Price Elasticity and Electricity Rate Design

John Caldwell

Abstract

The level of price elasticity for electricity service has always been a subject rife with controversy. Estimates of price elasticity in this industry have varied widely, and little if any consensus exists on what the true level of price elasticity is. This lack of consensus is evident in regulatory filings involving rate increases, where price elasticity is generally ignored as a factor influencing future sales and revenues after the rate increases occur. Complicating the issue further is the question of exactly what price (if any) electricity customers are responding to: the total bill, the marginal (per kWh) rate, or some combination thereof. And of course the answer to this question will be affected by the existence of any customer-facing programs that make consumers more aware of and/or provide incentives to respond to time-varying electricity prices.

This paper examines the issue of price elasticity among electricity consumers. After citing the diverse results obtained in measuring price elasticity, it describes the alternative – and not necessarily mutually exclusive – ways that customers are reacting to price, and reviews the evidence that weighs the relative importance of each, and the factors influencing these weights.

Building upon the results of this examination, this paper proposes a new approach to rate design which explicitly takes into account the impacts of price elasticity and the mechanisms by which price elasticity affects electricity usage. Two explicit objectives for rate design are identified – revenue recovery and load shaping – and a process is described for effectively applying the typical features of an electricity rate (customer charge, energy charge, demand charge) in the service of these objectives. The paper concludes with a discussion of the difference between the "ideal" proposed approach and the reality of current rate design, and how to best adapt current rate designs to benefit from the insights that have been presented.

Background

Accurate forecasts of future electricity demand have always been critical to providing electricity in an efficient and reliable manner. This is clearly evident in the need to meet hourly obligations of electricity through the effective dispatch of available generation, but it is also true over a longer time horizon, as planners decide on when new power plants will be required for their system, and what the production capacity of these new generators should be. The losses associated with incorrect long-term forecasts can be devastating, as evidenced in the 1980s, when many electric providers found that they had overbuilt new generation capacity, due to long-term forecasts done during the prior decade which predicted that electricity demand growth would continue at the high annual rates that had been seen up to that time. The consequences of adding excess generation capacity (much of this was expensive nuclear power in the 1980s) was that electric utilities faced resistance from their local regulatory commissions to pass the costs of the new generation onto their customers, on the grounds that the excess capacity was not "used and useful", and therefore not cost-justified. Many utilities were forced to take write-offs totaling hundreds of millions of dollars, and in some cases expensive plants that were nearly completed had to be dismantled, at a substantial incremental cost that also could not be passed on to consumers. Many of the events of the 1970s which had contributed to reduced electricity demand growth (such as the recessions brought on by the OPEC price hikes and Iranian revolution, and the high energy prices and inflation that accompanied these) could not have been foreseen by utility planners early in that decade, but the forecast models that were used at that time were often quite basic in design, and could not have anticipated changes in growth due to falling income or rising energy prices, anyway.

As the presence of distributed energy resources in electricity systems continues to grow, this will only heighten the need for more sophisticated models, which will have to account for the behavior of customers who have easier access to real-time price information and a greater capability to modify their consumption patterns in response to this information. A growing number of customers will even have the ability to choose between being net consumers or net providers of electricity, based upon current electricity prices. Forecasting models will have to be increasingly attuned to the impacts of prices on demand for electricity, which is termed price elasticity.

Elasticity is formally defined as the ratio of the change in usage or consumption to the change in some causative factor – generally price or income. Hence, the price elasticity (σ) of demand represents the relative impact of changes in price on changes in demand. Since it can be assumed that increases in price will cause demand to decrease, and vice versa, price elasticity will be negative. (By contrast, since increases in income will generally result in increases in electricity demand, the elasticity of income can be expected to be positive.)

