differ from the marginal price, if consumption occurs at the step-point $\bar{x}$ where the price rises from p_1 to p_2). To account for this discontinuous feature when calculating elasticities, we use the following decomposition. Consider an increase in the price of the specific tariff segment in which the household initially consumes. Denoting this initial marginal price as mp, and the consumer's initial marginal willingness to pay as $mwtp$, the total change in consumption can be written as

$$\frac{dx^*}{d(mp)} = \left[\underbrace{\frac{\partial x^*}{\partial(mwtp)}}_{\substack{\text{slope of}\\ \text{demand}}} + \underbrace{\frac{\partial x^*}{\partial y}}_{\substack{\text{marginal}\\ \text{income}\\ \text{effect}}} \cdot \underbrace{\frac{d\,\Delta y}{d(mwtp)}}_{\substack{\text{change in}\\ \text{infra-marginal}\\ \text{expenditure}}} \right] \underbrace{\frac{d(mwtp)}{d(mp)}}_{\substack{0 \text{ if at } \bar{x},\\ 1 \text{ if not}}}$$

where $\Delta y = \bar{x}_{it} \cdot (p^*_{it} - p_{1,it})$ (cf. (3)). The first term in the square brackets is standard. The remaining terms in the bracketed expression yield the (income) effect of changing the infra-marginal price discount. For an optimizing consumer, the term outside the brackets will be zero if consumption occurs at the step-point, $\bar{x}$, and one otherwise.

For the demand specification and two-tier tariff we analyse, this expression takes the simple form:

$$\frac{dx^*_{it}}{d(mp)} = \alpha \cdot \mathbf{1}(x^*_{it} \neq \bar{x}_{it}) + \beta\, \bar{x}_{it} \cdot \mathbf{1}(x^*_{it} > \bar{x}_{it}) \tag{B.1}$$

where $\mathbf{1}(\cdot)$ is the indicator function, and α, β are the price and income coefficients from equation (10). We define a household's monthly price elasticity, η_{it}, in terms of the effect of price on the margin:

$$\eta_{it} = \frac{(mp)_{it}}{x^*_{it}} \cdot \frac{dx^*_{it}}{d(mp)}.$$

A wrinkle arises in computing η_{it}. Since our consumption data are aggregated to an annual level, we do not observe the household's monthly consumption, x^*_{it}, nor its monthly marginal price. Instead, we estimate x^*_{it} with the "plug-in" estimator

$$\hat{x}^*_{it} \equiv E[x^*_{it} \mid w_{it}; \hat{\theta}]$$

using the conditional moment equation derived in (6) evaluated at the estimated parameter values. We then obtain the marginal price estimate, $\widehat{mp}_{it}$, from the household's rate schedule in month t for the quantity $\hat{x}^*_{it}$. Finally, we can compute each household's monthly price elasticity using equation (B.1) as

$$\hat{\eta}_{it} = \frac{\widehat{mp}_{it}}{\hat{x}^*_{it}} \cdot \left[\hat{\alpha}_i \cdot \mathbf{1}(\hat{x}^*_{it} \neq \bar{x}_{it}) + \hat{\beta}_i\, \bar{x}_{it} \cdot \mathbf{1}(\hat{x}^*_{it} > \bar{x}_{it}) \right]$$

where the "hats" indicate estimated quantities.

To obtain the annual price elasticities reported in Tables 3 and 4, we calculate (pointwise) the percentage change in annual electricity consumption for a per cent change in the household's marginal price in *each month* of the year. That is, for each household in the sample we compute

$$\hat{\eta}_i = \frac{1}{x_i} \sum_{t=1}^{12} \hat{\eta}_{it} \cdot \hat{x}^*_{it}$$

where x_i is the household's actual annual electricity consumption. The tables report estimated population means obtained by averaging these household-level annual elasticity estimates using the RECS survey weights.

Income elasticities are obtained similarly, after observing that

$$\frac{dx^*_{it}}{dy} = \beta \cdot \mathbf{1}(x^*_{it} \neq \bar{x}_{it}).$$

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