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PRICE ELASTICITY VARIATION: AN ENGINEERING-ECONOMIC APPROACH

J. Sathaye, E. Kahn, and D. Robbins

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PRICE ELASTICITY VARIATION: AN ENGINEERING-ECONOMIC APPROACH

Jayant Sathaye, Edward Kahn and Donald Robbins

Energy Analysis Program
Applied Science Division
Lawrence Berkeley Laboratory
University of California
Berkeley, California. 94720

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PREFACE

This report discusses variable elasticities and an engineering-economic approach to estimating elasticity in the residential sector. The report is in two parts. The first part includes a discussion of the factors that affect price elasticity estimates, a survey of estimates of price elasticities in the residential sector from 1978 to 1982, and a critical evaluation of interesting and controversial studies during this period.

The second part of the report is an application of engineering-economic methods to estimate long and short run price elasticities in the residential sector. The elasticities were estimated using data for Gulf States Utility Company, based in Beaumont, Texas. The price forecast used in our analysis, to estimate future residential electricity demand, is one of the many forecasts that the utility company uses for analysis purposes, and should not be construed as an official company forecast of electricity prices. Our short run model examines how income, prices, and other independent variables influence capacity utilization of appliances rather than electricity demand. Long run elasticity is estimated using an engineering economic approach, by combining our estimate of short run elasticity with projections of stock changes.

The above approach to estimating short and long-run elasticities is useful for utility companies that are medium to small in size and have limited access to data. It requires that a utility company have data on saturation of appliances but not on individual customer holdings of stocks and their characteristics. The approach is between strict econometric analysis to estimate elasticities, and an end-use analysis of the REEPS type. It is therefore suitable for utility companies that are currently using pure econometrics, and would like to, but are not in a position to adopt REEPS yet.

SUMMARY

An important motivation of this study was to investigate whether the price elasticity of residential demand varied in any systematic manner. In this section we summarize our findings on this question. We divide the discussion into two parts. In the first, we review the findings of our survey of existing studies. In the second, we formulate the issues in the context of our capital stock model.

Literature Survey

Existing studies illustrate a wide range of elasticity estimates. Only a few of these studies attempt in any systematic way to account explicitly for elasticity variation. There are two general approaches to the elasticity variation question employed by writers using time series data. One is empirical; based on dummy variables or other ways to segment data. In this approach elasticity is estimated over different time periods and parameter values are compared. It is difficult to attribute causality to different estimates unless the data segmentation implies it. For example, a study of Virginia Electric Power Company found higher elasticities for summer periods compared to other seasons of the year.

A more explicit approach to elasticity variation involves the specification of a functional form in which elasticity is dependent on explanatory variables. This typically involves an expansion of the price co-efficient in a log-linear demand model. Unfortunately, there is no a priori correct way to make these expansions. One version attempts to incorporate appliance stocks into a model of variable elasticity. Existing studies do not motivate the function forms chosen in any way that accounts explicitly for the underlying process.

A more promising over-all approach emphasizes the determination role of budget share in price elasticity. The diminishing marginal utility of consumption of one good in the consumers budget will be more important behaviorally if that good is a larger fraction of total expenditure.

Thus consumers who spend a large share of income on electricity can be expected to have a higher elasticity. Two recent studies report results which can be interpreted in this context. We summarized this interpretation in Figure 3 from section 2, which is reproduced again here.

The Lawrence and Robinson study was based on conditional demand methods applied to a national data set. The elasticities calculated are assumed to be true long-run measurements. This is the case because the cross-sectional nature of the data base implies a full stock adjustment to price change. Such models do not capture short-run price responses which are typically estimated in time series models.

The REEPS estimates are based on a study of the income distribution impacts of various national energy policies. Segmentation of residential customers by income group allows the simulated demand response to be associated with different average budget shares of electricity. The REEPS simulations in this study are not ideal tests for the calculation illustrated in the figure. The stock adjustment is only allowed to proceed for ten years. Furthermore, prices are continually changing over the simulation period. This may be realistic for the study purposes, but a simulation designed to test long run price elasticity using this model should be done differently.

The best experiment would to be induce a one-time price shock and then allow its affects to propagate out over a 20-30 year period. All that matters is that the period be long enough to capture the full adjustment of stocks to the price change. This will be apparent when the quantity of energy demanded becomes stable.

These problems illustrate the inherent difficulties of using time series data. The change of stocks, which is the long-run demand response, is slow relative to the changes in price and income exhibited by the data. It is very difficult to control all effects, including the vintage-specific stock changes that are associated with certain time-dated price and income changes. Thus the "long-run" can be observed more easily in cross-section than time-series.

The studies which are best at capturing long run effects are very weak on short-run utilization responses. Because these studies seek to "explain" the ownership decision, they "assume" behavior with a given appliance stock, i.e., they assume a short-run elasticity. In principle, if one could control time series data for changing levels of stocks, then short-run utilization response could be observed statistically. Although there have been some attempts at this, they are largely ad-hoc and data-poor. In our study of Gulf States Utilities, we attempt a more systematic approach of this kind.

The current situation can be summarized in the following way. Long-run price elasticity clearly increases with budget share, but is difficult to observe from time series data. These data are typically aggregated to a level which obscures the distributional factor that produce long run elasticity variation. Short-run elasticity appears to vary by end-use and climate factors, but not in a way that is well understood. There does not appear to be any simple way to link short run elasticity determinants with long run stock adjustments.

Capital Stock Demand Model

Our model of residential electricity demand for Gulf States Utilities represents a systematic effect to link short run with long run phenomena. We use an explicit representation of the appliance stock as an explanatory variable in a short-run time series model. The model structure assumes that short-run elasticity is constant once the appliance stocks are controlled. The short run constant elasticity assumption does <u>not</u> mean that all end-uses exhibit the same utilization demand behavior. There can be different demand curves associated with each end-use.

We attempt to separate end-uses in our estimation procedures in a number of ways. First, we distinguish between weather sensitive demand and those end-uses which are fixed in the short-run. We then separate space heating from air-conditioning by segmenting the monthly observations using climate data. Having made these separations we then assume that price elasticity is constant for both cooling and heating demand and estimate it jointly. It is entirely possible that the resulting estimate is an average of constant but different heating and cooling utilization elasticities; further tests could explore this.

Our estimation procedure also indicated potentially interesting facts about the distribution of consumption. To avoid the simultaneity problems of using average price as a regressor, we use two price variables at fixed consumption levels. The resulting co-efficients are quite different. We rely on the general properties of residential sales frequency distributions to interpret and weigh these co-efficients. Generally speaking, these distributions have substantial positive skewness. It is typical for 75% of the sales to occur at or below the mean level of consumption. This means that there are a large number of low usage customers and a much smaller fraction of high usage customers. Our estimated co-efficients indicate a high short-run elasticity for the low users (-0.4) and essentially zero elasticity for the high users. It is plausible to assume that this is just the budget share phenomenon again. The elastic low-user has lower income and a larger budget share for electricity than the higher income high user, whose budget share and elasticity are small. Of course this association should be tested empirically to determine if it is really true.

Long-run elasticity is inherently variable in our model. This follows from our treatment of appliance stocks. In the short run we assume that stocks are exogenous. In the longer run, however, stocks are a function of price and income. Since any change in price will have both a short-run and long run effect, elasticity in the long-run cannot be constant. To account for this we decompose average residential use in the long run into nine principal end-uses. We use engineering and economic models to project changes in the saturation and efficiency of each end-use. Due to the inherent uncertainties in this process we only consider a ten year projection. The resulting percentage change in average use divided by the percentage change in real price gives an estimate of the stock adjustment part of long run elasticity. This estimate is "path-dependent," being influenced by any number of factors (housing stock changes, natural gas availability, projected time path of electricity prices, etc.).

Thus our model will not yield a conveniently constant price elasticity in the long run. It does provide, however, an explicit account of the components of future demand and their dependence on price. This after all is what the elasticity concept attempts to express in one single parameter.

In our analysis we have investigated the factors that might cause short and long run price elasticity estimates to vary. Estimates of future short-run price elasticity would be different if these factors were to change. For example, estimates of future short-run price elasticity depend on an estimate of the sales frequency distribution. This distribution reflects, among other things, the distribution of income across customers. It is clear that aggregate price elasticity depends on how many consumers have high income versus how many have low income, even though sales frequency distributions have shown stability over time (at least with respect to cumulative fraction of sales at the mean), this could change. Moreover, there is variation observed even now in the data across several utility companies. Thus our estimate of short run price elasticity for GSU may be different than for for other utilities or for GSU in the future.

Our approach to estimating long-run price elasticity is based on explicitly accounting for the changes in efficiency and saturation of appliances and in the household envelope due to changes in price of electricity. Due to limited time and resources, we used this approach to estimate the demand for electricity for a single year, 1992. The same approach could be used to estimate demand for other years, thus establishing a series of estimates of long-run price elasticity.

To extend this approach in the future will require a more explicit account of the distributional aspects of price response. Our budget share graph illustrates how important this is, and the range of uncertainty. Such extensions would bring our framework closer to the methods and data requirements of REEPS. Studying demand using a capital stock model, however, is a good transition strategy away from aggregated flow-adjustment models with their inherent imprecision. If elasticity estimates vary in a flow adjustment model, there is no way to understand why. A capital stock model can at least provide an explicit account of elasticity variation in the long run.

PART I

DEMAND ELASTICITIES IN THE RESIDENTIAL SECTOR : CONCEPT PAPER

DEMAND ELASTICITIES IN THE RESIDENTIAL SECTOR: CONCEPT PAPER

1 INTRODUCTION

The purpose of this project is to investigate the price elasticity of energy demand in the residential sector using a mixed estimation approach. This approach would combine econometric and end use analysis to estimate and validate elasticity estimates. The project will be conducted in two phases. The result of the first phase is this concept paper. The second phase will include estimation of price elasticities to demonstrate the applicability of our proposed approach to utility service areas. The concept paper includes a discussion of price elasticities and the various factors that affect elasticity estimates, a review of the literature on price elasticities in the residential sector from 1978 to 1982, and a critical evaluation of some of the more interesting and controversial studies during this period. The concept paper in intended to shed some light on the question, is there a single number estimate of price elasticity or does it vary with time and region? If yes, what is the variation?

2 BACKGROUND

The price elasticity of demand is widely used by decisionmakers to understand the behavior of demand to price changes. The price elasticity shows the responsiveness of demand to changes in electricity prices. It is defined as the percent reduction in demand produced by a one percent change in price, everything else held constant.

The magnitude of elasticity is subject to considerable uncertainty. There is little agreement on 1) the best approaches to evaluate elasticities, 2) the accuracy of elasticities obtained and 3) most importantly for this project whether elasticities are constant or change as energy prices or other variables change.

Surveys of electricity demand response to price changes indicate a wide variance in elasticity estimates. These estimates vary with the time period chosen for study, the geographic region, the frequency of observations (month/annual) and other relevant data such as weather. Furthermore, the

estimates vary with the method of statistical analysis.One survey by Bohi [1] indicates no general agreement with estimates of residential elasticities varying from -.08 to -.54 in the short run and from -.45 to -1.56 in the long run. These values are from studies done in the period 1962 to 1977 with most of the studies being done in mid and late seventies. In extreme cases, the short run elasticity defined as a utilization but not an stock adjustment exceeds the long run elasticity estimates which are expected to incorporate both effects.

Elasticity estimates may be compared by the type of model chosen to reflect the demand price relationship. In the following paragraphs we outline the models used to estimate price elasticities and assess the estimates obtained by using these models. The description by model will serve as a guide for chosing one or more methods for estimating price elasticity for our test case.

In reviewing the literature on reduced form models since 1978, we have found that the elasticity estimates are as widespread as those reported by Bohi. Generally, these estimates vary by model specification, by the quality of data, and by geographic region. Geographic regions by themselves are not the influential variables rather it is the weather, appliance saturation, efficiency of electricity use, and other structural parameters that determine electricity use and hence the price elasticity of demand. In our presentation we distinguish between studies conducted by utility companies and those conducted by others principally academic researchers. This distinction will help in understanding the differences in elasticity estimates, model specifications and data quality between utility companies and others. As an initial generalization we observe greater care with data quality and validity in the utility studies and more interest in methodology in the academic studies.

2.1 Reduced-Form Fuel Consumption Models

A reduced form model expresses the quantity of electricity consumed in terms of the price of electricity and other competing fuels, income, and other relevant variables such as the weather, stock of appliances etc. The variables are often normalized with respect to number of households, number of

persons, or customers in the sample. In market share models consumption is often expressed as a share of total energy consumption. Reduced form models have two basic difficulties: (1) the economic theory of consumer demand is not sufficiently well specified to dictate the functional form of econometric equation, and (2) adequate data is typically not available to estimate the more completely specified models. The art of econometric modelling involves the fundamental trade-off between data adequacy and theoretical well-foundedness. Working out the compromises between the requirements of theory and the constraints of data is a gradual and experimental process. Our survey of recent studies provides some guidance on how to make the necessary judgments.

2.2 Data Quality

It is inevitable that some form of averaging, sampling or interpolating be imposed on the data used to estimate price elasticities. While there are few affirmative guidelines on the degree of acceptable approximation, a few recent studies suggest limitations that should not be crossed. A study conducted by V.Kerry Smith [2] estimated electricity values for 27 different utility companies. The results show a great intrastate variation in these estimates. In a single state such as Texas he estimates price elasticities of -0.39 and -0.83 for Houston Power and Light and for Southwestern Public Service respectively. This variation implies that state level estimates are not very applicable to individual utility companies.

A similar example is the estimates made by Consolidated Edison and Long Island Lighting. The former finds a short run price elasticity of about -0.12 compared to values that are at least 2-3 times that for the latter.[3]

This problem of heterogeneous data sources is illustrated in a recent study by Wills.[4] This study attempts to analyze cross-section consumption data for 1975 using income variables from 1969, household data from 1970, prices from 1976 and weather data from 1941-1970. The author's primary interest is exploration of the correct specification of the price variable using utility specific tariffs. This forces him into unsatisfactory choices for all other variables. The empirical result, that all-electric customers have a smaller

long run average price elasticity than other residential customers, runs counter to the results of a large number of studies. It is possible that the counter-intuitive empirical result is a statistical artifact of the inappropriate values for non-price explanatory variables.

The more common data problem involves interpolation of time series estimates for either dependent or independent variables. One form of this problem is the tradeoff between monthly estimates of electricity consumption and annual estimates. A model based on monthly consumption will require monthly data for explanatory variables. This is not too difficult for weather variables, although there are problems involving billing lags.[5] For economic variables there is a Department of Commerce series published in Business Week, although most variables are annual. Demographic variables such as population and household size are only available annually. Appliance holdings are rarely even available annually, so that models using these must interpolate. Another complicating factor is the inconsistency with which monthly meter readings are collected.

3 MODELS ALLOWING VARIABLE ELASTICITY

A central focus of our investigation is the question of whether price elasticities have shown any systematic variation over time. In particular we would like to know if they have been increasing or decreasing as electricity prices and appliance saturations have increased. There are essentially two different approaches to this question. First, the modeller can specify a fixed-parameter model and then evaluate its results for parameter stability over-time. Alternatively, a fixed parameter model can be estimated over disjoint time periods to test for different values of the price elasticity. The principal alternative to these fixed-parameter methods is the selection of a functional form which explicitly allows elasticities to vary with independent variables. The literature includes examples of both kinds. We will begin with the models that allow explicit variation of elasticity.

$$\ln x_t = a_o + a_1 \ln p_t + a_2 \ln y_t + a_3 \ln z_t + e, \qquad (1)$$

where x_t = consumption in period t

p_t = price in period t

y_t = income in period t

z_t = other demand determinants

t = random error term.

The coefficient a_1 in such a model is the price elasticity of demand. To explore its possible variation, an equation explaining a_1 can be written in the following form

$$a_1 = b_o + b_1 \ln p_t + \ln y_t + b_3 \ln w_t, \tag{2}$$

where w_t is a vector of variables that may or may not overlap with z_t in eq. (1). Combining equations (1) and (2) yields an expression for consumption of the form

$$\ln x_t = c_o + c_1 \ln p_t + c_2 (\ln p_t)^2 + c_3 (\ln p_t)(\ln y_t)$$

$$+ c_4 (\ln p_t)(\ln w_t) + c_5 \ln y_t \tag{3}$$

$$+ c_c \ln z_t + e.$$

For a demand equation in the form of (3), price elasticity n_p is given by

$$n_p = \frac{d \ln x_t}{d \ln p_t} = c_1 + 2 c_2 \ln p_t + c_3 \ln y_t + c_4 \ln w_t \tag{4}$$

Two recent studies which explore the possibility of price elasticity varying according to a form such as eq. (4) are Betancourt (1981) and Chern, Just and Chang (1982).[6] [7] Each takes a somewhat different approach to eq. (4) and its estimation, illustrating some of the practical problems associated with detecting structural changes in the price responsiveness of demand. It will be useful to contrast these studies since their different focus illustrates the range of issues relevant to the variable elasticity problem.

Betancourt is primarily interested in peak demand. To isolate the effects of weather and price, he uses versions of eq. (2) which are limited to these variables. Furthermore, he uses a lagged price variable and works only on rates of change in demand, rather than physical consumption per se. This alters the form of eq. (3), simplifying its structure so that the actual equation estimated is linear and involves no cross terms. Varying elasticity is

captured by evaluating elasticity at the sample mean (reference case) of weather and price and comparing this with elasticity at the sample mean plus two standard deviations. This comparison tells us whether and how elasticity changes with extreme conditions. At extreme prices, Betancourt finds that elasticity increases. Conversely under extreme weather conditions, consumption becomes less elastic, although this effect is more substantial for cooling than heating.

Betancourt reports other interesting results concerning the statistical validity of his models and parameter estimates. Generally speaking all the models worked better in the older more fully developed areas of Boston, Philadelphia and Detroit, than in the rapid growth areas of Northern Virginia, Houston and Portland. Of all the explanatory variables, the measure of cooling degree days was the most consistently significant, followed by income. The price variable showed substantially less consistent significance across models.