While demand forecasting has come a long way since the 1970s, and many if not most models used by utility planners and energy analysts have incorporated the impact of price response on demand, the estimates of this impact, as reported in measurements published in academic and trade journals, vary over an extremely wide range. An early survey of twenty-five studies in which residential long-term price elasticity of demand was estimated (Bohi, 1981) found that these estimates ranged from -2.1 to -0.45. And a meta-analysis (Espey, 2004) of thirty-six studies published from 1971-2000 reported an even wider range in estimated long-run residential price elasticities of from -2.25 to -0.04. A more recent survey of published literature by Paul, Myers, and Palmer (2009), while finding a relatively tight range in short-run residential price elasticity of -0.35 to -0.2, also reported a wide range in long-run residential price elasticities of -0.98 to -0.32, although not as wide as those reported in the earlier papers. But extreme ranges can even appear within a single study: the RAND Corporation published a report (Bernstein and Griffin, 2005) on its own estimates of price elasticities which included a national estimate of long-run residential price elasticity of -0.32, regional estimates which ranged from -0.62 to -0.06, and state-level estimates which ranged from -0.999 to +0.666. Hence, there is no uniform standard measure of price elasticity for the industry. This disparity could be the result of one or more of the following causes: 1) actual elasticities vary significantly by location, 2) they change over time, and 3) their actual estimation is extremely contingent upon the method of estimation chosen.

Clearly, price elasticity will also vary based upon the type of electricity customer served, with, for example, larger industrial customers probably being more sensitive to price than smaller residential and commercial customers. But, as will be discussed below, it is not unreasonable to expect that price-responsive behavior will be different at different times of the year, and – if not now than at some future time – at different times of the week, and even different times of the day. Based on the summaries described above, there has been little consensus on what the price sensitivity of electricity customers is. If variation in price sensitivity does increase along other dimensions, there seems to be little hope of establishing a better consensus in the future. On the other hand, a more explicit acknowledgment and recognition of the factors responsible for this variation might make the science of estimating electricity consumer price elasticity a more practical and useful one.

That these estimates matter can be easily illustrated. Consider an electric utility that has been granted an increase in revenue requirements (RR) by its regulatory commission, and is planning to increase rates (P) to recover this greater amount. Clearly, the increase in revenue requirements (ΔRR) will be directly proportional to the increase in rates (ΔP), and is generally assumed when calculating the new level of revenue requirements. But what is often ignored is the impact of the rate increase upon consumption, which will be equal to the change in price multiplied by the price elasticity. The net relative change in revenue requirements will be approximately equal to the sum of these two changes:

$$
\begin{aligned}
\Delta RR \quad &\approx \Delta P + (\Delta P \text{ x } \sigma) \\
&\approx \Delta P\ (1+ \sigma).
\end{aligned}
$$

Hence, to achieve a certain targeted increase in revenue requirements, more than a proportional increase in price will be required. In fact, the necessary price change, ΔP, must be:

$$\Delta P \quad \approx \Delta RR\ /\ (1+ \sigma).$$

The implications of this could be very significant. For example, for customers with a moderate price elasticity of -0.5, a rate increase of 10% will only produce an increase in revenue from these customers of about 5%, and for customers with a relatively high price elasticity of -0.9, the same increase will result in a revenue increase of only 1%! Either ignoring or grossly misestimating the impact of price elasticity could have potentially catastrophic consequences. The following section will illustrate some common approaches to get at this estimate.

Four Simple Estimation Methods and Results

The simplest approach to modeling the impact of elasticity is to use an ordinary least squares (OLS) linear regression model of the form:

$$\mathbf{E_t} = \quad B_0 + B_1\mathbf{P_t} + B_2\mathbf{Y_t} + \varepsilon_t,$$

where $\mathbf{E_t}$ in this example represents electricity usage in period t, $\mathbf{P_t}$ represents the price of electricity usage in period t, $\mathbf{Y_t}$ represents the electricity consumer's income in period t, and ε_t is an error term. The coefficient B_0 can be interpreted as the level of electricity usage before price and income effects, B_1 as the effect on this usage by the price, and B_2 as the effect on this usage by the level of the electricity consumer's income.

The simplicity of the basic OLS model actually leads to some complications when computing elasticities. Because the model is linear, the relative impact of a change in any of the variables will vary with the magnitude of both the independent variable (e.g., price) and the response variable (in this case, electricity sales). This means that, rather than being a single number, elasticity will depend upon both the level of the response variable and the level of the independent variable corresponding to the elasticity measurement. The formulas for elasticity for the above equation would be as follows:

Price elasticity = $B_1(\mathbf{P_t}/\mathbf{E_t})$,
Income elasticity = $B_2(\mathbf{P_t}/\mathbf{Y_t})$.

There is a second complication with the basic OLS model, and this is that additional variables would have to be added to measure long-term elasticity effects, which could differ significantly from the immediate impacts. The question, when adding these variables, is what the length should be of the time lag to be used. One common approach is to use a twelve-month lag of each variable, as follows:

$$\mathbf{E_t} = B_0 + B_1\mathbf{P_t} + B_2\mathbf{Y_t} + B_3\mathbf{P_{t-12}} + B_4\mathbf{Y_{t-12}} + \varepsilon_t,$$

The questions of lags, however, is not simply limited to measuring long-term effects. There is often a debate, for example, about whether current period electricity usage will really be an effect of current period price, since customers do not see how much they are presently paying for electricity until they receive their next monthly electricity bill. If the time period denoted by t corresponds to a particular month, some would contend that for the price variable at least, the equation should be modified as follows:

$$\mathbf{E_t} = B_0 + B_1\mathbf{P_{t-1}} + B_2\mathbf{Y_t} + B_3\mathbf{P_{t-13}} + B_4\mathbf{Y_{t-12}} + \varepsilon_t,$$

(Note that the twelve-month lag for the price variable has been adjusted to t-13). Such questions involving what time period to use for the short-term variables as well as for the long-term lagged variables are generally resolved by linear regression analyses with alternative lags, and seeing which analysis best explains the empirical observations.

The simple OLS model can be modified to enable a more direct measure of elasticity, and one which is not dependent on the magnitude of the variables, by using logarithmic transformations of the variables in the equation:

$$\log(\mathbf{E_t}) = B_0 + B_1\log(\mathbf{P_t}) + B_2\log(\mathbf{Y_t}) + \varepsilon_t.$$

With this equation, B_1 becomes the single measure of price elasticity, and B_2 that of income elasticity. The elasticity measures are invariant in this case because an underlying assumption of this equation is that relative changes in electricity usage are proportional to relative changes in price and income. For example, if B_1 were estimated to be -0.2, then this would mean that a 1%

increase in price would result in an 0.2% decrease in electricity usage – which is precisely how price elasticity is defined. Price elasticity as measured by B_1 will be the same regardless of the level of electricity usage or price, and similarly the income elasticity as measured by B_2 will not vary with the level of electricity usage or income.

Another common method of estimating the impacts of price and other factors on consumption incorporates the assumption that changes in these factors impact consumption gradually over time. Rather than using discrete long-term and short-term variables, the model assumes a distributed lag effect over an extended period of time. The partial adjustment model assumes an infinite time horizon, and while this seems unrealistic, the model also incorporates the assumption that variable impacts decay with each successive time period, asymptotically going to zero at infinity, and generally being negligible even after a relatively short time horizon. The partial adjustment model simply adds, to the other independent variables in the equation, a one-period lag of the dependent variable. A consumption model of this type measuring the impact of price would be of the following form (excluding the error term):

$$
\begin{aligned}
\mathbf{Et} &= B_0 + B_1\mathbf{P_t} + B_2\mathbf{E_{t-1}} \\
&= B_0 + B_1\mathbf{P_t} + B_2(B_0 + B_1\mathbf{P_{t-1}} + B_2\mathbf{E_{t-2}}) \\
&= B_0 + B_1\mathbf{P_t} + B_2\mathbf{B_0} + B_2B_1\mathbf{P_{t-1}} + B_2^2(B_0 + B_1\mathbf{P_{t-2}} + B_2\mathbf{E_{t-3}}) \\
&= \ldots,
\end{aligned}
$$

which implies that for any sustained unit change in the variable P, the long-term impact will be:

$$
\begin{aligned}
&= (1 + B_2 + B_2^2 + B_2^3 + \ldots B_2^{\infty})\, B_1\Delta\mathbf{P} \\
&= [1/(1- B_2)]\, B_1\Delta\mathbf{P}
\end{aligned}
$$

The model then lends itself to a straightforward interpretation of the coefficients. In the above example, B_1 is measuring the short-term impact of a price change, while $[1/(1- B_2)]\ B_1$ is measuring the long-term impact of a sustained change of that magnitude. A limitation of the model is that if more than one independent variable is used, the the ratio of long-term to short-term impacts – $1/(1- B_2)$ – will be the same for all variables.

This model retains the same limitation as the simple OLS model, in that price elasticity varies with the magnitude of the usage and price variables. But as with the simple OLS model, logarithmic transformation of the variables in the partial adjustment model will enable a measurement of elasticity from direct inspection of the coefficients, with B_1 corresponding to short-term price elasticity and $[1/(1- B_2)]\ B_1$ corresponding to long-term price elasticity.