The Chern, Just and Chang study explicitly adopts the framework of equations (1) - (4). The vector w_t is specified as appliance saturations for electric space heating, air conditioning, water heating and clothes drying. These are estimated at the state level, the unit of analysis for consumption, price, income and climate adopted throughout the study. The results of the study are summarized in Table 1 which gives the estimated values of the coefficients $\hat{c}_1$ - $\hat{c}_4$ in eq. (4).

Table 1
Chern, Just and Chang Variable Elasticity Estimates

Variable	Co-efficient	VALUE
$\ln p_t$	$\hat{c}_1$	-4.707
$\ln p_t \cdot \ln p_t$	$\hat{c}_2$	0.487
$\ln p_t \cdot \ln y_t$	$\hat{c}_3$	0.369
$\ln p_t \cdot S_{stl}$	$\hat{c}_{4,1}$	-0.00268
$\ln p_t \cdot S_{ac}$	$\hat{c}_{4,2}$	0.00118
$\ln p_t \cdot S_{wh}$	$\hat{c}_{4,3}$	0.00754
$\ln p_t \cdot S_{cd}$	$\hat{c}_{4,4}$	0.0134

These results show that numerically the co-efficient $\hat{c}_1$ dominates all other terms in eq. (4), the price elasticity. The positive sign of $\hat{c}_2$ implies that increasing price will reduce elasticity. This would make sense if some limit on basic needs were being approached, i.e., if the demand curve were constant, but such a limit is difficult to identify. Therefore, the sign of $\hat{c}_2$ must be treated as inconclusive. In practice as prices change, the estimated coefficients of a model like eq. (1) - (4) will also change. Therefore, it is important not to put too much emphasis on the appropriateness or interpretation of the value found for $\hat{c}_2$.

The other co-efficients listed in Table 1 all have reasonable interpretations. The term expressing cross-effects between price and income, $\hat{c}_3$, indicate that elasticity decreases with income. This is an expected result whose intuitive basis is the widely observed decline in budget share devoted to energy or electricity with rising household income. The vector of co-efficients, $\hat{c}_4$, is broken down into components representing the saturations of each end-use appliance type. The results indicate that electric space heating increases average or aggregate elasticity. This is a widely observed result from other studies. Air conditioning tends to lower the average elasticity, but by substantially less than water heating or clothes drying. There is much less literature on elasticities associated with these other end-uses, so that comparisons are not straight-forward.

Neither the Betancourt not Chern, Just and Chang studies address the most recent experience. Both studies rely on data which goes only through the mid-1970's. Thus, any structural changes in the residential electricity market which may have occurred more recently are not visible in this work.

The main alternative to functional forms incorporating variable elasticity are empirical methods. A number of recent studies adopt this approach to the question of elasticity variation. These will be reviewed next.

4 EMPIRICAL APPROACHES TO ELASTICITY VARIATION

simple direct approach to the elasticity variation problem is to estimate a consumption model over different time periods. If the co-efficients of the model which determine price elasticity show significant variation across estimation periods, price elasticity may be said to have changed. Studies designed in this general framework, however, have not achieved consistent or easily interpretable results. The modelling possibilities can be illustrated by examining several recent studies of this kind.

Huq and Dynes (1982) analyze consumption behavior in the Virginia Electric Power Company (VEPCO) service territory for the period 1969-1980.[8] They estimate a linear model of electricity use per customer using a price variable representing the customer weighted average of the marginal prices. To account for seasonal variation in heating and cooling requirements, independent variables are constructed which weight seasonal degree days by appliance saturation. The model has the form given by

$$\begin{aligned} AVSUE = {} & \alpha_0 + \sum_i \alpha_{1i} \cdot SAT_i \cdot DD \cdot NORM_i \\ & - \left[\sum_i \alpha_{2i} \; SAT_i \cdot DD \cdot NORM_i\right] RP \qquad (5) \\ & + \alpha_3 x_3 + e, \end{aligned}$$

where AVUSE = average residential electricity use per customer in a given quarter,

SAT_i = saturation of weather sensitive appliance holding i, for i = heating, cooling and both.

DD = degree days (heating and/or cooling) in a given quarter

$NORM_i$ = average usage of appliance holding i under normal weather

RP = real marginal price (customer weighted average)

x_3 = other determinants including income

e = random error term.

The price elasticity in a linear model such as eq. (5) is calculated directly, and in this case yields

$$N_p = \frac{-P}{Q} \frac{dAVUSE}{dP}$$

$$= \frac{P}{Q}\left[\sum \alpha_{2i} \; SAT_i \cdot DD \cdot NORM_i\right]. \qquad (6)$$

Huq and Dynes first estimate eq. (5) over 1969-1980 and then test for stability of the model co-efficients. They find that stability fails and locate two specific dates in which structural shifts are significant. To account for these, dummy variables are introduced to eq. (5). The model is re-estimated with these dummies. The resulting equation satisfies the parameter stability test. Estimated values for the dummy variable co-efficients indicate downward shifts in the demand function. The α_{2i} co-efficients are principal determinants of the price elasticity which is calculated for each quarter of 1970, 1975 and 1980. The results are given in Table 2.

Table 2.

VEPCO Price Elasticity Estimates

	1970		1975		1980	
	Elasticity	Fraction of Annual Use	Elasticity	Fraction of Annual Use	Fraction of Elasticity	Annual Use
Quarter						
1	-.050	27	-.097	29	-.0198	31
2	-.079	20	-.120	22	-.207	19
3	-.245	28	-.407	27	-.758	28
4	-.072	25	-.239	22	-.418	22
Annual	-.12		-.22		-.40	

The results in Table 2 must be interpreted carefully. To some extent the large seasonal elasticities in Quarters 3 and 4 as well as the tendency for the values to increase from 1970 to 1980 is a feature of the model specification. Equation (6) shows that elasticity is linear in both degree days and price. Quarters 3 and 4 have more degree days than Quarters 1 and 2, therefore, they should have higher elasticities. Similarly prices have increased on the average from 1970 to 1975 and from 1975 to 1980. Offsetting these trends are quantity adjustments indicated to some extent in Table 2.

An alternative to the Huq and Dynes procedure is an approach which estimates parameter values determining price elasticity over different time periods. Two recent studies using national samples of state-level observations use this approach. Results of Taylor, Blattenberger, and Rennhack (1982)[9] are summarized in Table 3 along with similar estimates by Chern and Bouis (1982).[10]

Table 3

Long and Short Run Elasticities, Logarithmic Flow Adjustment Models, Disjoint Time Periods

A. Taylor, Blattenburg and Rennhack

	1960-65	1965-70	1970-75
ln LAG USE	0.888	0.862	0.622
ln Marginal Price	-0.141	-0.100	-0.065
Long Run Elasticity	-1.26	-0.72	-0.17

B. Chern and Bouis

	1956-65		1966-75
ln LAG USE	0.434		0.790
lN AVERAGE PRICE	-0.729		-0.136
Long Run Elasticity	-1.29		-0.65

Both of these studies use logarithmic models with a one period lagged dependent variable (LAG USE) to measure either average use (A) or total residential sales (B). The co-efficient of the lagged consumption variable allows calculation of a long run price elasticity, η_{LR} as follows

$$\eta_{LR} = 1 - \frac{\text{Co-efficient of LN PRICE}}{\text{Co-efficient LN LAG USE}}. \qquad (7)$$

The data in Table 3 indicates a tendency for long run elasticity to decline. Like the opposite conclusion of the VEPCO study, this result must not be taken too literally. Declining elasticity, in these models may be a conclusion due more to method than underlying reality. The problem stems in large part from the national scope of these studies. Both estimate data for most individual states, pooling observations, and separating state specific effects by the use of dummy variables. Thus the co-efficient of the price term represents an average response.

Such averaging can be useful it the cluster of data is close and the same general trends can be observed across all observations. This is not the case, however, especially over the sub-periods studied.

One indicator of variation across the state level observations can be calculated from the Chern, Just and Chang study cited previously. The same data base is used there as in Chern and Bouis, covering the period 1955-1976. Price elasticities are reported by state. A mean value of -0.46 can be calculated from this data for short run average price elasticity. The standard deviation, however, is about 0.18. The two standard deviation range of values then, is from -0.10 to -0.80.

In terms of the fundamental economic conditions, the 1970-1975 period was very hetergeneous. the residential price of electricity rose rapidly from some utilities, for others it was still declining. Of the utilities we will be discussing in detail, two had increasing real prices (Philadelphia Electric and Long Island Lighting) for one real prices was declining (Public Service of Indiana) and the other had fluctuating prices which trended lower (Gulf States Utilities). A major unsolved question in economic demand theory is whether elasticities are expected to be symmetric or to vary with changes in the price trend. Pooling data from demand regimes with very different price trends can be misleading if one is attempting to discern changes in elasticity over time.

Consider the representation of price trends illustrated by Figure 1. This shows the real average revenue per residential kwh for the investor-owned electric utilities as a group, and for individual utilities. The general pattern indicated here is a period of declining prices, up to 1970, stable prices in the early 1970's, then an irregular upward trend. This average behavior includes considerable variation in the individual utility price paths. It is therefore uncertain whether demand behavior, particularly in the early 1970's, can be meaningfully pooled across utilities. Those experiencing declining prices may respond quite differently from those experiencing increasing prices.

Because the data in both Tables 2 and 3 is both contradictory with one another and inherently ambiguous, there is need for a more basic approach to elasticity variation. Such an approach needs to be grounded in consumer behavior theory and observable with available data. In the following

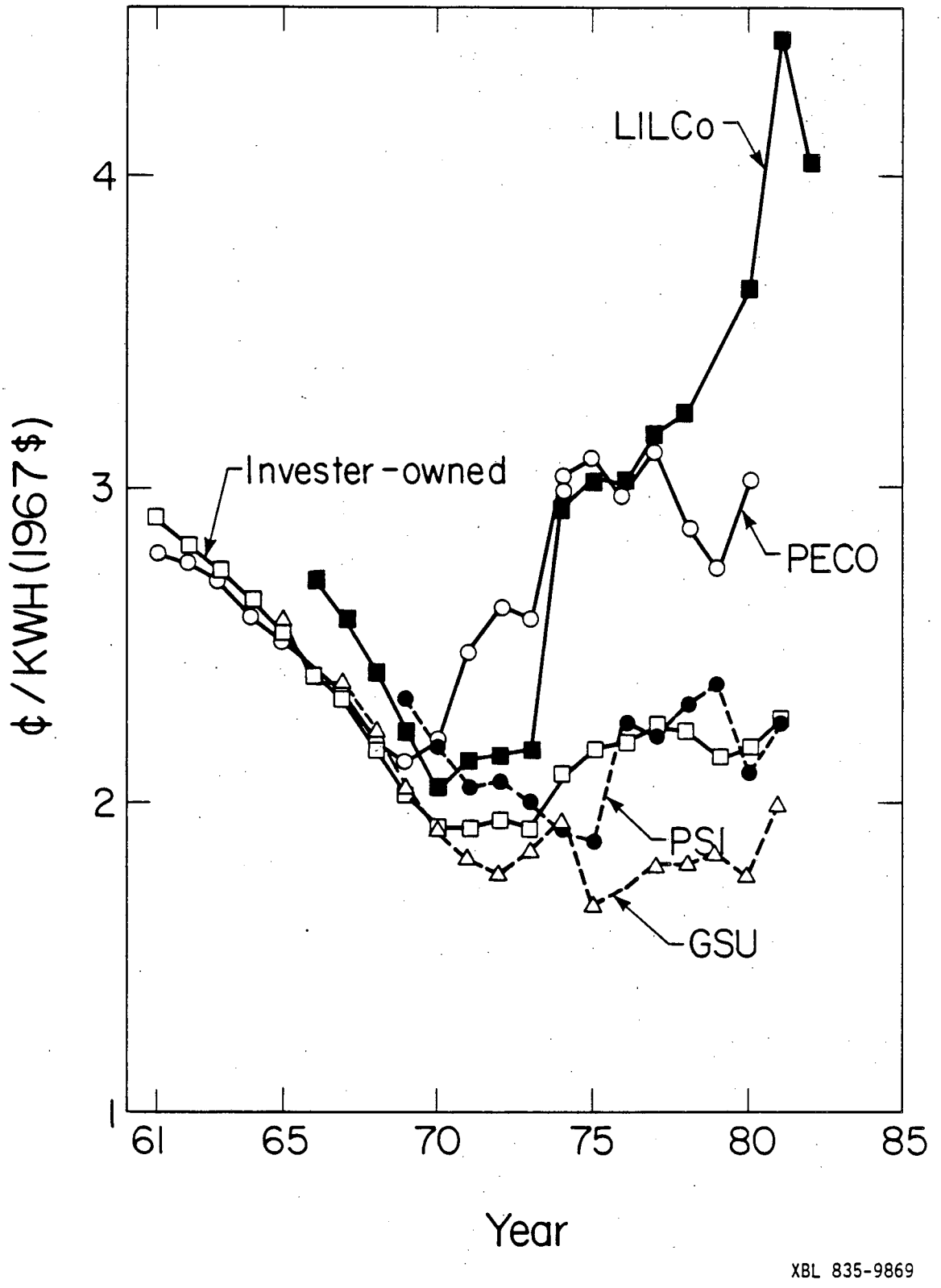


Figure 1: Average Revenue Trend for Utility Companies

sections, we discuss some candidates for such a theory. We begin with a discussion of budget shares and price elasticity and then examine appliance saturation and efficiency.

5 BUDGET SHARE AND PRICE ELASTICITY

It is commonly observed that price elasticity can be expected to increase for a given commodity as the share of the consumer's budget devoted to that commodity increase. Despite the plausible intuitive basis of such an assertion there have been no empirical studies devoted explicitly to this thesis. One reason for this gap in the literature is the substantial data requirements necessary for such an analysis. In this section, we will review a number of studies that allow such assessments, although they were not primarily designed for that purpose.

Two of the most informative recent studies relevant to the budget share perspective are the conditional demand analysis of the NIECS data base by Lawrence and Robinson (1982)[11] and a distributional policy analysis using the REEPS model by Berkovec, Cowing and McFadden (1982).[12] These studies differ substantially in method, but both depend on extremely detailed data characterizing the distribution of household characteristics (demographic, economic and energy-related). The data must be drawn from one or more highly detailed surveys which capture the range of variation in dwelling type, size, locations, and the existing appliance portfolio. The survey data is then matched with energy consumption, often represented on a monthly basis. From these large data bases price elasticity can be calculated from model estimations which reflect the role of budget share.

The approach of Lawrence and Robinson is in the genre of conditional demand models. The unit of analysis is average household electricity use, explained by a linear sum of appliance holdings. Formally a model such as the following is estimated

$$Q(j) = \sum_i U_{i,j} \, x_{i,j} + v(j), \tag{8}$$

where $q(j)$ = average use of household j,

U_{ij} = average consumption of the ith appliance in household j,

x_{ij} = a dummy variable equal to one when the household j has the ith appliance, and

V(j) = random error term.

The variables $U_{i,j}$ in turn are explained by household characteristics, energy prices and climate variables, usually in a linear fashion.

Because price enters into a number of the consumption terms, price elasticity involves a sum of estimated model co-efficients. Conditional demand models are typically used to estimate average consumption for various end-use devices. Because average consumption must come out positive for all appliances and households, price enters the specification in reciprocal form. This complicates the elasticity calculation, i.e., its is not just a sum of model co-efficients. The basic relations in this model are given for the derivative of consumption with respect to price as follows

$$\frac{dq}{dP} = \frac{d}{dP}\left[\alpha \sum_{i=1}^{m} MISC_i/P\right] + \frac{d}{dP}\left[\sum_{j=1}^{4} WS_j/P\right] + \frac{d}{dP}(P), \qquad (9)$$

where $MISC_i$ = dummy variables equal to one for households with appliances used for cooling, hot water, freezing, refrigeration, dish and clothes drying,

α = estimated co-efficient,

$WS_j = \beta * HVAC_j$ where j ranges over household heating and cooling appliances

$HVAC_j$ = dummy variable equal to one for households with the jth appliance, weighted by degree days, and dwelling size, and

B_j = estimated co-efficients.

The empirical results reported by Lawrence and Robinson are based on the Department of Energy's 1979 National Interim Energy Consumption Survey (NIECS). Equation (9) can be evaluated at sample mean values, using reported co-efficients, to calculate a mean elasticity. The relevant data are tabulated below in Table 4.

Table 4

Lawrence and Robinson Mean Elasticity Estimate

Parameter	Estimated Coefficient Label	Value	Sample Mean
Σ MISC$_i$	α	2.16	3.46
Wtd. Room AC*	β_1	.0181	146.45
Wtd.Central AC*	β_2	.0058	485.81
Wtd.Heat Pump* Cooling	β_3	.017	43.59
Wtd.Elec.SH*	β_4	.0012	1426.90
Price		-1.88	5.015

Elasticity at mean daily use = 26.62 kwh is -.709

*Parameter is multiplied by reciprocal price.

The mean elasticity estimated from the Table 4 data and eq. (9) is somewhat lower than the elasticity reported as the average of the values for all individuals in the sample (-0.91) or the mean elasticity of the group with mean usage (-0.789). The differences are due to aggregation bias. Such bias is a major problem confronting models that do not rely on the large survey data used in the conditional demand approach, or other disaggregated modelling techniques. Typically, an aggregated model will rely on sample mean values of explanatory variables to account for consumption variations. In this study even the limited use of mean values results in an elasticity which is too small in absolute value compared to the arithmetic average of the individual elasticities. The subject of aggregation bias will be reviewed below in both cases. Lawrence and Robinson study which indicate relations between individual price elasticity and the budget share devoted to electricity.

Table 5 summarizes the consumption budget share and elasticity estimates of the Lawrence and Robinson study by income group.

Table 5.

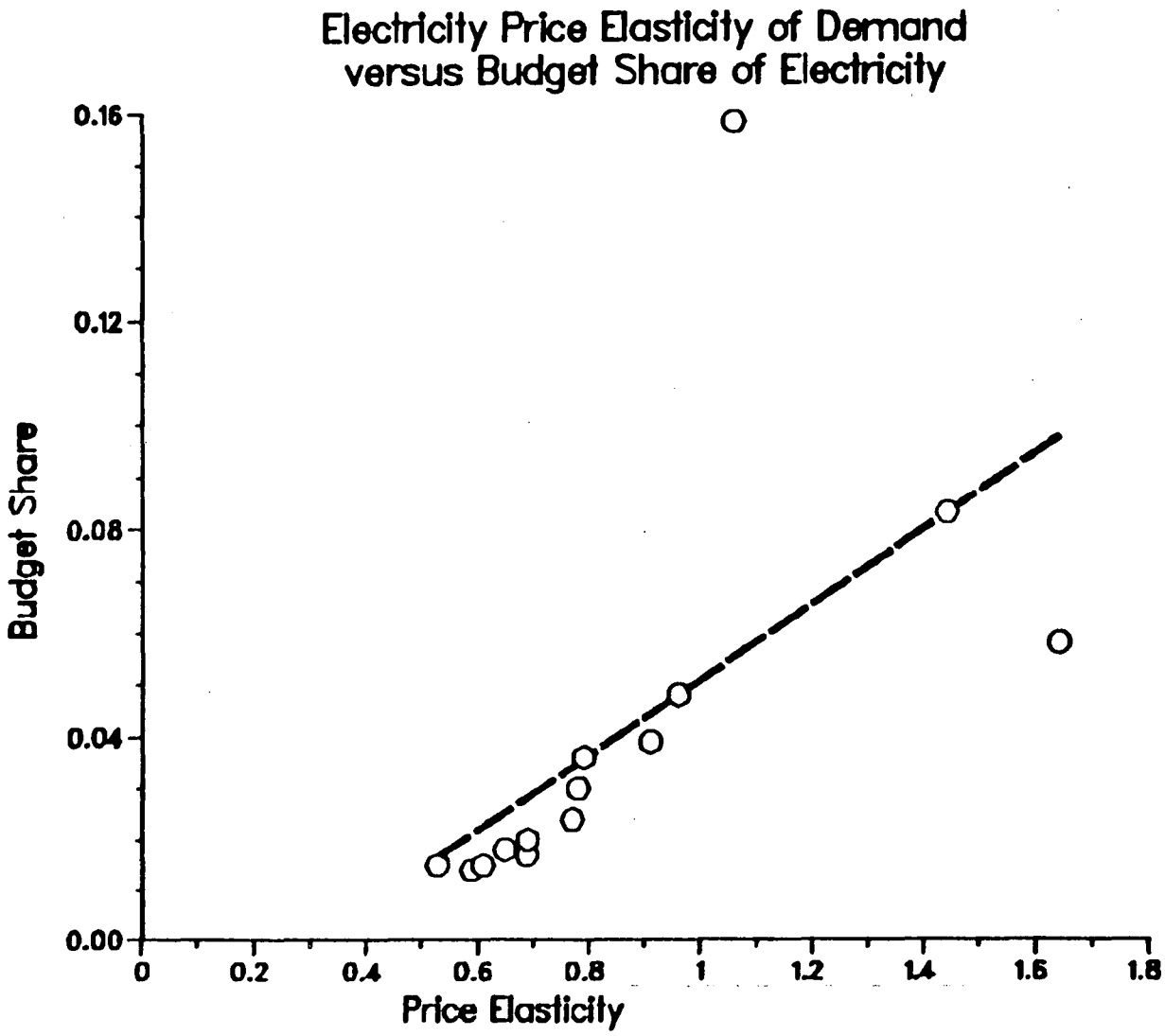
Elasticity by Income Group

Mean Income of Group ($000)	Budget Share	Annual kwh (Group Mean)	Price Elasticity	Income Elasticity
2	.158	5618	-1.06	0.02
4	.083	5803	-1.44	0.04
6.5	.058	6949	-1.64	0.07
9	.048	8634	-0.96	0.07
11	.039	8578	-0.91	0.08
13.5	.036	9709	-0.79	0.08
17.5	.030	10,934	-0.78	0.11
22.5	.024	10,759	-0.77	0.15
27.5	.020	11,920	-0.69	0.17
32.5	.018	12,333	-0.65	0.19
37.5	.017	13,540	-0.69	0.23
42.5	.015	14,447	-0.61	0.24
47.5	.014	13,731	-0.59	0.27
55	.015	18,108	-0.53	0.28

In Figure 2, the price elasticities are plotted against budget share. The points produce a reasonable consistent pattern except for three extreme values at budget shares greater than 5% (corresponding to groups at and below the group wih $6500 mean income). The upward sloping line suggested by the other eleven data points implies a reasonably smooth and stable increase in the absolute value of elasticity as budget share increases. This confirms intuition in a qualitative way. It would be useful, however, to compare the relationship shown in Figure 2 with other estimates of the budget share/price elasticity correlation. Such a comparison can be derived from a recent policy analysis simulation study using the REEPS model.

REEPS is a large scale model simulating residential appliance choice and utilization behavior. It builds upon the discrete choice statistical framework associated with D. McFadden and associates. The data for REEPS are similar to those used in conditional demand modelling, i.e., detailed surveys of consumer characteristics and behavior from a representative sample. Unlike the cross-sectional approach of conditional demand models, REEPS reproduces the dynamics of appliance choice and consumption over time. Distributional properties of the sample are fundamental features of the simulation, which is structured to propagate certain correlations among exogenous variables through time. Therefore, it is straight forward to analyze the distributional impacts

Figure 2


Electricity Price Elasticity of Demand
versus Budget Share of Electricity
Budget Share
0.16
0.12
0.08
0.04
0.00
0
0.2
0.4
0.6
0.8
1
1.2
1.4
1.6
1.8
Price Elasticity

of energy policy using REEPS. Income groups can be followed separately through the simulations to discover specific impacts on each group.

The recent paper by Berkovec, Cowing and McFadden (1982) pursues this approach in simulations of natural gas price de-control and the imposition of federal appliance standards. For our purposes, it is the unperturbed base case described in the study which is most interesting. Table 6 reports the primary data from the study from which elasticity estimates can be calculated and correlated with budget share. For six income groups specified in REEPS, mean income, electricity bills, and annual kwh use are estimated for 1979, 1983, and 1991. With the data listed in Table 6, an estimate of price elasticity can be derived. Prices can be inferred from bills by dividing quantity estimates into total electric bills. The change in quantity for a given change in price can then be calculated. From this, price elasticity is calculated using the usual formula. The calculations are tabulated in Table 7 where price and quantity changes are estimated over the 1979-1991 period. Finally, the 1991 budget share and price elasticity evaluated in 1991 are given in Table 8 for each income group.

Table 6.
Electric Bills and Quantities 1979-1993
By Income Group from Berkovec, Cowing & McFadden

Group	Mean Income	79	83	91	Bills (1975$) 79	83	91
1	3.5	134.32	135.12	128.02	12.82	11.29	9.93
2	8.0	218.08	228.91	229.30	20.77	18.89	17.78
3	13.0	278.57	298.12	296.42	26.59	24.72	22.98
4	19.0	378.69	405.69	420.20	35.33	32.98	31.87
5	36.0	570.95	618.15	657.45	52.05	49.34	49.07
6	51.0	808.71	873.49	941.09	69.28	68.22	70.60

Table 7
Prices, Price and Quantity Changes

Group	Prices ($/10^6 Btu) 79	83	91	ΔP	ΔQ	$\Delta Q/\Delta P$
1	10.48	11.97	12.89	.230	-.225	-.978
2	10.50	12.12	12.90	.229	-.144	-.689
3	10.48	12.06	12.90	.231	-.136	-.589
4	10.72	12.30	13.19	.230	-.098	-.426
5	10.97	12.53	13.40	.222	-.057	-.257
6	11.67	12.80	13.33	.142	+.0019	+.134

$$\Delta P = \frac{91-79}{79} \qquad \Delta Q = \frac{79-91}{79}$$

Table 8
Budget Share and Price Elasticity

Group	Budget Share	Elasticity
1	.0365	-1.27
2	.0286	-0.46
3	.0228	-0.33
4	.0221	-0.18
5	.0182	-0.07
6	.0184	+.03

Before comparing the Table 8 results with those in Table 5, it is important to compare methods and modelling technique. The cross-sectional approach of conditional demand models produces elasticity estimates that are thought to represent the full long run response. REEPS results are much more like a time series model in which there is no simple lag term to embody the long run elasticity. In the Berkovec, Cowing and McFadden study there is good reason to believe that the full long run elasticity is not reflected in the quantity adjustment. Stock adjustment requires more than the twelve year period simulated in this study. Given the slow turnover in the appliance and housing portfolio, at least twenty years simulation would be more appropriate.

Without making significant adjustments to the data, the relationship of Table 8 is compared to Table 5 in Figure 3. Because the Lawrence and Robinson study resulted in three widely scattered outlier for low income groups (see Figure 2), these points have been neglected. Including all three would only perturb the fitted line slightly. None can be plotted at the scale of Figure 3, which is finer grained than Figure 2. Similarly the REEPS study yields an anomalous point at the high income side of the scale, a positive price elasticity, although of small absolute value. This point has also been omitted from Figure 3. Again including it would only perturb the fitted line slightly.

Figure 3 illustrates the contrasting estimates of the elasticity variation. The conditional demand results all show consistently higher elasticities compared to REEPS at budget shares of less than 3%. REEPS, however, suggests that elasticity increases quickly once the budget share exceeds 3%, much more quickly than Lawrence and Robinson find. It would be satisfying if the differences illustrated in Figure 2 could be reconciled. This is not currently known, but it may be feasible. One approach would be to design a REEPS simulation deliberately to estimate price elasticity in the long run by income group. There is some reason to believe that the slope of the REEPS line would increase as the simulation period is extended. Sensitivity analysis of the data in Table 6 and 7 suggests that over shorter periods than the twelve year cycle shown in Figure 3, the corresponding line is even flatter. This implies that in the long run, the slope would increase, bringing the estimate closer to the Lawrence & Robinson one.

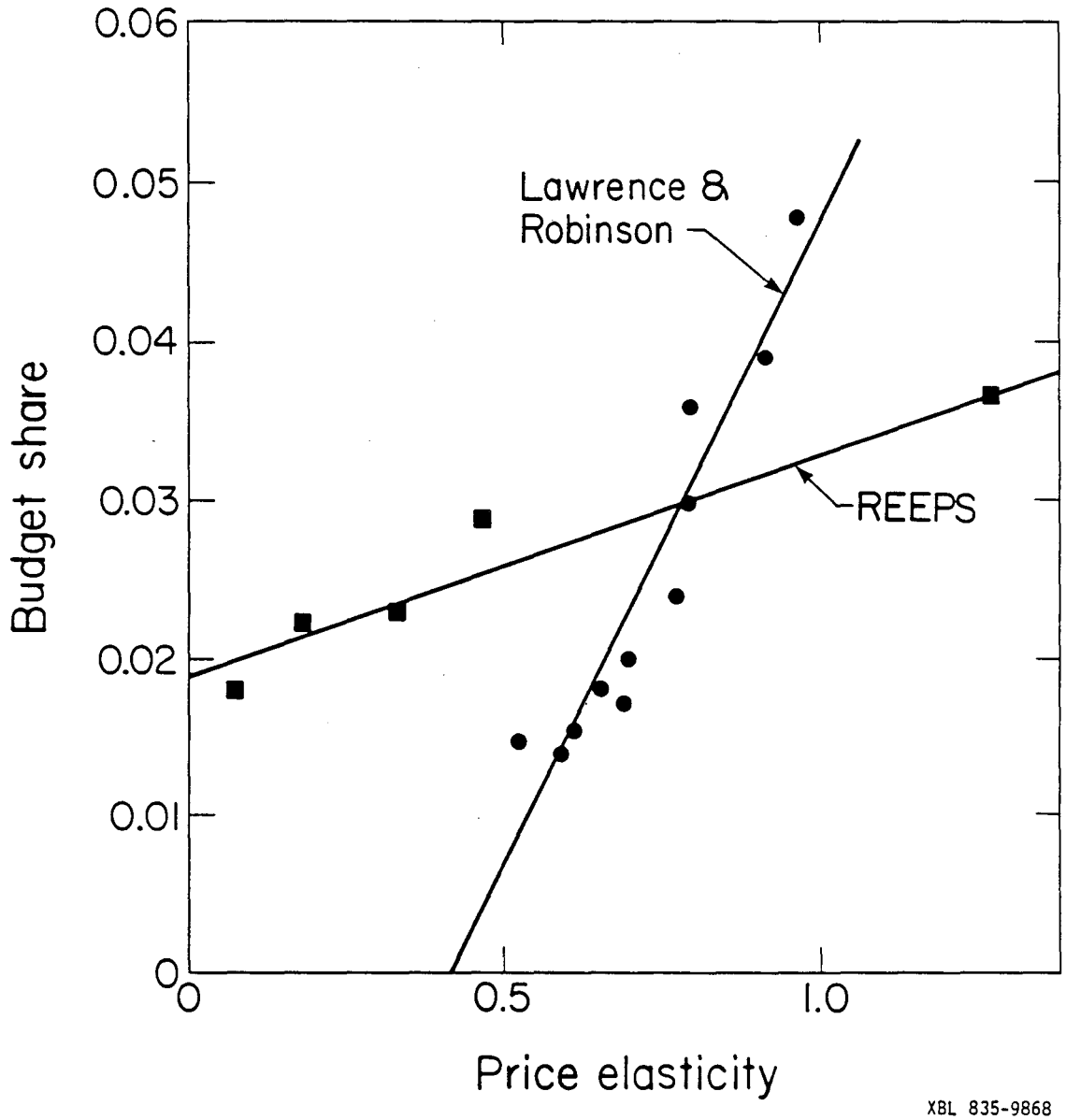


Figure 3: Comparison of Price Elasticity and Budget Share

Finally, it should be noted that results such as those shown in Figure 3 are consistent with the general theory of consumer behavior as summarized, for example, in the Slutsky equation. This equation expresses the total quantity response to a price change as the sum of a substitution and an income effect. Formally, the partial derivative of the demand for a commodity i, is the difference between the derivative of the compensated demand curve (i.e., ($\partial Q/dP$ at Utility = constant) and the quantity adjustment induced by the income change. This is written

$$\frac{\partial Q_i}{\partial P_i} = \left[\frac{\partial Q_i}{\partial P_i}\right]_{u=\text{const}} - Q_i\left[\frac{\partial Q_i}{\partial I}\right]_{\text{prices}=\text{constant}}, \tag{10}$$

where Q_i = quantity of commodity i,

P_i = price of i,

and I = income.

This equation can be expressed in terms of price and income elasticities. Multiplying eq. (10) through by P_i/Q_i and the last term on the right by I/I,

$$\frac{P_i}{Q_i}\frac{\partial Q_i}{\partial P_i} = \frac{P_i}{Q_i}\left[\frac{\partial Q_i}{\partial P_i}\right]_{u=\text{const}} - \frac{P_i Q_i}{I}\left[\frac{I}{Q_i}\frac{\partial Q_i}{\partial I}\right]. \tag{11}$$

Eq. (11) says that the ordinary price elasticity is the difference between the uncompensated price elasticity (or substitution) term and the income elasticity multiplied by the budget share of commodity i.

Eq. (11) cannot be directly fit to results such as those illustrated in Figure 3. This would only be possible if the compensated elasticity were the same for all groups. Such a simple assumption implies unrealistically large income elasticities for either model. A more likely fit would result from assuming that compensated elasticities increase in absolute value with budget share. Such effects are difficult to observe.

The models summarized in Figure 3 represent the extreme of data complexity in the elasticity literature. The data requirements are so severe that it is not practical for most utilities to use either approach. Of the two approaches, conditional demand is somewhat less data intensive than REEPS. For practical purposes, however, only a small number of large utilities will even adopt conditional demand. The alternative, small scale aggregated

models, are much more the industry norm. It will be useful to understand data limitations and the problems of small scale modelling by reviewing recent utility models of residential consumption.

6 SMALL SCALE UTILITY MODELS

In this section, residential electricity demand models used by several utilities will be reviewed and assessed. Elasticity estimates result from these models. The utilities studies are Long Island Lighting Company (LILCO), Philadelphia Electric Company (PECO) and Public Service Indiana (PSI). The discussion will focus on details of model specification and address the question of elasticity variation as much as possible.

We begin with a model of short-run average electricity consumption used by Long Island Lighting. It is a linear model resembling the VEPCO model in some respects, but without explicit use of heating and cooling saturations. Electric space heating customers have a different rate schedule than other residential customers. Their consumption is modelled separately. Cooling and water heating are aggregated with other end uses.

Table 9 summarizes the results of a few variations on the basic LILCO approach. Models A and B differ somewhat in specification. The B version includes an income variable which is not used in the A version. B also uses the square of household size as opposed to A in which it is not squared. The subscripts indicate different estimation periods for each specification.

Table 9

LILCO Short Run Average Residential
Consumption Models: Non-Heating

Variable	A_1	A_2	B_3	B_4
Real Average Price	-84.9	-68.1	-51.8	-53.7
Appliance Price Index	-87.9	-93.2	-84.0	-79.1
Household Size	2371.2	2904.2		
$(\text{HH Size})^2$			561.1	431.7
Cooling Degree Days	0.563	0.86	1.347	0.97
Conservation Dummy 1	-116.3	-289.4	-216.0	-221.6
Conservation Dummy 2	-304.6	-496.9	-460.6	-458.4
Lagged Per Capita Income			0.486	0.54
Price Elasticity	-.439	-.426	-.324	-.277

Notes: a) Conservation Dummy 1 corresponds to years exhibiting moderate conservation. Conservation Dummy 2 corresponds to years exhibiting severe exogenous supply shocks.

b) Subscript 1 indicates a 1967-1979 estimation period, Subscript 2 indicates a 1967-1982 estimation period.

c) All elasticities are evaluated in the last year estimated.

It is worth noting that Model A_1 was adopted by LILCO in its 1981 Report on Load Forecasting to the New York State Energy Office. Model B_2 is the currently used version (personal communication, T. Russo).