The Problem with Elasticity, Part I: Short Term vs. Long Term

A fundamental issue with all forms of elasticity is the duration of the effect and/or how this effect changes over time. As discussed above, there will generally be a short-term response to a change in price, income, etc., but this may be significantly different in magnitude from the longer-term reaction to the change. In some cases, the immediate response will be muted, but will grow over time as the consumer makes more lasting adjustments to the change. In other cases, a sharp immediate response may diminish and even disappear as the consumer grows to accept the change. In the electricity industry, the distinction between short-term responses to price changes and longer-term or permanent responses to these changes is of critical importance. While both may affect the load shape of electricity consumption, it is only the long-term price response that will tangibly impact the amount of revenue that is being collected for electricity service. Any projections of future revenue from electricity sales, and *especially* those that have been prepared to model requested or expected changes in electricity rates (e.g., as part of a rate case), should adjust changes in revenue in accordance with the expected impact of the rate changes on electricity consumption due to price elasticity.

Both long-term and short-term price elasticity could come into play in determining the hourly and seasonal electricity usage of consumers. A general rate increase – because it might cause consumers to reduce certain electricity applications deemed less vital than others – could change the load shape of demand as consumers make permanent changes in their relative usage of different applications. Changes in rate design – for example the introduction or increase of a demand charge – will also have an effect upon load shape due to long-term price elasticity. But if electricity rates have hourly or seasonal components, then even short-term price elasticity could affect demand patterns as consumers either curtail or shift load usage in response to hourly or seasonal rate changes.

Fortunately, most academic studies of price responsive behavior include estimates of both long-run and short-run price elasticity. When applied properly, both sets of estimates can be utilized to develop a complete picture of how price is influencing consumer demand for electricity: in terms of both total consumption and patterns of electricity usage.

The Problem with Elasticity, Part II: Different Applications Have Different Elasticities

A discussion of the price elasticity of electricity would be different than, for example, that of gasoline, or coffee, or most commodities, because electricity is actually enabling the usage of a variety of different activities and applications. The willingness of a customer to curtail any of these activities or applications in the wake of an electricity price increase will vary – sometimes significantly – with each of them, and this in turn will affect how much electricity usage will be reduced, and when (i.e., in terms of the time of day, time of week, and time of year) these reductions will occur.

While there are of course a large number of diverse applications for electricity, particularly in the typical household (e.g., washer and dryer, dishwasher, computer, television, lights air conditioning), these can be grouped into three general categories: space heating, space cooling, and non-weather-sensitive appliances. Nationwide, on average, 25% of residential electricity usage is for space heating, 28% for space cooling, and 48% for all other, non-weather-related applications. These first two categories exhibit very predictable and distinctive seasonal usage patterns, with space cooling peaking in the summer, virtually non-existent in the winter, and greatly attenuated in the shoulder months, while space heating follows an opposite seasonal pattern: peaking in the winter, non-existent in the summer, and much less present in the shoulder months. These two categories also exhibit predictable hourly patterns in usage, but these are not as distinct from each other as the seasonal patterns, since both tend to be much higher in the daytime. The third category, which includes all other household appliances, collectively tends to exhibit less pronounced swings in usage from month to month, although a seasonal pattern is still apparent. (Electricity usage for lighting, as an example, tends to be higher in the winter than in the summer, when residential customers are spending more time indoors, and there are fewer hours of daylight than in the summer.) There is also an hourly and daily pattern that corresponds to increased electricity usage of household appliances when people are at home in the evenings and on weekends.

It is not unreasonable to expect that these categories, with clearly distinct patterns of usage, will also exhibit different elasticities, and that these differential responses to price and income will have distinct impacts on both the level and shape of electricity usage. But estimating different elasticities for different applications would be a challenging task, since all of these applications are receiving electricity through the same meter, and therefore cannot be readily modeled separately. Electricity usage from space-heating and space-cooling can be modeled by including variables for heating degree-days (HDD) and cooling degree-days (CDD), respectively, which will help to separate direct effects of weather upon usage from other influences, such as pricing. But the differential impacts of pricing and income upon space-heating vs. space-cooling vs. non-weather applications might require an impractical amount of modeling sophistication. A more suitable approach might be to simply have multiple models corresponding to different seasons of the year (e.g., summer, winter, and shoulder months) and perhaps even distinct models within these seasons for weekdays and weekends.