In going from A_1 to B_2 one might conclude that short run price elasticity had declined in the LILCO service territory. Such a conclusion, however, is due more to changes in model specification than anything else. The coefficient of the price variable in both models does in fact decline when the 1980-1982 data is added to the 1967-1979 base. In the B version, however, price increase are a large effect. Thus in the B model elasticity increases somewhat. In the A version price elasticity declines by a small amount. The electric bill for the average LILCO non-space heating customer went from 1.77% of household income in 1979 to 2.11% in 1982.

A few other observations about the LILCO model are in order. Like the VEPCO model described earlier, both the A and B versions use dummy variables for structural changes due to conservation effects. Sensitivity tests indicate that without these dummy variables, the models fit the data less well. It should also be noted that Table 9 points to an increasing weather

sensitivity of the LILCO load from 1979 to 1982. This appears in both the A and B version of the model. Finally, the elasticities calculated in Table 9 are reasonably insensitive to logarithmic transformation of the model. In particular, logarithmic versions of models A and B estimated to 1982 produce price elasticities of -0.4 and -0.35 respectively. This is within 10% of the Table 9 values.

Turning to Philadelphia Electric Company, however, illustrates a case where model specification changes induce substantial differences in the price elasticity estimate. Philadelphia Electric (PECO) chooses total residential sales as the dependent variable in its consumption model. This is a far less common choice than average sales per customer, but it is not unique. The Chern and Bouis study and the Chern, Just and Chang paper both use this approach. The number of customers is then used as an explanatory variable.

PECO uses a logarithmic specification to explain consumption. The model is estimated on data from 1959 to 1979. The model adopted by PECO (Version C_1) and some variations are illustrated in Table 10.

Table 10

PECO Residential Consumption
Non-Space Heating

Dependent Variable	C_1 Sales 1959-1979	C_2 Sales 1966-1979	D_1 Average Use 1959-1979	D_2 Average Use 1966-1979
Explanatory Variables				
Real Price	-0.055	-0.08	-0.098	-0.102
Real Income	0.391	0.75	0.341	0.37
Lagged Sales	0.530	0.26		
Customers	1.099	2.29		
Lagged Average Use			0.756	0.754
Long Run Price Elasticity	-0.117	-0.108	-.402	-.415

Version C yields a long run price elasticity estimate of about -0.10. There is little difference due to changing the estimation period. The price coefficient in model C_2 increases, indicating a larger short-run response than in the C_1 version. Since the lagged adjustment term decreases in C_2 compared to C_1, there is little overall change in the long run response. The D version

is substantially different. Not only is the price co-efficient about twice as large as in C_1, but the larger lag term indicates a considerably greater long run response. The long run price elasticity is about -0.40 in the D version. There is no noticeable difference between D_1 and D_2.

The corresponding analysis was also performed for PECO's residential space heating customers. In that case, elasticity estimates in the long run did not appear to change significantly when the dependent variable was shifted from total sales to average use per customer. The results of this test are shown in Table 11 for the PECO model and its average use equivalent. Both versions yield the large long run price elasticity estimates that are commonly found for electric space heating customers.

The use of a lagged dependent variable in aggregated logarithmic consumption models is the only simple approach to estimating long run elasticities for a utility service area.

Table 11
PECO Residential Space Heating Consumption

Dependent Variable	E. Sales 1962-1979	F. Average Use 1962-1979
Explanatory Variables		
Real Price	-.55	-.41
Change in Degree Days (weighted by customers)	.55	.23
Number of Heat Pumps	.077	.016
Number of Customers	.47	
Lagged Sales	.44	
Lagged Average Use		.54
Long Run Price Elasticity	-.99	-.89

Cross-sectional approaches are either based on many different utilities and regions, or require the highly disaggregated approach of conditional demand models. It is natural to add a lagged dependent variable to models which do not include them to test for differences in the long and short run price response. While PECO does this in their models, other utilities do not. We will examine one case where this variation can be added, Public Service of Indiana (PSI).

Public Service of Indiana uses a simple logarithmic model to explain average use per customer in terms of real per capita income, degree days and real average price. Only thirteen data points are used covering the years 1969-1981. Models and data are taken from PSI's "Peak Demand and Energy Forecasts 1982-1993: Databook," July, 1982. Table 12 shows estimated co-efficients for some variations on the basic PSI approach. Both non-space heating customers and winter average use for space-heating customers are included.

Table 12

PSI Model Coefficients

	G_1	G_2	G_3	H_1	H_2
	Non Space Heating			Winter Average Space Heating	
Explanatory Variable	13 yrs.	12 yrs.	12 yrs.	13 yrs.	12 yrs.
Income	1.005	0.407	0.910	0.182	0.273
Degree Days	0.074	0.118	0.069	0.692	0.718
Price	-0.384	-0.256	-0.282	-0.396	-0.486
Lagged Use		0.466			0.476
Long-Run Elasticity		-0.479			-0.927

Examination of Table 12 indicates little difference in the short-run price response between space heating and ordinary residential customers. G_1 and H_1 have nearly identical price co-efficients. The G model is quite sensitive to estimation period however. Comparing G_1 with G_3 shows a significant drop in the price co-efficient with deletion of one year (1969) from the data. The H model is less sensitive. Changes between H_1 and H_2 are as much due to the changed specification as to changes in the estimation period.

The differences in long run price elasticity between space heating and other residential customers are apparent in Table 12. While the lagged dependent variable has roughly the same co-efficient in G_2 and H_2, the price co-efficients diverge from G_1 and H_1. The resulting long run elasticity estimates approximate the corresponding value for PECO (see Table 11 and the D models for Table 10). Moreover, it is interesting to note that the 1979-1980 budget shares are roughly equivalent and fall within the middle range of the Figure 2 estimates. The non-space heating budget share is .013 for PECO and 0.0175 for PSI, for space heating the share is about .033 in both cases.

An attempt was made to put the LILCO data and model in the same perspective. First, the linear models of Table 9 must be put in logarithmic form. Next a lagged dependent variable must be added. The resulting co-efficients are reported in Table 13.

Table 13
LILCO Model: Logarithmic Version of A and B

Variable	Co-efficient (same as A and B models)
Price	-0.255
Lagged Average Use	0.367
Long-Run Elasticity	-0.403

This result is somewhat similar to the PSI result for non space heating customers, but even more extreme. Table 13 produces estimates of the long run elasticity that are very little different than the short run. In the PSI case (Table 12) elasticity goes up slightly in the long run, but less than the usual large increase. The LILCO data suggest that the long run is not distinguishable by these methods, or that the full response occurs quickly.

It is diffficult to interpret these results. Are they accurate representations of demand behavior or statistical artifacts? It would be useful to develop some perspective on such questions by a deeper study of the demand response. In the discussion which follows, we will indicate the reasons for distrust of the simple time series models reviewed here, and indicate various strategies for improved methods.

6.1 Methodological Issues: Aggregation Bias and Regional Variation

Simple aggregate time series models such as those just described are known to exhibit certain biases. The basic difficulty is that average values of explanatory variables are used to account for behavior that is not the result of simple summation processes. The Slutsky equation in budget share form (eq. (11)) indicates one way in which price elasticity varies with income. This equation holds at the level of the individual consumer. Adding up all the individual behavior to produce an aggregate requires that we take account of

the income distribution. There is no provision for this in the simple time-series approach.

Variation in appliance holdings across customers is another source of aggregation bias. Different consumers have both different utilization patterns and posses devices with different efficiencies. Unless some method can be constructed to account for these distributions, aggregation or average methods are apt to be misleading. One study of this problem by Cambridge Systematics indicates that depending on the end-use either over-estimates or under-estimates of consumption can result (see EPRI EA-2512, sec. 6.5).

It would be useful to understand the magnitude of these biases and develop methods to correct them. This would provide useful perspective on the aggregate time series approach. It could tell us when the simpler methods are apt to yield representative results and when they are suspect. A useful line of attack upon this problem would be to find a method which applies the results of conditional demand and other household behavior models to the aggregate data. Such an approach would require distributional characterization of appliance holdings and other explanatory variables. Regional variations may be characterized by different distributions of such variables.

One particular problem which requires further investigation is the role of cooling demand in overall consumption behavior. The studies we have reviewed indicate contrary findings. Lawrence and Robinson conclude that cooling demand is very elastic. Chern, Just and Chang find the opposite. Price elasticity is related to the notion of weather-sensitivity. When climate variables are introduced into aggregate models, the estimated co-efficient is interpreted as a measure of weather-sensitivity. There has been no discussion, however, of explicit relations between changing weather sensitivity and price elasticity changes. Recent studies of weather sensitivity show cases in which cooling degree day co-efficients have diminished. This effect must be attributed in part to rising prices. On the other hand, during the period of falling electricity prices, large price elasticity was correlated with growth in the saturation of air conditioning and increased weather sensitivity. It would appear that prices, appliance saturation and weather sensitivity are linked in more complex fashion than previously studied.

There is a clear need to improve the aggregate time series models which are widely used in the industry. The existing results from cross-sectional analysis must be brought to bear on the aggregate methods, and explicit account must be made of appliance saturation changes. In our detailed study of Gulf States Utilities, efforts will be made in this direction.

7 EFFICIENCY AND SATURATION OF APPLIANCES

In this section we examine the end-use of electricity. An examination of end-use patterns will help in estimating the potential for changes in electricity sales. Current and potential appliance efficiency and saturation changes are key to understanding residential electricity sales.

Electricity is used for certain basic needs such as lighting in every electrified area. In addition almost every wired home has a refrigerator, a TV, a radio, a coffemaker, an iron, a food mixer, toasters and vacuum cleaners. Except for food mixers, saturation of these appliances is over 99 percent. Food mixer saturation is 93 percent.[13] These figures are based on the number of homes with these types of appliances. Unit energy consumpton for these appliances however varies enormously with refrigerator being the most energy intensive appliance of these.

The ultimate efficiency of appliances is one factor that limits long-term demand elasticity. As part of its engineering analysis of energy efficiency standards for consumer products, the Department of Energy estimated the maximum technologically feasible energy efficiency levels of a number of appliances (DOE 1980).[14] These possible efficiency improvements are summarized in Table 14

Gas and oil furnaces could achieve efficiency increases of 47 and 20.5 percent through the use of pulsed combustion and better heat exchangers. Little improvement in the efficiency of electric furnaces or resistance heating is expected. If electricity prices increase less rapidly than gas or oil prices, heat pumps could replace furnaces in areas where they are feasible. Already they account for nearly two-thirds of electric heating system sales. An electric hot water heat pump could increase the efficiency by 73 percent over a conventional water heater as compared to a potential increase of 17

Table 14

Shipment Weighted Efficiency (SWEF)†

Appliance	1980 SWEF	Max. Tech. SWEF	% Improvement
Gas Furnace	65.9	97.0	47.2
Oil Furnace	78.6	94.7	20.5
*Room A/C	7.1	11.1	57.4
*Central A/C	7.2	13.8	91.9
*Elec Water Heat	81.0	95.0	17.2
Elec Heat Pump		140.0	
Gas Heat Pump	49.6	86.0	73.5
*Refrigerators	5.7	12.4	116.0
*Freezers	11.0	25.3	129.6
*Elec Clothes Dryers	2.9	3.0	6.3
Gas Clothes Dryers	2.5	2.7	7.1
*Elec Ranges/Ovens	43.3	50.2	16.1
Gas Ranges/Ovens	25.8	43.0	66.5

$$\dagger SWEF = \frac{\sum_i EF * Shipments}{\sum_i Shipments}$$ where i = appliance classification

*Electric Appliances.

percent in efficiency of conventional heaters. Future market penetration and efficiency of heat pumps must be considered in projecting electricity consumption.

Larger heat exchangers and better compressors could lead to significant increases in the efficiency of room and central air conditioners. Central air conditioners with two-speed compressors could show an increase in Shipment Weighted Effeciency(SWEF) from 7.2 to 13.8. Similar percentage increases for room air conditioners are possible.

To achieve the maximum efficiency levels for gas water heaters, foam insulation and a condensing design will be used. Foam insulation will also be used in electric water heaters. However these changes will make only marginal improvements in efficiency. Much larger reductions in energy use would occur if heat pump water heaters become common.

With rising prices it is argued that consumers will resort to reducing their electricity consumption at an increasingly faster rate. In the short run the options available to most consumers focus on reducing the usage of a particular appliance. Reduced usage is possible for all the appliances to varying degree. Heating and cooling loads can be further reduced by improving the thermal integrity of the house. Knowing the thermal integrity of houses and the stock of appliances it is possible to estimate the changes that can be expected in electricity consumption.

In the long run most of the reduction will occur because of improved efficiency of appliances or switching to alternative fuels. Efficiency will not improve uniformly for all the appliances. Refrigerators can be improved considerably more than cooking stoves and ovens and clothes dryers. The main reason is that appliances in which a motor is the main electricity consumer can be improved only marginally.

The scope for reducing electricity consumption in the short run by changing usage is far less than in the long run by changing appliance efficiency. If other fuels are available then the consumer will switch from electricity to gas or oil thereby reducing the electricity consumption further than what just efficiency considerations would suggest. Fuel switching is possible today for space and water heating and clothes drying and to a lesser extent for washers

and refrigerators. Availability of fuels cannot be taken for granted in every part of the country. The long run potential for switching has to be examined individually for each service area.

For areas such as the Long Island Lighting Service Area appliance saturation remained constant over the last few years as prices increased. If prices were to increase further, consumers would reduce electricity consumption by reducing usage rates and by buying more efficient appliances. Fuel switching is unlikely since the alternative, fuel oil is uncertain and expensive and very few customers, less than 8 percent, use electricity for heating. If prices were to increase rapidly one would see a large immediate drop in consumption but a larger long term potential for reduced electricity consumption. A variable price elasticity model would show that elasticity increases as usage rates decline rapidly and then reaches a constant or declining value. The magnitude of long run elasticity would not be very large since fuel switching is unlikely.

In the Gulf States service area appliance saturations have changed rapidly with little or no increase in prices. Fuel switching is a real possibility since natural gas is readily available. The fraction of homes heated with electricity is larger than in Long Island. In 1980 electricity was used for water heating in 27 percent, and for space heating in 19 percent of the dwellings. If the saturation of appliances has reached the limit any price increase would cause both the long and short run electricity consumption to decline by a very large margin. However air conditioning sales which form a major fraction of household electricity use would be affected only by lower usage and efficiency improvements and not by fuel switching.

A detailed analysis of these types of saturation patterns combined with fuel efficiency data ahown in Tables 14 and 15 will be used in our analysis to assess the ultimate potential for reducing electricity consumption. Data on thermal integrity will be gathered from surveys such as NIECS and NAHB. The potential reduction in electricity consumption due to thermal integrity improvements suggested by Gulf States surveys will be based on DOE 2 simulated electricity consumption levels. The rate at which these changes will take place will depend on the individual consumer`s decision and the fuel and appliance choices available to him. Time and effort permitting we will derive

Table 15

Estimate of historical SWEF

	Central space heat		Air Conditioning*		Water heaters		Refrigerators*	Freezers*	Range	Oven	Dryers	
	N. gas	Oil	Room	Central	Elec	Gas			Elec.	Gas	Elec.	Gas
1981			7.1	7.2			6.3	11.4			2.9	2.6
1980			7.1	7.2			5.7	11.0	43.3	25.9	2.7	2.5
1979			-	7.1				-				
1978	63.6	75.2	6.8	7.0	80.7	48.2	5.1	10.1	41.4	17.7	2.6	2.4
1977				6.8								
1976				6.7								
1975	62.7	73.6										
1974												
1973												
1972			6.0	6.7	79.8	47.4	3.9	7.4	35.8	13.8	2.6	2.1

Note:

*Energy use stated in terms of SEER. For all other appliances figures indicate unit efficiency.

Dryer: pounds of clothes dryed per kwh of input

pounds of clothes dryed per ??? of input

appropriate forecasts based on fuel prices and discount rates for each service territory. These forecasts will supplement the forecasts based on econometric analysis and will be used to cross check the econometric analysis results.

8 CONCLUSIONS

Following general conclusions can be drawn from our report.

(1) Elasticity estimates show great variation. This has been reported by Bohi for studies published prior to 1978. Our review of studies since 1978 reveals the same result. In extreme cases short run estimates are higher than long run estimates.

(2) Studies show great variation, factor of two, in elasticity estimates within a state. State level analysis therefore averages over broad estimates without adequate justification for doing so. The results of such analysis are not representative of utility area elasticities and should be used with caution.

(3) Studies using monthly models rely on independent variables that are not observed monthly but are interpolations of annual data e.g., income. In some cases the dependent variable is observed monthly but the data are suspect. Annual models have none of these problems. However, since the annual data result in very few data points over a long time period, the underlying structural and economic relationships can change drastically during this long period e.g., prices declined until the early 1970's, were stable for a short while and then increased rapidly. Elasticity estimates will be sensitive to the period chosen for study.

(4) Elasticity estimates are sensitive to cooling loads. However studies show elasticities both increasing and declining with inclusion of cooling loads. Lawrence reports very high cooling elasticities whereas Betancourt and Chern have shown lower elasticities.

(5) The confluence of weather sensitivity and price trends on elasticity estimates has not thoroughly been examined. It appears that prices, appliance saturation and weather sensitivity are linked in more complex fashion than previously studied.

(6) Elasticities appear to increase with increasing fraction of income devoted to electricity consumption i.e., a higher budget share. The precise trend is not clear. Our observations from two studies indicate diverse trends.

(7) Generally studies in academic literature are methodologically sophisticated and advanced but are generally unusable without highly detailed data that require matching survey data to with customer bills. Utility companies wish to rely on simpler techniques that would yield reliable and consistent results.

(8) Analysis of simple models by 3 utility companies LILCO, PSI, and PECO confirms that the elasticity of customers with electric space heating is around -1 and is much higher than for customers with non-space heating. The short run elasticity in most cases is around -0.3 to -0.4.