The Problem with Elasticity, Part III: Elastic to . . . What?

There is a third problem with price elasticity as it is measured and applied in the electricity industry, and this stems from the fundamental question of exactly what "price" customers are responding to. When a consumer purchases gasoline, the price that will be paid is displayed predominantly on the pump. Similarly, items available for purchase in stores generally have their prices listed either on the items themselves or nearby on the shelves. In these cases, it is very clear what customers are responding to, but in the case of electricity, it is not so clear how customers are using price information to affect their usage behavior. Is their behavior solely influenced by the magnitude of the monthly bill that they receive? Do they look at their bill at all, to determine how it was calculated, or do they merely note the total amount when they pay it? Complicating this even further is the fact that electricity rates are rarely if ever simply charges per unit of product delivered, but a combination of fixed and per-unit charges. If customers are inspecting their bills, then how are the different billing components – the fixed monthly charge, the per-kilowatt-hour energy charge, and the demand charge (if one is included) affecting their behavior? The answer to this question will – or should – have a critical impact on rate design.

Do Consumers Respond to Marginal Price or to Average Price (i.e., Their Bill)?

One of the most interesting recent studies that has examined the question of what electricity consumers are actually responding to is the one performed by Koichiro Ito of Boston University and summarized in his paper "Do Consumers Respond to Marginal or Average Price? Evidence from Nonlinear Electricity Pricing" (2014). Ito begins the paper by referencing several empirical studies that have challenged the basic economic idea that firms and consumers optimize their behavior by responding to marginal prices. Consumers do not often have ready access to information about marginal prices, and, at a more fundamental level, often do not understand the concept of nonlinear pricing systems. Ito identifies two alternative drivers: expected marginal price, which would be derived from general knowledge about the pricing structure of the product, and average price, which would be used when the pricing structure of the product is so complex that a consumer finds it impractical to try to comprehend it. Each of these response behaviors (i.e., to marginal price, expected marginal price, or average price) would exhibit a distinct usage pattern after a price change occurred, and therefore an empirical examination of actual usage patterns should reveal which of the behaviors is occurring.

Ito found an ideal opportunity to study the response of electricity consumers to price changes in Orange County, California, where the service territories of two electric utilities, Southern California Edison (SCE) and San Diego Gas & Electric (SDG&E), border one another, and do so in a way that arbitrarily bisects the area, leaving two areas that have very similar demographic and electricity usage characteristics. SCE and SDG&E have offered distinctly different rate designs to their respective customers in this county, and during the time period from 1999 to 2009 rate designs for both utilities changed significantly, and in significantly different ways, particularly during the California electricity crisis in 2000 and 2001. For example, when wholesale electricity prices spiked in 2000, SDG&E passed this increase on to its customers immediately, while SCE maintained prices at 1999 levels until the end of the year. Both utilities eventually introduced additional price tiers after the onset of the crisis, but at different times, and at price levels that did not parallel one another. Hence, not only were the marginal prices offered by each utility different, but average prices were not the same, either. (This was due not only to timing differences in rate increases and adjustments, but also to the fact that the two utilities had different generation mixes and infrastructure costs.)

While Ito tested a variety of lags for prices, the most illuminating analyses consisted of his comparative evaluation of the impacts of marginal price, average price, and expected marginal price upon electricity demand. He conducted two sets of these analyses, the first comparing marginal price effects to average price effects, and the second comparing expected marginal price effects to average price effects. The first set of analyses consisted of six alternative linear regression models, with the first including only the marginal price variable, the second including only the average price variable, the third including both, and the other three essentially replicating these first three but with one-period lags of all of the price variables. The second set of analyses consisted of four alternative equations, with the first including only the expected marginal price, the second including both the expected marginal price and the average price, and the other two replicating these with one-period lags of the price variables. In all cases, the sample period covered the time period from January 1999 to December 2007.

In the comparisons of marginal price effects versus average price effects, it was the variable corresponding to a one-period lag of the average price which proved to be the most statistically significant. This variable corresponds most closely with the phenomenon of customers reacting mainly to their monthly bill, which reports prices after the fact. In the model which included both marginal and average price variables, the marginal price variable was always statistically insignificant and had the wrong sign (i.e., positive, suggesting that an increase in marginal price would lead to higher usage). The comparisons of expected marginal price effects with average price effects produced virtually identical results, including that of the expected marginal price variable being statistically insignificant and with the wrong sign when included with the average price variable in a single model.