Further generalizations regarding elasticity changes with respect to data period and model specification are difficult. For LILCO and PECO, model specification strongly influences elasticity estimates while for PSI time period has a stronger effect.

(9) Empirical studies show elasticities declining from 1956 to 1975. Since these were done for periods of declining prices and suffer from aggregation bias, the implication for forecasting elasticities in a period of increasing prices is unclear.

(10) Data is available on maximum appliance efficiency potential, and saturation of appliances for Gulf States Service Area. In addition, information on average thermal integrity of houses is available and the potential consumption changes due to thermal integrity changes can be computed. End use analysis can reveal the potential for changing electricity consumption for Gulf States.

PART II

CAPITAL STOCK DEMAND MODEL CASE STUDY

CAPITAL STOCK DEMAND MODEL CASE STUDY

9 INTRODUCTION

With increased availability of residential appliance saturation data, demand models have been developed based on explicit representation of the capital stock. The nature of such models is explored here through a case study approach. This will illustrate the advantages and limitations of the general method.

9.1 Capital Stock Demand Model Specification

Broadly speaking we can define a capital stock model to have a form such as the following

$$E = CP^{\alpha_1} Y^{\alpha_2} Z^{\alpha_3} S, \tag{12}$$

where E = electricity consumption,

P = electricity price,

Y = income

Z = other explanatory variables, such as weather,

S = representation of the appliance stock, and

C, α_i = constants.

Equation (12) is a simple modification of the flow adjustment demand model. The stock representation, or index S, replaces the lagged dependent variable which is commonly used as a proxy for the capital stock in flow adjustment models. It is clearly superior to account for the stock explicitly through an index representing it in detail, rather than through an unexplainable proxy such as lagged consumption.

By a capital stock model we mean a functional explanation of consumption in which the physical/engineering properties for the appliance stock are explicitly represented as explanatory variables. The whole purpose of a lagged dependent variable is to provide a proxy for the capital stock. Now that appliance saturation and efficiency data are widely available, this proxy

can be rejected for a more direct representation.

In our formulation, we develop a notion of capacity utilization to express the variations in observed consumption. This notion is based on a distinction between end-use activities which are sensitive to price in the short run and those which are not. In our case, this amounts to distinguishing weather-sensitive consumption (heating and cooling) from that which is not. The capacity utilization variable which we define allows us to estimate short run price elasticity, while controlling for changes in appliance stocks, prices, incomes and actual weather conditions.

The price elasticity of residential electricity use in the long run is determined by changes in the appliance stock. We estimate these long run changes using an engineering economic approach. The most important long run stock changes are the saturation of electric heating and the efficiency of appliances. Each of these are modelled separately. What is usually called the long run price elasticity is the sum of the short-run utilization elasticity and the long run stock adjustment.

The case study is based on Gulf States Utilities (GSU) using historic data from 1970-1981. Appliance saturations grew substantially during this period. Central air-conditioning was present in 30% of homes in 1972. This increased to 53% in 1982. The corresponding figures for electric heating are 10% saturation in 1972, and 20% in 1982. For longer run estimates we use price and income forecasts from GSU.

The plan of the paper is as follows. In section 1.1 we define the short run model, including the definition of capacity utilization and the rationale for our particular approach. Section 1.2 defines the procedure used for estimating the long run adjustment of the capital stock to price changes. The actual estimates are described in section 2 for the short run model and section 3 for the long run. We end with some conclusions on the broader applicability of this approach in section 4.

Constructing the index S presents problems. What features of the appliance stock should be represented? How should the different end-uses be aggregated or related to one another? Our solution depends upon a notion of capacity utilization. We distinguish between end uses for which consumption is

essentially fixed in the short run, and those which are more variable. To account for observed fluctuations in use, we want to net out the fixed end-uses and concentrate only on those which vary. For practical purposes we identify the weather-sensitive end-uses with our "variable" category.

We implement the fixed/variable distinction by thinking of S as the maximum possible consumption associated with a given appliance stock. S is measured in energy units (kWh), but it is best thought of as the sum of maximum appliance loads (kW), times the number of hours in a consumption period. Now we want to separate S into a fixed and variable component and remove the former from the model. We do this in a way that will leave net variable capacity utilization as the dependent variable.

The first step requires that we transform Eq. (12) into capacity utilization terms. This is achieved by dividing Eq. (12) by S to get

$$E/S = CP^{\alpha 1}Y^{\alpha 2}Z^{\alpha 3}. \tag{13}$$

Next we define E^* to be that part of observed consumption E which is fixed. We want to remove this from both the numerator and denominator of the left-hand side of Eq. (13). Let us define net variable consumption E_v as

$$E_v = E-E^* \tag{13a}$$

The corresponding notion for S will be called net variable capacity, S_v, defined as

$$S_v = S-E^* \tag{b}$$

S_v is defined (like S) in energy terms, not in kW terms. When we form the ratio of E_v to S_v, however, we get a "capacity utilization factor." Let us call it e_v,

$$e_v = E_v/S_v \tag{14}$$

This is the fraction of maximum possible consumption due to weather sensitive end-use devices that is actually observed. The model which we will be estimating, then, uses the variable defined in Eq. (14) explained by variables

on the right hand side of Eq. (13). We write the model in logarithmic form as

$$\ln(e_v) = \ln C + \alpha_1 \ln P + \alpha_2 \ln Y + \alpha_3 \ln Z \qquad (15)$$

This specification relies on the qualitative results of more complicated consumption models such as the conditional demand approach.[15,16] Conditional demand models indicate that many end-uses have essentially fixed consumption levels. It is obvious, however, that weather-sensitive appliances have variable consumption. This distinction cannot be easily incorporated in models such as Eq. (12) without some way of weighting the fixed and variable end-uses. DRI has attempted such a model, but without a clear method for weighting fixed and variable consumption.[17]

Our approach requires data on E^* and S_v. The former is estimated by a simple procedure described in section 2.1. S_v can be measured directly from characteristics of the appliance stock. It can be expressed as follows:

$$S_v = S - E^* = \sum_j P_{makj} * 730 * Sat_j$$

where P_{makj} = Average installed kW capacity of appliance j

and Sat_j = Saturation of appliance j.

The scaling factor 730 is simply the number of hours in a month, and is necessary to translate kW capacity ratings into maximum kWh consumption. Saturations are defined typically as the percentage of households with a particular appliance type. Since households may have more than one appliance of a specific type, we multiply saturations by the number of appliances per household. The average installed capacity of a weather sensitive appliance is estimated from operating characteristics of units sold in a given year. These data when combined with change in stock of that appliance yield the average capacity. We estimated the net variable capacity S_v for room and central air conditioners and space heaters using the above procedure. Construction of S_v is explained in detail in Appendix 1.

9.2 Long Run Projections Methodology

Estimation of Eq. (15) provides a measure of the short run price elasticity, namely α_i. To estimate long-run elasticities it is necessary to understand the change in S over time. The complexity of this problem can be illustrated by writing an explicit expression for the total capacity of weather-sensitive appliances stock

$$WSS_j = \sum Cus_j \times Sat_i \times TL_i/Eff_i, \qquad (16)$$

WSS_j = weather-sensitive appliance stock index at time j,

Cus_j = number of customers at time j,

Sat_i = percentage of customers with appliance i,

TL_i = maximum thermal load to be met by appliance i, (Btu/h)

Eff_i = efficiency of appliance i (KW/Btu).

In Eq. (16) the physical process corresponding to electric loads is represented. Space-heaters and air-conditioners must meet a certain thermal load (TL_i) with a particular equipment efficiency (Eff_i). The thermal loads depend upon the distribution of housing characterists among the customer population. These include the size and type of dwellings and their thermal properties. As the housing stock changes so will these thermal characteristics.

In principle, one must distinguish changes in the housing stock due solely to "housing" demand and supply, from the building practices which determine thermal loads. We might expand the variable TL_i in Eq. (16) as

$$TL_i = k\ (R\text{-}Val_i)\ (SQFT_i), \qquad (17)$$

where

$R\text{-}Val_i$ = index of thermal integrity of the building stock,

$SQFT_i$ = average size of dwellings (square feet), and

k = constant

Presumably, changes in the average size of dwellings is not responsive to changes in the price of electricity. On the other hand, thermal properties might well change with electricity price changes. The price elasticity of demand in the long run should reflect the latter relation, but not the former. Total electric demand, however, will change with dwelling size and number of customers. Moreover, other terms in Eq.(16) which are clearly elements of

long run price elasticity will be influenced by "exogenous" changes in the housing stock. This can be illustrated by examining the change in appliance saturation with respect to price.

The choice of electric heating is probably the most thoroughly studied of all appliance choices. A particularly attractive model for this choice is the multinomial logit formulation associated with McFadden. A recent study by Goett and Earl provides a concrete setting to examine the relations of "exogenous" factors on long-run price elasticity.[18] The basic orientation of this research is toward the portfolio aspect of appliance holdings. There is a "jointness" to the choice of fuel and appliances not captured in most demand modelling. For our purposes, it is convenient to focus on the choice of electric or gas heating in new housing, given that central air conditioning has already been chosen.

Not only is this focus convenient theoretically, it corresponds well to the GSU circumstances. The warm and humid climate of Louisiana and Eastern Texas make air conditioning extremely desirable. As of 1979, NAHB reported that 94% of new single- family homes in Louisiana has central air conditioning. In Texas the corresponding figure was 97%.[19] Space heating fuel choice, however, is more evenly split. On the average, gas heating has captured between 40 and 45% of the new market in GSU territory during 1980-1982. It is therefore interesting to determine what influences the choice of heating fuel.

The multinomial logit model estimates the probability of choosing a space heating alternative j, having chosen an air conditioning alternative i by the following equations:

$$P_{j/i} = \frac{e^{w_{ij}}}{\sum_{j'} e^{w_{ij}}}, \qquad (18)$$

where the w_{ij}'s are representative utility of the alternative ij.

Following Goett and Earl we can write an expression for the wij's in the

case of interest in the following form:

$$w_{ij} = a_o + a_1 \left[CAP_j/OP_{ref}\right] + a_2 \left[OP_j/OP_{ref}\right], \qquad (19)$$

where

CAP_j = incremental installed capital cost of alternative j,

OP_j = annual operating costs of alternative j,

OP_{ref} = annual operating cost of an electric baseboard reference system,

and a_i = constants.

Applying Eq. (19) requires knowledge of heating loads and equipment specifications. The operating costs of a space heating system are calculated easily from a relation such as:

$$OP_j = TL/Eff_j \times Price \qquad (20)$$

The thermal load is a function of both dwelling size and thermal integrity as indicated in Equation (17). The efficiency term of Equation (20) interacts with both the capacity cost term CAP_j in Equation (19) and the thermal load. Equipment is sized to meet maximum hourly thermal loads. The capacity of available heating equipment is not continuously varying, but is only produced in certain discrete sizes. Similarly the operating efficiency of given size equipment can vary and its costs will also change with efficiency level. Many of these terms are exogenous to the choice of fuel type, but clearly impact on the values resulting from application of Equation (19). An example will illustrate the interactions.

The main economic advantage of electric forced air heating over gas forced air heating is the lower equipment cost of the former. According to the 1982 edition of the Means Building Construction Cost Data,[20] the smallest listed gas furnace had an installed cost that was more than twice as great as the electric furnace with which it competes. The capacity of the smallest gas furnace was much greater than the corresponding electric furnace. Part of the capacity difference is due to the lower efficiency of gas furnaces. But efficiency differences do not account for all the capacity differential. Some fraction of the extra cost of gas furnaces may be due to building construction

practices. An "exogenous" change in either such practices, or in equipment efficiency would alter the economic trade-off embodied in Equations (18) and (19). Such changes will affect estimates of the price elasticity of Equations (18) and (19) under any given set of assumptions about relative fuel costs.

Despite these complexities, Equations (18) and (19) provide a convenient framework for estimating the space heating component of the long-run response of stocks to fuel price changes. Parameter values for the co-efficients a_1 and a_2 appear to be transferable across geographic regions according to results of Goett and Earl. Only the constant term a_0 appears to vary regionally. To make projections for GSU, it is necessary to have service area specific estimates of future customer growth, housing type choice and equipment efficiency. This will be done in Section 3. The remaining elements of the stock adjustment to price change will be estimated using various methods. With such results we can calculate a long-run price elasticity associated with the basic capital stock demand model of Equation (12). The form of the long-run price elasticity is:

$$\mu^{P}_{LR} = \alpha_1 + \left[\frac{\partial S}{\partial P} \cdot \frac{P}{E}\right] \tag{21}$$

The first term in Equation (21) will be estimated from Equation (15). The price derivative of the stock index is calculated for both the weather-sensitive appliances and the other end-uses whose consumption is fixed in the short run. We begin with the short-run model, and describe its estimation.

10 ESTIMATION OF THE UTILIZATION MODEL

10.1 Data

GSU provided the data from which Equation (15) was estimated. Because the utility operates in both Louisiana and Texas observations are separated for each jurisdiction. Prices, economic conditions and to some degree climate conditions vary in these two states. As indicated above, the GSU service territory as a whole exhibits a large fraction of weather-sensitive demand for electricity. One indication of the variation is shown in Figure 4. For each

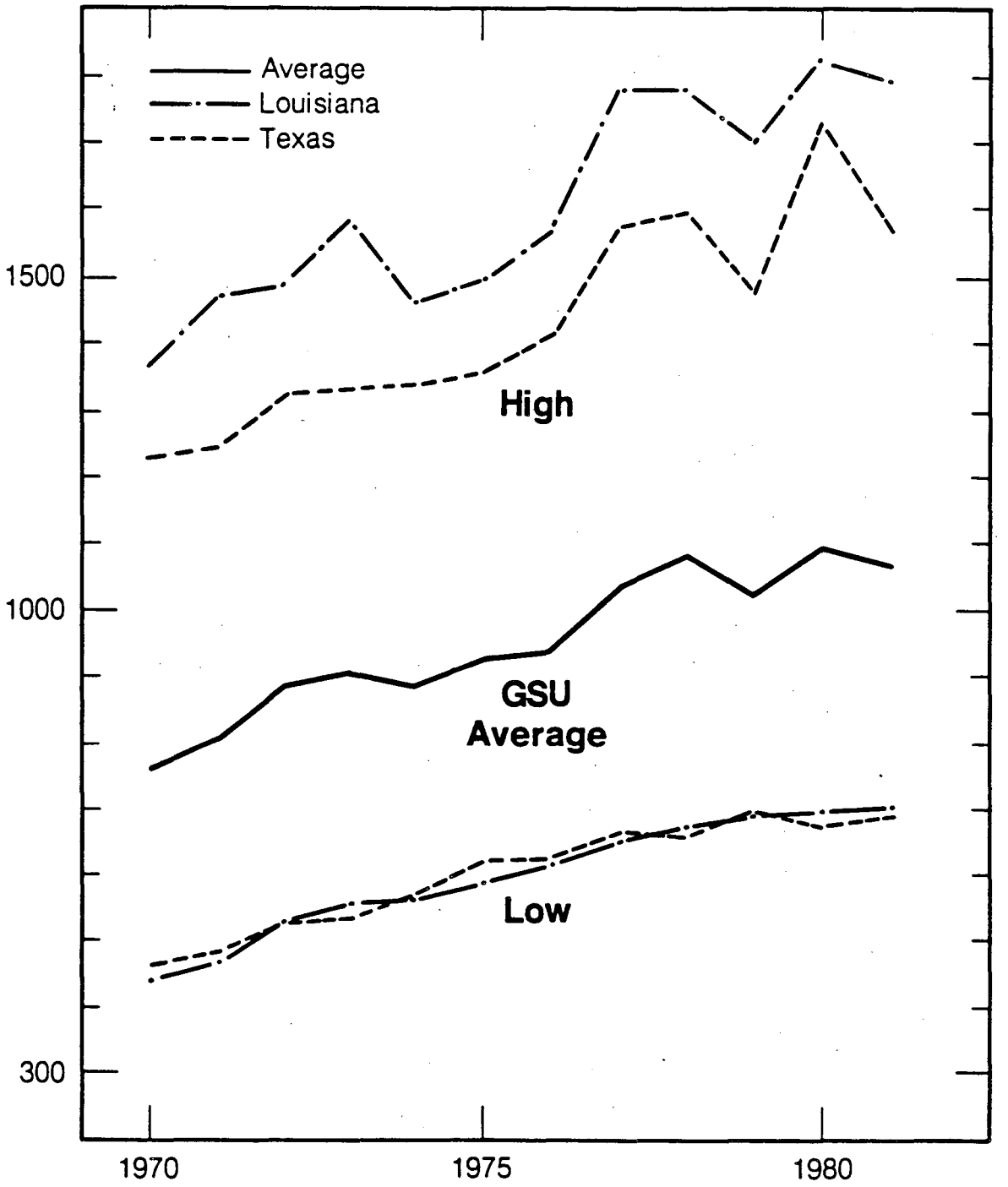


Figure 4

Historic Electricity Consumption in the Gulf States Utility Service (GSU) Area

XBL8310-604

year we plot the system average residential monthly consumption, the high month for Texas and Louisiana customers and the low month for each jurisdiction. The highest months always exhibit twice the consumption per customer compared to the low. The high is typically 50% greater than the average.

We take advantage of the smooth pattern of annual low months to provide a proxy for E*, the fraction of consumption which is fixed in the short-run. An ideal proxy for E* would be consumption in a month for which there was no heating or cooling demand. Measured by heating and cooling degree days, there are no such months for GSU. The low month is usually April during which some heating degree days typically occur and often a small number of cooling degree days. To correct for this problem we estimate E* as 80% of consumption in the low month for a given year.

To estimate the stock index for weather-sensitive appliances we approximate Equation (15). The number of households with electric space heating and air conditioning is calculated from GSU appliance saturation surveys and customer data.[21-24] The appliance surveys were conducted in 1971, 1972, 1980, and 1981. Years in between were interpolated linearly. This procedure is essentially the same as a fit to a logistic curve for the GSU data since the points lie on the linear part of a logistic curve. Instead of the thermal load and efficiency variables of Equation (16), we use estimates of installed capacity. Data is available for room and central air conditioners on capacity (Btu/h) of units sold during the 1970's and the average EER of such equipment. GSU surveys indicate 1.78 room air conditioners per household in 1983. We assume this ratio is constant over the period. The kW capacity of electric heating is also estimated. Further discussion of stock data is given in Appendix 1.

10.2 Price

The GSU data presents some particular problems with regard to electricity prices. During the period 1970-1981, the real price of electricity to residential customers showed no secular trend. Compared to other utilities there was very little change over the period when nominal prices are adjusted for inflation. This presents statistical problems. Ordinarily econometric

demand models must deal with how to identify the demand function by adequate representation of the supply side. This has led to a large literature on the appropriate price variable to put into models such as Equation (12) or (15). In the case of GSU the identification problem is especially important because there is so little price variation.

Two different approaches were considered. One price representation is the use of data from Typical Electric Bills. The actual rate structure facing customers can be inferred from this data since it provides the total bill associated with fixed levels of consumption. The price at two or more of these levels can be used as explanatory variables, and the circularity commonly associated with the use of average prices will be eliminated. The resulting version of Equation (15) would be a function of the form:

$$\ln(e_v) = \ln C + \alpha_1 \ln P_a + \alpha_2 \ln P_b + \alpha_3 \ln Y + \alpha_4 \ln Z, \qquad (22)$$

where

P_a and P_b are the prices at fixed levels of consumption a and B.
The short run price-elasticity of a model in the form of Eq. (22) is

$$\mu_{SR} = W_1\alpha_1 + W_2\alpha_2, \qquad (23)$$

where the W_i are weighting factors applied to the co-efficients such that $W_1 + W_2 = 1$.

While Eq. (22) solves the identification problem, there is no obvious way to determine the relative weights that should be attached to the price coefficients. This limits the usefulness of the approach because interpretation of results is a problem. Where a satisfactory weighting system can be described, then Eqs. (22) and (23) are useful.

An alternative approach to the identification problem which circumvents the difficulties of Eq. (23) is described in McFadden, Puig and Kirshner.[25] In this study, three price variables are introduced on the right-hand size of the equation. Two of them are designed to characterize the "shape" of the rate structure, and the third is designed to reflect its average level. It is the latter variable which is of particular interest because the usual price elasticity is calculated with respect to changes in average prices. McFadden et al., developed an instrumental variable which is related to average price,

but different from it. The "average" price variable is constructed by a three stage process. First, quantity is regressed against all the right hand variables except price. From this regression an average quantity $\bar{Q}$ can be calculated corresponding to average values of the right hand variables. The $\bar{Q}$ estimated from this second state is then put into the rate structure appropriate for a given set of observations. The price $\bar{P}$ corresponding to $\bar{Q}$ for a given rate structure is then the "average" price used in Eq. (5).

10.3 Climate

Representation of climatic variation, and its incorporation into the estimation process is a subtle issue. Our capacity utilization dependent variable is defined so far to be formally equivalent for heating and for cooling. In practice, however, there is no reason why the capital stock for one use should perform in an equivalent manner to the other. It is more probable that the household "cooling factory" operates differently from its "heating factory" therefore average capacity utilizations will differ. To separate the operating characteristics of the two "factories" we have chosen to segment the data. This allows an unambiguous definition of capacity, but one which is different for heating and cooling months. Therefore, we break up the aggregated stock index into components appropriate for estimating each kind of capacity utilization. This is particularly important because of the existence of "overlap months" in which both heating and cooling degree days occur. Such months confound the estimation with a mixed index because we do not know how to attribute variance to either the heating or the cooling capacity. We found that elimination of about 12% of the points corresponding to "overlap" periods provided a complete segmentation of the data into either pure cooling or pure heating months. The criterion used was that a heating month had more than 100 heating degree days and had at least 75 more heating degree days than cooling degree days, and conversely for cooling. To allow for further separation of heating from cooling a heating dummy was incorporated.

10.4 Logit Formulations

A further statistical issue which arises from our formulation concerns the boundedness of the dependent variable. The variable defined by Eq. (4) measures the average fraction of capacity utilization, a number between 0 and 1. By segmenting the data into heating and cooling months, we can use a stock index appropriate to each period. Estimating a log-linear model of capacity utilization by ordinary least squares, however, ignores the boundedness of the capacity utilization measures. We explored the use of the logit transformation to make the constraint binding in actual estimation. This amounts to transforming the capacity utilization variable CU in the following manner

$$\text{Logit CU} = \frac{CU}{1-CU}. \tag{24}$$

We then take the logarithm of Logit CU which is regressed on the logarithms of the explanatory variables using ordinary least squares.

The coefficients of the explanatory variables are not simple elasticities however. They must be scaled to account for the original transformation. Pindyck and Rubinfeld [26] suggest an interpretation of the co-efficients of the form

$$\eta_i = \beta_i \; CU_i \; (1-CU_i), \tag{25}$$

where

η_i = elasticity with respect to the ith variable and
β_i = estimated co-efficient of the ith variable.

Eq. (15) says that elasticities are a function of utilization level CU_i. To evaluate them we must choose an appropriate level, say the mean. Whatever the choice of CU_i it should be noticed that the maximum value of $CU_i \; (1-CU_i)$ is 0.25 for $CU_i = -.5$. thus, the β_i's must be scaled down by at least a factor of four.

10.5 Statistical Properties of the Estimated Model

Consumer electricity demand elasticities were originally estimated using flow-adjustment models, which attempted to incorporate the response of stocks of appliances to changes in exogenous variables by adding lagged consumption as a regressor. Conceptually, this method tends to conflate the short-run response to changes in exogenous variables while stocks are constant with the long-run response wherein stocks are allowed to adjust. Aside from this conceptual overlap, the estimated models inherently face strong autocorrelation due to inclusion of a lagged dependent variable as a regressor.

By introducing a variable to represent the stock in each time period, one can separate the long-run adjustment from short-run responses. While using stock substitutes the actual variable instead of a proxy and increases the conceptual separation between short and long-run response over the flow-adjustment models, use of stocks inevitably introduces some measurement error.

We may understand the source of such measurement error by noting that surveys of stock-ownership - even when excellently conceived and performed - typically provide sample distributions of qualitative variables. The variables are of the form: type of heating appliance, and the year of manufacture. The basic observations are one/or zero for ownership or not. Such qualitative measures must be converted to quantitative measures expressing their energy usage and aggregated to some degree. We have elsewhere discussed the conceptual issue of aggregation and the method employed in our study. Here we note that all methods of conversion to quantitative stock measures involve some measurement error.

The usual manner of including a measure of the stock has been to use it as a regressor. However, it is widely known that such errors-in-variables will bias not only the coefficient of the stock variable, but also all other coefficients. It should be noted that measuring stocks by average usage is circular and would probably lead to simultaneity bias.

Our model's inclusion of stocks into the dependent variable serves two purposes. The first purpose is to arrive at a capacity utilization measure which implicitly incorporates stocks of variable-use appliances as a constraint. We do this by measuring stocks - net of constant use appliances- in

terms of potential energy use, and dividing actual usage by potential usage. The second purpose relates to the measurement error. By incorporating stocks into the dependent variable the measurement error - which is not inherently correlated with the exogenous variables - becomes part of the white-noise in the usual linear model, thereby satisfying BLUE (Best Linear Unbiased Estimator) conditions on the error term for OLS estimators.

A moment's reflection reminds us that use of a 'constructed' dependent variable is quite common. Output measures - even for micro-data - must be deflated by a constructed price index. Aggregate consumption-function equations aggregate or construct the nominal dependent variable which then must be similarly deflated to isolate the desired 'true' variable. While such remarks do not legitimize our method of isolating the desired dependent variable, they do emphasize that such a procedure is far from unusual.

One aspect of isolating the desired dependent variable - capacity utilization of short-run variable use appliances - is the netting-out of constant use appliances from total use or consumption. Elsewhere we discuss the details of this method. Here we address the question of biases resulting from the general technique. As explained, we used yearly minimum total consumption levels as indicators of a secular trend in constant-use consumption.

10.6 Results

We collect the results of various models in Table 1a. All the coefficients turn out to be significant at the 1% level except in two places indicated. The least satisfactory variation involved in the instrumental variables approach to modelling the supply side (Model 3A). The co-efficient for average prices (AVI) has the wrong sign and the co-efficient representing the slope of the rate schedule is insignificant. Logit versions of this model (unreported here) are no better. Other models are more reasonable.

In all models there is a consistent pattern of co-efficients for degree days and income. The cooling co-efficient is substantially larger than the heating co-efficient. As we will see in Section 3 cooling consumption on the average was three times greater than heating in 1982 (see Table 17 below). It has always been larger in the GSU service territory over the estimation

period. The income co-efficient is typically quite small in all models.

Interpreting the price co-efficients requires some discussion since models based on Eq. (22) require a weighting scheme as in Eq. (23). The sales frequency distribution is a natural statistic for weighting the price co-efficients in our model. It is the ideal measure of how much sales correspond to each quantity where a price coefficient is estimated. The literature on this subject is unfortunately incomplete and much of it is out of date. Nonetheless certain regularities are observable. Most studies note the highly skewed nature of sales frequency data.[27] Modern studies have attempted to fit standard probability distributions such as the log-normal.[28] For our purposes only a very simple representation of the distribution is necessary. The relevant statistic is the cumulative fraction of all sales at the mean level of consumption. Early data shows that the cumulative fraction is about 75% of the mean.[29] A survey of recent data shows a range from 65% to 80% at the mean with most observations close to 75%.[30] We will use the 75% value to interpret our results.

Table 16
Weather Sensitive Demand Models for GSU

	A1	A2	A3	B1	B2
Dependent Variable	CU	CU	CU	Logit CU	Logit CU
Price Variables					
500	-0.451	-0.443		-0.589	-0.582
750					
1000		0.031			0.041
AVI			1.689		
Slope	-0.181		0.001*	-0.205	
Income	0.008	0.008	.001**	0.010	0.010
HDD	0.104	0.102	.090	0.134	0.131
CDD	0.490	0.489	0.359	0.662	0.660
Dummy HDD	1.946	1.947	1.477	2.641	2.644
Dummy LA	0.136	0.122	-0.096	0.194	0.177
R^2	.476	.476	.555	.493	.493

* Insignificant, i.e t statistic = .04
** Significant at 5% level only

This says that the sales frequency distribution has a very long "tail" consisting of a small number of larger users. Since 1000 kWh/mo corresponds roughly to the average GSU residential use, the PG&E rule of thumb suggests a 25% weight applied to the price co-efficient at that level. The short run price elasticity then for model A2 would be calculated from Eq. (23) and Table 16 as

$$\eta_{A2} = .75(-.44) + .25(.03). \qquad (26)$$
$$= -0.32.$$

The value calculated in (26) must be scaled further to be comparable with the usual short-run price elasticity. Elasticities calculated from Eq. (22) only represent the weather-sensitive consumption. For GSU this averages about half of total consumption (see Table 18 below). Since we have assumed that

the other half of consumption is fixed, the value calculated in (16) should be divided by two. This is only strictly true if non-weather sensitive uses were completely inelastic with respect to price. Of all these uses, only water heating appears price responsive in the short run. The ORNL residential model uses a price elasticity of utilization of -0.25 for water heating.[31] In section 3 we estimate that water heating is about 13% of average GSU residential electricity use in 1982. A consumption weighted short-run elasticity based on (26) and the ORNL estimate then would be

$$\mu = .5(-0.32) + .13(-0.25) \tag{27}$$

$$= -0.19 .$$

The logit models (B1 and B2) imply substantially lower elasticities. The discussion of Eq. (25) indicates that the co-efficients listed listed in Table 1a for the B models must be divided by four or more to be comparable to the A models. This means that the co-efficient of price at 500 kWh cannot be greater than -0.147. Scaling this after the manner of (26) and (29) results in an elasticity no greater than -0.087.

It is instructive to compare Table 16 with the results of GSU's flow-adjustment model. This model uses a lagged dependent variable as a proxy for capital stock, average price per kWh as the supply variable, and average kWh per customer as the dependent variable. Estimated co-efficients, all of which are significant, are listed in Table 17. The results differ substantially from Table 16. GSU's estimates of price and income elasticities are much larger than those found with the capital stock models.

Table 17
GSU Flow-Adjustment Model

Explanatory Variable	Estimated Co-efficient
Log Average Price	-0.373
Log Income	0.515
CDD	0.00113
HDD	0.00056
Log Lagged Dependent Variable	0.396
HDD Dummy	-0.00031

The climate variables have much smaller co-efficients in Table 17 compared to Table 16. The GSU model does not use logarithms of HDD and CDD, which are used in Table 16 models. Even adjusting for this difference and differences in dependent variable leaves a substantially larger estimate of weather sensitivity in the capital stock version.

We believe that the income term in Table 17 is the source of many of the discrepancies between the two approaches. GSU's model involves substantial collinearity between income and average use per customer. Both increase over the estimation period. In our model we remove this by the definition of the term E^*, the "fixed" portion of consumption. We define E^* to be 80% of the lowest average monthly consumption in a given year. As Figure 4 shows, E^* will increase over time. This represents the increase in stocks due to rising income. Our procedure removes the collinearity between income and utilization. The resulting estimates of income elasticity are much smaller than what GSU found. The variation in use comes from heating and cooling degree days.

Given our procedure, the income elasticities estimated in Table 16 are likely to be too small if they are interpreted with reference to average consumption. The Table 16 income co-efficients are reasonable for the weather sensitive utilization decision, but do not incorporate the income effect on non-weather sensitive demand or upon stocks themselves. Over the 1970-1981 period appliance saturation in GSU service area increased significantly. This is clearly an income effect. The decision to purchase a freezer or clothes washer is income related. When we come to project consumption for GSU, the role of income is directly related to projected saturations. Insofar as saturations are not thought to grow much, the effect of income is

correspondingly small. The results of section 3 will show that qualitatively we expect price effects to dominate income. This is more in keeping with the Table 16 results than those of Table 17.

11 LONG RUN STOCK ADJUSTMENT: ENGINEERING ECONOMIC PROJECTIONS

In this section, we illustrate a method for estimating long run changes in average use per customer that are related explicitly to changes in the capital stock. The basic logic is quite simple. We decompose average use per customer into the sum of contributions from each end use. Each end use has an average unit energy consumption (UEC) which is weighted by its saturation. Formally we can write this as

$$AVU = \sum_i Sat_i \times UEC_i, \tag{28}$$

where

AVU = average use per customer,

SAT_i = saturation of end-use device i,

and UEC_i = average unit energy consumption of end-use i.

Using Eq. (28) requires explicit knowledge of the capital stock and how it changes over time. Changes in average use are due to both price and income effects. We expect price increases to reduce UEC's by making more efficient appliances economically attractive. Income increases will typically increase saturations. In our analysis we emphasize the role of price. This is appropriate to GSU because the expected rate of price increase is far greater than expected income gains. With this assumption, we can use Eq. (28) to estimate the long run component of price elasticity as follows

$$\mu^*_{LR} = \frac{\Delta AVU / AVU}{\Delta P \ / P}, \tag{29}$$

where

Δ AVU = the change in average use,

ΔP = the change in price,

and P = price in the initial period.

The term μ^*_{LR} is the same quantity as the second term of Eq. (21),

$$\mu^*_{LR} = \frac{\partial S}{\partial P} \frac{P}{E} \tag{30}$$

Thus, estimating Eq. (25) and adding it to our results on short-run utilization yields a total long-run price elasticity.

11.1 Electricity Use - 1982

To illustrate this general framework we must specify Eq. (28) first for the current capital stock and consumption levels. Table 18 shows a decomposition of 1982 average use. This is expressed in terms of kWh/customer-month. The 1982 level of this variable is approximately 1070 kWh. Table 18 separates the total into a weather-sensitive part and a non-weather sensitive part. The sum of the nine end-uses in Table 18 is 975 kWh. This leaves about 100 kWh/month for miscellaneous devices.

Underlying Table 18 is another level of analysis which takes account of the dependence of certain UEC's on the mix of dwelling types and the linkages of appliance portfolios. Water heating consumption depends strongly on the number of persons per household, which is strongly correlated with dwelling type. It also depends upon the holdings of dishwashers and clothes washers. The Table 18 estimate is derived explicitly in Table 19 using data from the California Energy Commission[32] on UEC's and GSU on saturations and dwelling type mix. The weather sensitive end uses are also sensitive to the mix of dwelling types. In addition, the thermal properties of buildings and equipment efficiency also determine energy use. In Table 20 the UEC averages from Table 18 are disaggregated. These calculations are based upon building energy simulations using the DOE-2 model.[33] Table 20 indicates the assumptions made about thermal properties and appliance efficiency. The Table 20 estimates are robust with respect to assumptions about thermal properties because heating and cooling loads do not change substantially for lower levels of insulation. As we will see in our projections, they drop substantially for higher levels.

Table 18 forms a baseline for projecting future changes in average energy use. Such a projection involves two separate components; projecting saturations and projecting UEC's. A schematic representation of these two components is shown in Figure 5. In each case future projections of customer growth are essential. This is because both saturations and UEC's are averages. Projected values are the weighted average of old customer and new customer behavior which can be expected to differ substantially. Particular factors are relevant to explaining both saturations and UEC's in the new market. Due to the relatively fast growth in customers, most stock changes will be due to the new market. Nonetheless, retrofit behavior and appliance stock turnover can also be important. The principal end-uses for which this is important are refrigerators, freezers, air conditioning and space heating. We will focus first on the new market representing additional residential customers for GSU.