The Ito study confirms what is generally believed about the price-responsive behavior of electricity consumers: to the extent that they respond to changes in electricity prices at all, it is to changes in their bills, rather than their hourly and/or marginal rates, even when these rates exhibit significant variability. But pricing programs have been implemented to create incentives for greater sensitivity to hourly prices. Wolak (2011) investigated three variants of these which were implemented in Washington, D.C. in 2008 as part of a pilot program called PowerCentsDC: straight hourly pricing (HP), critical peak pricing (CPP), and critical peak pricing with a rebate (CPR). Customers on the hourly pricing program were notified a day in advance if prices were going to be “high”. Similarly, CPP and CPR customers were notified if the next day was going to be a critical peak pricing day, during which the standard hourly electricity rate was replaced with a significantly higher rate. CPP customers would simply be charged that higher rate, but CPR customers would continue to be charged the standard fixed utility rate, and receive a rebate roughly equivalent to the difference between the CPP rate and standard utility rate, multiplied by a measured reduction in usage below some reference level. The program randomly assigned 857 customers to these programs and monitored their usage, and observed an additional 388 customers not on these programs for comparison. Customers were distinguished as either regular (R) or all-electric (AE) in order to compare differences in impacts of the programs upon these two classes.

Wolak conducted a statistical analysis of the behavioral responses of customers under each of the programs. He found that demand response to all three programs was statistically significant for both regular and all-electric customers. For both classes, the program which produced the most significant response was critical peak pricing, and for regular customers, the measured magnitude of the response for this program was over twice as high as for the other two programs. For regular customers, the program which had the second highest significant impact was critical peak pricing with a rebate. However, for all-electric customers, hourly pricing had the second most significant impact. Collectively, the responses of all-electric customers to each of these programs was higher than the corresponding response rate among regular customers, and much higher in critical peak pricing and hourly programs.

The results of Ito’s analyses clearly suggest that the typical residential electricity consumer will not respond to marginal prices – actual or expected – while the Wolak study indicates that such a response can be induced with proper program design. Ahmad Faruqui and Sanem Sergici of the Brattle Group conducted a meta-analysis (2013) of studies analyzing the impact of dynamic pricing programs throughout the world, and found tangible evidence of the impact on peak load reduction by both time-of-use pricing programs and dynamic pricing programs (e.g., critical peak pricing, variable peak pricing). As would be expected, the studies collectively display a pattern of peak reduction behavior which increases in proportion to the ratio of peak to off-peak prices, although the increase in this behavior diminishes as the proportion increases. There is also a tendency for the programs to be more effective when technology is present which automates or enhances the capacity of consumers to respond to price changes.

What is the Impact of Demand Charges?

The question of how consumers respond to electricity prices is further complicated by the fact that it often does not merely involve whether consumers respond to average or marginal prices (or expected marginal prices), but whether they also respond to demand charges in their rates. A demand charge is calculated based upon a customer's peak usage, and will rise or fall in tandem with increases or reductions in this peak usage. A customer's peak (and corresponding demand charge) could be reduced in one or both of two ways: 1) through a total decline in electricity usage – particularly at times when this usage peaked and/or 2) by shifting electricity consumption from peak periods to other times of the day. While utilities have traditionally only included demand charges in their commercial and industrial customers' rate designs, many of them have begun actively exploring the addition of a demand charge component to residential rate designs as well.

Sanem Sergici of the Brattle Group addressed the issue of residential response to demand charges in a presentation made to the EUCI Residential Demand Charge Conference (2016). She observed that there has been a limited amount of empirical research on consumer response to demand charges, citing three pilot projects that have examined this. The range of the average observed reduction in peak consumption varied widely (from 5% to 29%), but the level of this reduction was influenced by several factors, including the magnitude of the demand charge itself, the magnitude of the per kilowatt-hour energy charge, and the existence and magnitude of a fixed charge. Sergici also described a simulation that she conducted that measured the relative impact of time-of-use vs. demand charges in influencing the consumption of three distinct types of customers ("small but peaky", "average", and "large and less peaky"). The results, as might be expected, suggested that the impact of demand charges is proportional to the "peakiness" of the customer type, which, while not surprising, is ironic, given that utilities have traditionally tended to include demand charges in those larger classes of customers that exhibit less "peaky" behavior, rather than smaller classes of customers, such as residential, which exhibit a much greater variability in hourly consumption behavior.