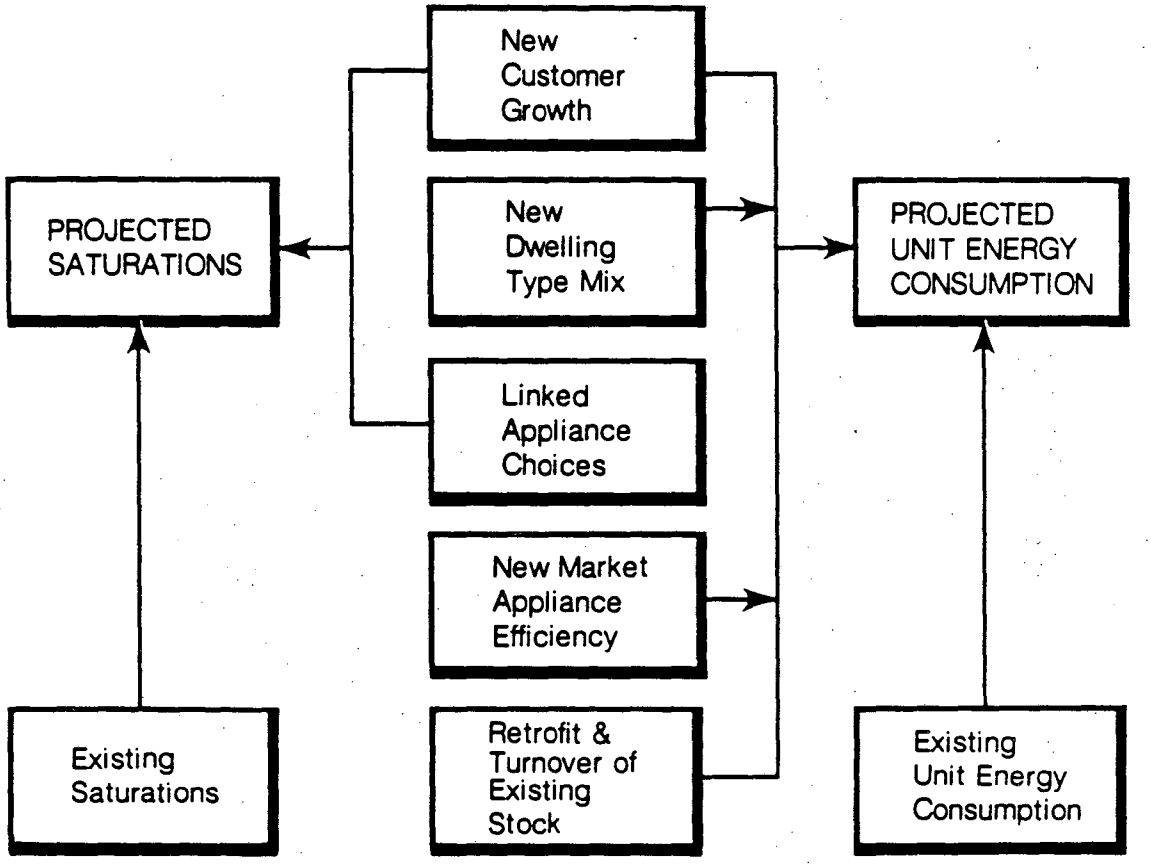


Figure 5

Methodology for Projecting Unit Energy Comsumption and Appliance Saturation

XBL 8310-611

Table 18.
GSU 1982 Average Use/Customer - Month

Non-Weather Sensitive	Sat_i	UEC_i[a]	Av. kWh/mo
Refrigerators	1.10b	100	110
Water Heating	.32	443c	142
Electric Range	.51	60	31
Freezer	.48	100	48
Clothes Dryer	.55	100	55
Lighting	1.00	90	90
			476
Weather-Sensitive			
Central Air Conditioning	.53	548d	290
Room Air Conditioning	.28	180 x 1.78e	90
Space Heating	.24	494af	119
			499

a) Based on California Energy Commission estimates

b) GSU only estimates saturation for frost-free refrigerators

c) Weighted by dwelling type shares and saturation of dishwashers and clothes washers (see Table 19)

d) Weighted by dwelling type using DOE-2 simulations corrected for EER (see Table 20)

e) GSU estimates 1.78 room air-conditioners per customer. UEC per unit is 1/3 of central air-conditioners.

f) Weighted by dwelling type using DOE-2 simulations and estimated building properties (see Table 20)

Table 19
GSU Water Heating UEC's (kWh/mo)

	Single Family	Apartment	Mobile Home	GSU Saturation
Domestic Hot Water	395	296	316	
Dishwasher	50	33	37	.46
Clotheswasher	69	46	52	.77
Average Use	471	347	373	
GSU fraction	.75	.125	.125	

Weighted Average = Σ Average Use x GSU fraction
= 443

Table 20.
GSU Weather Sensitive UEC (kWh/mo)

Building Type	Typical Propertiesa	UECb	Saturation	Average Use
1. Central Air Conditioning				
Single Family	19-11-0-1	584	.75	438
Apartment	19-11-0-1	495	.125	62
Mobile Home	11-7-11-1	387	.125	48
				548
2. Electric Space Heating				
Single Family	11/19c-11-0-1	520	.75	390
Apartment	11/19-11-0-1	310	.125	39
Mobile Home	11-7-11-1	520	.125	65
				494

a) R-values for ceiling-walls-floor-number of panes of glass

b) Assumes average EER = 7.2 for CAC, efficiency for electric furnace = .90.

c) small changes 11-19

From 1970 to 1982 GSU increased its residential customer market by 46% (an average of 3.2% growth per year). For the next ten years this growth rate is expected to slow only slightly to about 3% per year. During the recent past, however, substantial change occurred in the mix of appliances and the type of housing constructed. The GSU service territory went from a region dominated by gas heating and room air conditioning to one in which all electric homes with central cooling have captured a majority of the new market. At the same time the share of single-family homes in the housing mix has shown dramatic fluctuation. While the total housing stock is 75% single-family, its share of the new market fell to less than 50% on the average over 1972-1982. In the period 1980-1982, essentially no new single-family homes were built and all new housing was either apartments or mobile homes. Tables 19 and 20 show how the mix of housing types interacts with average UEC for water heating and space conditioning. Thus, a projection of future UEC's requires a projection of the mix of dwelling types.

Equally sensitive is the projection of electric space heating in the new market. This is due not only to the large UEC for this end use, but also because other appliance fuel choices are linked to heating fuel choice. If a home is heated electrically, then it is almost certain to have electric water heating and cooling as well. The converse with respect to gas is true on the average, but not as rigidly. The basic story underlying these linkages is the limited availability of natural gas distribution mains. If gas is available it will probably be used for all three end-uses. If not, electricity is the only alternative. For this reason we focus on the choice of electric space heating. Eqs. (18) and (19) provide a framework to estimate the share of electric heating which depend explicitly on price.

11.2 Projecting Average Use - 1992

The projections focus upon 1992 average use per customer. Table 21, which parallels Table 18, disaggregates projected average consumptions for this period. Saturation changes are based on three major assumptions. First, all new housing of whatever type has central air-conditioning. Second, water heating and electric cooking in new housing uses the same fuel as the heating in that housing. Third, all other saturations remain unchanged (i.e.,

refrigerators, freezers, clothes dryers, and lighting). As a consequence of the first assumption, room air-conditioner saturation declines. Customer growth from 1982 averages 3% per year.

A wide range of forecasts is possible for the mix of new housing. What turns out to be important is the share of apartments.

Table 21
1992 GSU Average Use/Customer-Month

Non-Weather Sensitive	Sat_i	UEC_i	
Refrigerators	1.10	70[c]	77
Water Heating	.36	331[a]	119
Elec. Range	.50	60	30
Freezer	.48	70	34
Clothes Dryer	.55	100	55
Lighting	1.00	80	80
			395
Weather Sensitive			
Central Air Conditioning	.65	387[b]	252
Room Air Conditioning	.21	142x1.78	53
Electric Space Heat	.30[c]	375[d]	113
			418

a) see Table 26
b) see Table 25. A 15% improvement in thermal integrity as estimated from Appendix 2 is included.
c) see Table 23
d) see Table 22

Table 22
GSU Electric Heating UEC's

Building Type	Typical Properties[a]	UEC	Saturation	Av. Use
1. New Market (Housing Vintage 1982-1992)				
Single Family	30/19-11-5-2	325	.11	36
Apartment	30/19-11-5-2	176	.47	83
Mobile Home	19-11-11-1	372	.42	156
				275
2. Retrofit Market (=50% of 1982 Customers)[b]				
	Δ UEC	UEC		
Single Family	-21%	411	.75	308
Apartment	-18%	254	.125	32
Mobile Home	-21%	411	.125	51
				391
4. 1982 Weighted Average[c]				
	Fraction	UEC		
New Market	.40	275	110	
Retrofit Market	.30	391	117	
Old Stock	.30	494	148	
			375	

a) R-values for ceiling-walls-floor-number of panes of glass

b) Retrofit of ceiling insulation to R-30 or slab floor out- side perimeter edge to R-5

c) The 25% saturation of electric space heating in 1982 corresponds to about 112,000 units. Projecting a market share of 47.5% for the 1982-1992 Vintage at a 3% growth rate for the latter implies 76,000 new units. Therefore the 1982-1992 vintage housing represents 40% of the 1992 stock.

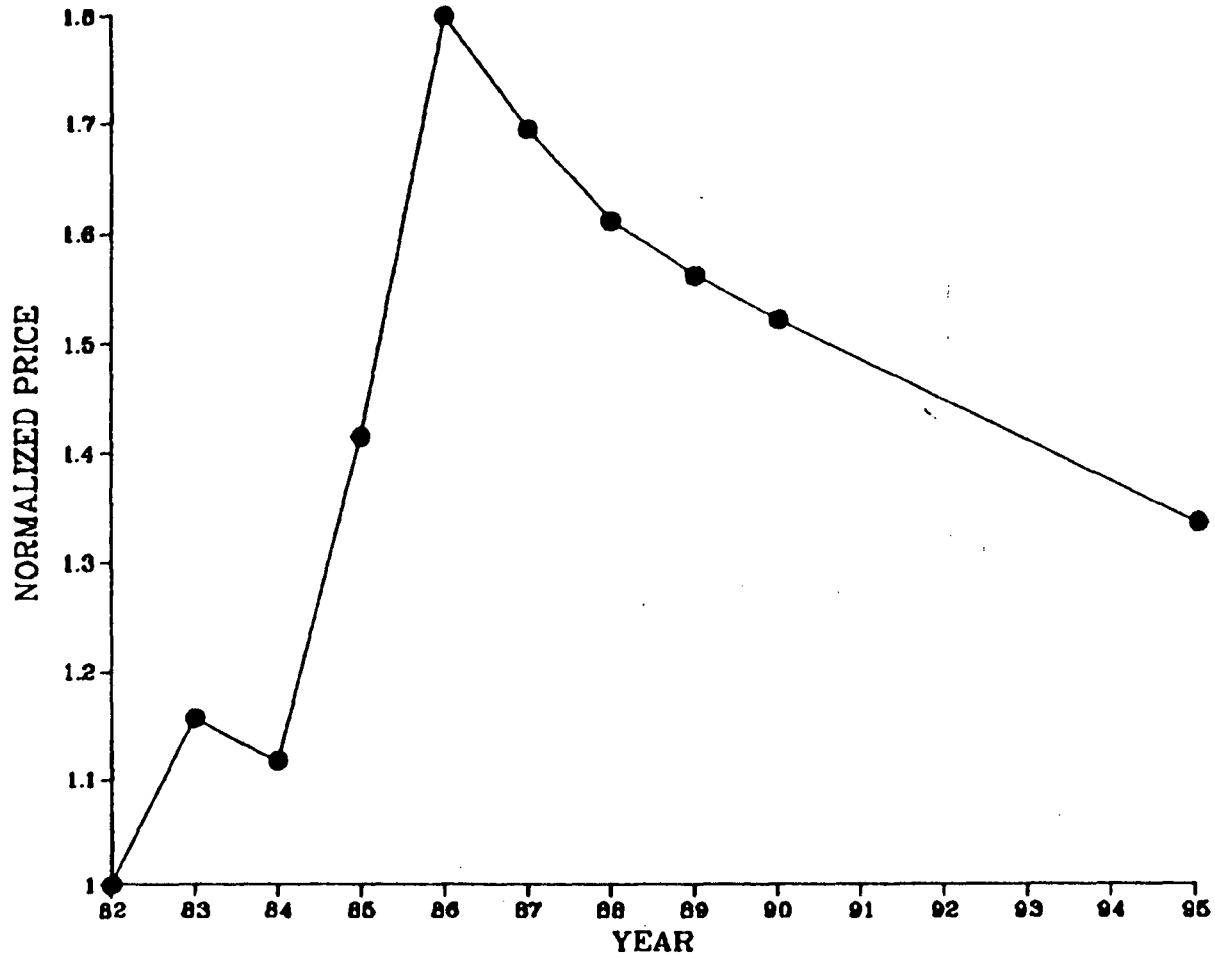
This can be seen in Section 1 of Table 22, where the average space heating UEC for new housing is calculated. In that Table single-family units have only 11% of the market, mobile homes have 42% and apartments 47%. Even though mobile homes in the GSU service area are typically only 2/3 the size of single-family homes,[34] their energy use is comparable. This is due to the poor thermal properties of mobile homes. Therefore the average UEC for space heating in new housing depends upon the share of apartments. GSU projects a smaller fraction for this, which would increase the average estimated in Table 22.

The Table 22 estimates for particular building types are based upon simulations using the DOE-2 model for the Lake Charles, Louisiana climate. As with the corresponding estimates from Table 20, energy consumption estimates depend upon an explicit characterization of the building thermal properties. In particular, R-values for ceiling, wall and floor insulation are required, as well as the amount and type of glazing and the air infiltration rate. The exact values for these properties assumed in Table 20 do not make very sensitive changes in energy use in the range considered for a 20 average. A little less insulation does not dramatically increase consumption. The same applies to cooling, where air-conditioner efficiency and total floor space determine energy use almost completely. Very substantial reductions in space heating load do occur at levels beyond those specified in Table 20. The Table 22 estimates of such reductions are conservative given the range of potentials. In Appendix 2 we reproduce detailed results for the single-family house case.

The average heating load of 19 MMBtu for 1982 stock is projected to fall to an average of 11 MMBtu for the housing vintage 1982-1992. The average new house in Texas and Louisiana built in 1979 would have a heating load of about 15 MMBtu according to specifications in the National Association of Home Builders survey for that year. Essentially it is double glazing and outside perimeter edge insulation of slab floors that will produce the lower heating loads. No extreme air infiltration rate changes are necessary for the projected results. Table 22 also projects more modest improvements in the existing housing stock from retrofit insulation.

Because of its importance in future growth projections we examine the share of electric space heating in the new housing market explicitly. This has been volatile in recent years and remains uncertain. The principal factors affecting new market fuel choice are projected prices for electricity and gas and future building practices such as those indicated in Table 22. GSU projects electricity prices which grow at an average 5-6% annual rate above inflation. The projected trajectory, shown in Figure 6, will be steep increases followed by a moderate decline. Natural gas on the other hand is expected to grow at about 3-4% annually in real terms. Under these circumstances it would not be surprising to see electric space heating losing market share compared to the recent past. We project a decline to 47.5% of the new market over the 1982-1992 period. This is below the 55% share of 1981

Figure 6: GSU Price Scenario



and almost 60% share of 1982. These projections are made using the Goett-Earl specification of the multinomial choice model, (Eqs. (18) and (19)) in slightly expanded form. Details are given in Table 23.

Table 21 incorporates substantial changes in the UEC's for several end-uses. Refrigerators and freezers are expected to improve by approximately 30% and air-conditioners by approximately 15%. This is an estimate of the stock average. We collect estimates of these efficiency changes in Table 24. The basic source is: the ORNL model scenario with no federal appliance standards. The ORNL model was used to project efficiency changes for appliances using the projected data provided by GSU for prices and other parameters. The trajectory of changes in efficiency for some appliances is shown in Appendix 3. These trajectories show the average expected efficiency of appliances sold in the years 1982-1995, normalized to the average unit sold in 1982. The Table 24 estimates are conservative interpretations of these trajectories, accounting for the turnover of existing stock. These trajectories provide a conservative estimate of efficiency changes since the discount rates used in the ORNL model are extremely high, accounting for imperfections in the market.35 The impact of efficiency changes affects air conditioning UEC again through the housing mix as illustrated in Table 25. For comparison purposes we include forecasts made by Philadelphia Electric Company.[36]

The final element of the Table 21 is the water heating UEC. As indicated in Section 2, water heating is a variable consumption end-use in the short run as well as the long run. Our statistical method for capturing short run utilization changes is not sensitive to water heating because its consumption does not vary with weather. Therefore, our estimated price co-efficients in Section 2 are biased downward to some degree. In our projections we rely upon estimates of the California Energy Commission for the components of water heating consumption changes. Reductions for a given household type average about 20%. Additional changes are due to the effects of dwelling type. The 20% reduction is consistent with a utilization elasticity of -0.25 and a price increase of 6% real/year for 10 years.

Table 23
GSU Electric Space Heating Market Share

1. Basic Framework: The Choice of Electricity (e) or Gas (g) Heating

$$\text{Electric Share} = \frac{e^{w_e}}{e^{w_e} + e^{w_g}}$$

$$\text{where} = w_i = \alpha_1 + \alpha_2 \left[\frac{CAP_i}{OP_{ref}}\right] + \alpha_3 \left[\frac{OP_j}{OP_{ref}} + \right]$$

$$\alpha_4 \left[\frac{OP_j}{OP_{ref}}\right] (AVI)$$

CAP_i = capital cost of alternative i
OP_i = operating cost of alternative i
OP_{ref} = operating cost of f electric resistance baseboard heating
AVI = average income/household in thousand of 1975$

2. Initialization of Model

The constant α_2, α_3 and α_4 have been estimated by Goett and Earl and appear to be invariant of region. The constant α_1 captures region-specific effects and must be fit to the data. We fit this for 1981, using the following baseline values:

CAP_g = $740
CAP_e = $456
OP_{ref} = $242
= 15 MBtu = 4395 kWh x $.055
OP_g = 90
= 15 MBtu (1/.7) x $4.20
AVI = 15.3

α_2 = -.166
α_3 = -2.473
α_4 = -.045

Electric Share in 1981 = .55 implies α_1 = 1.797
Note that OP_g assumes a furnace efficiency of 70%. We assume OP_e = .9 x OP_{ref} to account for duct losses. OP_{ref} is just the heating load (15 MMBtu) converted to kWh at 100% efficiency.