The Two-Fold Objective of Rate Design

Electricity rates are designed to fulfill two fundamental objectives: the effective recovery of allowed revenue requirements, and the shaping of electricity demand to more efficiently match it with available supply. Knowledge of price elasticity enables a better attainment of both of these objectives. Two cases will illustrate how this can be achieved, with the first corresponding to a more desirable rate design, and the second corresponding to a rate design that is more prevalent in the industry today.

Ideal Case

Ideally, the structure of electricity rates would reflect the manner in which the underlying costs to be recovered have been incurred. Cost causation can be grouped into three general categories:

- Variable costs: These are the expenses that vary directly with consumption, such as fuel expenses and most operations and maintenance costs.
- Capacity costs: These vary with total electricity demand, as the distribution and transmission system must be sized to meet the maximum level of electricity consumption that is being served.
- Fixed costs: These correspond to those expenses that will be incurred independently of the actual level of electricity consumption and do not vary with the level of demand, and include such things as billing, customer service, metering, and overhead expenses.

A rate structure which reflected these categories would include an energy (per kilowatt-hour) charge to recover variable costs, a demand (per kilowatt) charge to recover capacity costs, and a monthly customer charge to recover fixed costs.

The elasticity characteristics of each of these rate components would have different implications upon revenue recovery and the shape of customer electricity demand. Changes in the energy charge, for example, which is generally adjusted regularly through cost adjustment factors between rate cases or even more frequently due to time-of-use pricing to reflect changing fuel and purchased electric power costs, will be of no consequence to total revenue requirements and earnings, since no revenue associated with this rate component contributes to net earnings. These changes will, however, have a potentially significant impact on customer load shapes, particularly if prices vary by season and/or by hour, and more so if programs exist to explicitly make customers more sensitive to these variations. The demand charge component will be of relevance both to total revenue requirements and to load shaping, since revenue associated with investments in capacity have an earnings component (allowed return on equity) and since the demand charge by its very nature will create incentives for customers to "flatten" their demand. Finally, the fixed charge element, since it also corresponds to infrastructure investment, will have an earnings component, and so any impact that increases in this element has on total electricity usage will be significant. However, it is doubtful whether changes in the fixed monthly customer charge will affect load shape, although this should probably be confirmed empirically.

<u>Practical Case</u>

In the electricity industry, actual rate design does not often comport with the ideal case described above. With residential customers in particular, the bulk of revenue requirements – including the earnings component – are recovered in the energy charge, with the remainder captured in a small, almost token, monthly customer charge, and demand charges are usually nonexistent. But the fact that there is such a gulf between the ideal and the real does not negate the need to properly address the impacts of price elasticity on revenue recovery and load shape. The same challenges apply, and the same techniques for addressing them can be applied with existing rate designs.

In summary, the procedure would be as follows:

1. Estimate the price elasticity of demand, and of consumption, for
   - the fixed charge component of rates,
   - the demand charge, and
   - the energy charge.

2. Adjust revenue requirement projections stemming from a rate increase (or rate decrease) in the energy charge, fixed charge, and demand charge (if a demand charge is present).

3. Adjust the demand forecast for changes in peak demand stemming from changes in the energy charge and the demand charge (if a demand charge is present).

This procedure will ensure that requested rate increases take into account the impact of these increases on future revenue requirements, and will also provide a realistic projection of system capacity requirements after the increases occur.

Conclusions

The measurement of price elasticity in the electricity industry has always been an issue of controversy, both because of the wide diversity in measurements obtained, and because of diverse views on how it should be interpreted. In this paper, it has been contended that the importance of price elasticity in determining future revenue requirements and in designing rates has been greatly underappreciated, and that more than proper measurement and interpretation of elasticity (which are significant challenges in their own right) is required: there must also be a proper application of elasticity to forecasting and rate design. This paper, in addition to highlighting and clarifying the interpretation issues, has attempted to provide a guide to proper application, both under ideal and more practical circumstances. It is hoped that it will also serve as a guide for future research, and that it will enlighten future discussions and debates about the role that price elasticity plays and should play in all rate-setting activities.

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