3. Projections

Electricity Price Average = 9.5¢/kWh in 1981 dollars
Gas Price Average = $6.10/MMBtu in 1981 dollars
Heating Loads = 11 MMBtu/year
Income Growth = 2% real/year

Substituting these values into the Electric Share equation yields an estimate of 47.5%.

Table 24.
Appliance Efficiency Improvement Estimates
Percentage Change over 1982 Average

	ORNL[a]	Philadelphia Electric
Refrigerators	30%	18%
Freezers	30%	18%
Central Air Conditioning	15%	36%
Room Air Conditioning	8%	-

a) Assume 1977 value of shipments for 1982 stock and 1987 value of shipments for 1992 stock. These 1992 estimates were derived for GSU service area using GSU price projections and other parameters. See Appendix 3 for projected annual changes to 1992.

Table 25
GSU Central Air Conditioning UEC* Projection - 1992

	UEC[a]	Saturation[b]	
Single Family	507	.58	294
Apartment	429	.21	90
Mobile Home	336	.21	71
			455

a) EER assumed to be 8.3 compared to 7.2 in Table 19
b) Assume market dwelling type split as in Table 21 for both new and old customer markets.

Table 26
GSU Water Heating UEC Projection - 1992

	Single Family	Apartment	Mobile Home	GSU Saturation
Domestic Hot-water	308	236	251	
Dishwasher	34	24	27	.46
Clothes Washer	52	37	41	.77
Average Use	363	276	295	
GSU Fraction	.58	.21	.21	

Weighted Average = $\sum$ Use x GSU Fraction
= 331

11.3 Projecting Electricity Growth Rate

With this explanation of the Table 21 projections it is possible to calculate total long run price elasticity and total kWh growth over the 1982-1992 period.

The change in average use per customer between Tables 18 and 21 is 17%. The corresponding price change over the 1982-1992 period should be an average which reflects the very steep increases projected early in the period with the modest changes at the end. The estimate used in Table 23 of an average 9.5¢/kWh (1982 $) reflects a heavier weighting of the earlier period. The real price is expected to average 8.9¢/kWh over the period. This compares with 6¢/kWh in 1982. Using the lower figure, the long run component of price elasticity (Eq. (25)) is -0.42. Using the higher price change variable the long run component would be -0.34. The total elasticity is the sum of the short run utilization component and the long run component just estimated. As indicated in Section 2, our statistical results can be interpreted to imply a short run elasticity of -0.16 - 0.19. Together this results in an estimate of -0.50 to -0.61 as the total demand elasticity.

An alternative form to represent our results, is a projected kWh sales growth rate for the residential customer class. This consists simply of the change in average use per customer times the change in customers. Between 1982 and 1992 GSU expects a 34.4% increase in the number of customers (3%/year). Table 21 indicates a 17% decline in average use which results in an overall increase in kWh sales of 11.5% in 1992 over 1982. This corresponds to a 1.1% annual rate of increase.

Projections such as these should be interpreted with caution. When conditions change rapidly it is always difficult to forecast magnitudes accurately. Among the factors neglected in this analysis there are those which would increase consumption and conversely. The most important limitations of our approach concern the role of new technology. Heat pumps for space conditioning and water heating have not been treated explicitly. These may become important for GSU. In addition solar space and water heating may also play a role. All these technologies will tend to reduce UEC's. On the other hand, the heat pump may increase electricity saturations, thereby increasing average consumption. A more detailed version of the model used in Table 23 might be able to estimate these trade-offs.

The real value of the method outlined here is the explicit account taken of the components of demand. Econometric models which deal with aggregated data cannot do this. Moreover, the engineering detail of our approach shows explicitly where large changes in consumption are possible, and helps in some degree to project them.

This analysis has focussed on the changes in electricity consumption that might occur in 10 years between 1982 and 1992. Although we have not shown the trajectory of energy consumption in this period, it can be determined using the data provided in this report. The effect of the dramatic price increase in 1984-86 on the efficiency of appliances such as air-conditioning is evident in the trajectories shown in Appendix 3. No doubt this would have a dramatic effect on electricity consumption in this period. However, refrigerators and freezers, which are relatively insensitive to price increases, would mitigate the suddenness of this price effect. Determining these demand trajectories would require further analysis beyond the scope of this report.

12 CONCLUSIONS AND OBSERVATIONS

In this paper we have developed separate methods for projecting short and long run electricity demand. The short run analysis distinguishes between weather sensitive and non-weather sensitive appliances. It explicitly accounts for stocks of weather sensitive appliances. The short-run fixed demand is assumed to be a constant fraction of annual minimum demand. The model is therefore intermediate in terms of data requirements between conditional demand models and lagged flow adjustment models. The model builds on earlier work in conditional demand analysis. As a result it is appropriate for utility companies that are not in a position to invest in conditional demand type models.

Our methodology for estimating long run demand combines short run econometric analysis with an engineering accounting approach to arrive at long run elasticities. The method makes use of thermal load models, such as the DOE-2, and appliance choice models and consumer behavior models to forecast thermal integrity improvements and appliance efficiency improvements. This methodology has the advantage of being able to foresee and identify the effects of turning points caused by sharp increases in price of electricity. The effect of rapid price increases on efficiency of appliances and on thermal loads in buildings is explicitly accounted for in this methodology. As a rule the approach we have presented trades off between statistical accuracy of econometric models , against an improved understanding of the multitude of parameters that cannot be satisfactorily modelled. The understanding provided is detailed and helps identify the reasons why demand for electricity might increase faster or slower than anticipated using econometric models.

Our projected growth rates are lower than those implied by the elasticity values provided by GSU. However this growth rate should be interpreted in light of the assumptions that we have made regarding several crucial parameters, the share of apartments in the number of new dwellings, the saturation and efficiency of air conditioners, etc. Most of the basic input data projections have come from GSU in arriving at the projected growth rate.

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APPENDIX 1

STOCK INDEX

STOCK INDEX

We construct the stock index for weather sensitive appliances using data on appliance saturations and installed capacity. The stock index will be used to calibrate monthly average consumption to maximum possible consumption, thereby yielding a capacity utilization factor. This is expressed formally by eq. (A-1)

$$CUF_i = \left[\overline{kWh_i} - E_i^*\right] / \left[kWh_{max_i} - E_i^*\right], \qquad \text{(A-1)}$$

where

$\underline{CUF_i}$ = capacity utilization factor in month i,

kWh = average use per customer in month i,

$kWh_{max}i$ = maximum possible consumption in month i,

and E_i^* = non-variable consumption in month i.

Eq (A-1) is a more specific version of Eq. (4) in sec. 1. Since we are assuming that only weather sensitive demand is variable, then the denominator of Eq. (A-1) can be expanded as follows:

$$kWh_{max_i} - E_i^* = \sum_j \overline{P}_{max_j} \times 730 \times Sat_{i,j}, \qquad \text{(A-2)}$$

where

P_{maxi},j = average installed kW capacity of appliance j in month i,

and $Sat_{i,j,}$ = saturation of appliance j in month i.

The scaling factor 730 is simply the number of hours in a month, and is necessary to translate kW capacity ratings into maximum kWh consumption.

The term $Sat_{i,j,}$ is straight-forward for central air conditioners, since the GSU data is explicit about this in all surveys. Room air-conditioners and electric space heating are somewhat ambiguous. Saturations are defined typically as the percentage of households with a particular appliance type. Room air-conditioners holdings commonly include more than one unit per household. The latest GSU survey estimates 1.78 units per household for 1983. This is larger than the national average of 1.45, as could be expected for the warm humid climate in the GSU service territory. To estimate Eq. (A-2) we multiply room air-conditioner saturations by 1.78 over the entire period 1970-1981.

The problem for electric space heating saturations is somewhat similar. Most electric heating in the GSU service area is supplied by central furnaces. There is a small amount of portable room heaters and electric built-in room heaters. For the purpose of constructing a stock index we can ignore everything except the central furnaces. In addition to the small saturations of the non-central systems, they also have much smaller kW capacity than central furnaces. The typical electric furnace in GSU service territory has 15 kW capacity. Portable or built-in units typically have 1.3 kW per unit. Homes with non-central electric heat are unlikely to have large numbers of these units. Thus, the total installed capacity of non-central electric heat per household is small relative to central furnace capacity. For this reason, and the low saturation, we neglect everything except central furnaces. These furnaces are assumed to have 15 kW in all years from 1970-1981.

The data on installed capacity for air-conditioners requires more discussion. The primary sources of data on this subject reflect operating characteristics of units sold in a given year. We summarize this data in Table A-1.

Table A-1.
Air Conditioning Engineering Specifications

Year	Capacity (Btu/h)	EER	kW Capacity
1. Central Units			
1975	35,400		
1976	35,570	7.08	5.024
1977	34,020	7.18	4.877
1978	34,970	7.39	4.732
1979	34,930	7.54	4.633
1980	34,320	7.60	4.516
2. Room Units			
1972	10,226	5.98	1.71
1978	10,827	6.72	1.61
1980	10,606	7.02	1.51
1981	10,924	7.06	1.55

To use this data we must know something about the competition between room and central air-conditioning so that we can characterize the change of the stock. Broadly speaking, central air-conditioning has been replacing room units as the dominant form of cooling. While this is true nationally, in the GSU

service territory the actual number of customers with room units has declined in the past ten years. This means that all growth in new air-conditioning comes from central units, and that the stock of room air-conditioners changes slowly driven only by replacement demand. Therefore, the weighted average capacity of the room air-conditioning stock in a given year will reflect the capacity of the average age of the devices which in this case is half of the average lifetime. Thus for 1980 the stock average capacity of the stock of room air-conditioners will be the average capacity of new units sold in 1975, assuming an appliance lifetime of ten years. With this characterization of the room air-conditioner stock P_{max} is easily estimated. We project the series of kW capacity back to 1970. Assume this is the value of the average capacity in 1970. We assume the 1975 value interpolated from Table A-1 is the 1980 stock value. All other points are assumed to lie on the line determined by the 1970 and 1980 values.

Central air-conditioners have changed average capacity (been down-sized) more rapidly than room air conditioners due to the more rapid stock changes. To weight these changes properly we need to look at incremental saturations in a given year. Let us call the change in saturation of central air-conditioners τ. Formally we define

$$\tau_i = (Sat_i - Sat_{i-1}). \qquad \text{(A-3)}$$

Then the average installed capacity $\bar{P}_{maxi}$ in period i is defined by

(A-4)

left (Sat sub {i} ~ - ~ τ sub {i} right)
~ + ~ P sub {maxi} sup {n} ~ (τ sub {i}),

where

P^n_{maxi} = new unit installed capacity in period i.

Typically changes in saturation and capacity are measured annually. For a given year we know P^n_{maxi} from Table A-1. All we need to use Eq. (A-4) is an initial value for P_{maxi-1}. As in the room air-conditioner case we choose this equal to the capacity of the new unit in 1970.

APPENDIX 2

THERMAL LOAD ESTIMATES

THERMAL LOAD ESTIMATES

In this appendix we collect sample outputs of the DOE-2 model simulations of energy use in a 1500 ft^2 single story ranch house in the Lake Charles, Louisiana. Heating and cooling loads are calculated for this house under various assumptions about insulation levels, glazing, and air infiltration rates. Each configuration is identified by a code and five parameter values. The parameters are: (1) ceiling insulation R-value (RC), (2) wall insulation R-value (RW), (3) floor insulation level (FLR), (4) air infiltration rate (IN), and (5) number of panes of glass (GLS). For FLR, we have three values: FMO is no insulation, FM1 is R-5 insulation 2 feet deep around the outside perimeter edge, and FM2 is the same as FM1 except the insulation is 4 feet deep. Air infiltration is HI (=0.7 ach, air changes per hour) or LO (=0.4 ach). The house is assumed to have 10% of floor area in glazing. Further details for other building types and parameter values are given in Ritschard et al., 1983.

Calculations of heating and cooling energy are made assuming a furnace efficiency of 70% and an air-conditioner EER of 9.2. The energy can be adjusted for other assumptions about appliance efficiency.

Lake Charles La
1 Story Ranch Slab

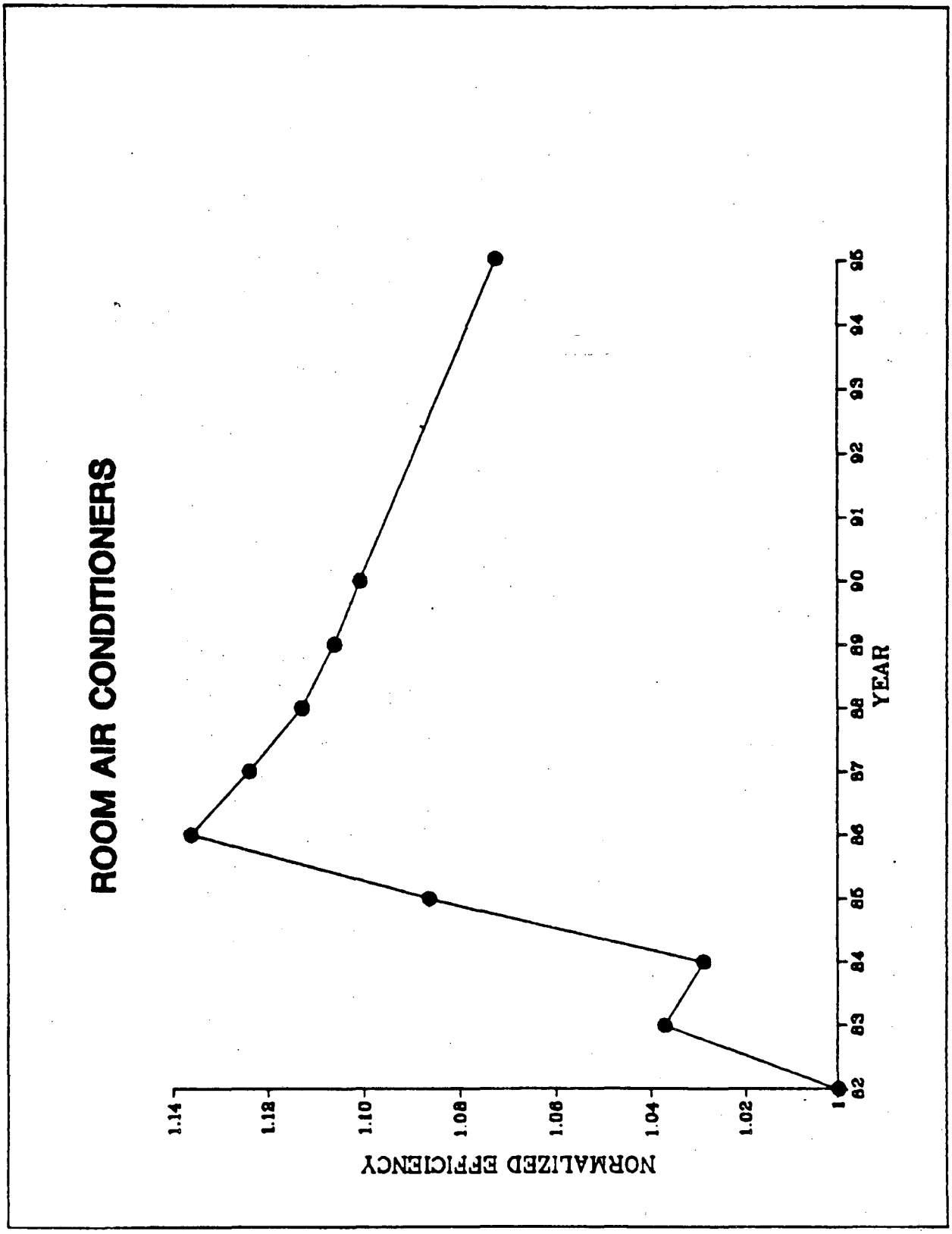
Code	RC RW FLR IN GLS	Heating Load Million Btu	Cooling Load Million Btu	Heating Energy Million Btu	Cooling Energy kWh
A01	00-00-FM0-HI-1	38.004	59.624	54.292	7122.0
B01	11-00-FM0-HI-1	26.179	49.421	37.399	6080.2
C02	11-11-FM0-HI-1	20.546	45.699	29.352	5692.8
D01	19-11-FM0-HI-1	19.127	44.324	27.325	5547.7
E01	19-11-FM1-HI-1	15.524	39.404	22.177	4994.5
F02	19-11-FM1-HI-2	12.507	37.850	17.868	4826.6
G05	19-19-FM1-HI-2	11.226	37.160	16.038	4752.7
G01	30-11-FM1-HI-2	11.510	36.912	16.443	4723.1
H04	30-19-FM1-HI-2	10.238	36.073	14.626	4630.8
I07	30-19-FM1-HI-3	9.391	35.128	13.416	4524.2
I06	38-19-FM1-HI-2	9.878	35.725	14.112	4592.1
J06	38-19-FM1-HI-3	9.032	34.759	12.903	4482.9
K03	30-19-FM3-HI-3	8.891	34.415	12.702	4442.1
K01	38-19-FM3-HI-2	9.378	35.029	13.397	4512.1
L04	38-19-FM3-HI-3	8.537	34.086	12.196	4405.2
M03	38-27-FM3-HI-3	7.870	33.598	11.243	4349.7
H54	30-19-FM1-LO-2	6.795	33.178	9.708	4279.7

APPENDIX 3

APPLIANCE EFFICIENCY PROJECTIONS

APPLIANCE EFFICIENCY PROJECTIONS

The figures included in this appendix show the efficiency improvements that might be expected for appliances in the GSU service area. The trajectories showing future efficiency improvements were estimated using the projected electricity prices and the values of other engineerng parameters provided by GSU. The effect of rising prices was thus seen in the changes in appliance efficiency. The efficiencies were calculated using our version of the ORNL Appliance Choice Model. In order to provide a conservative estimate of efficiency changes the implicit discount rates were not allowed to change from their base values in 1977.


ROOM AIR CONDITIONERS
NORMALIZED EFFICIENCY
1.14
1.12
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82
83
84
85
86
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88
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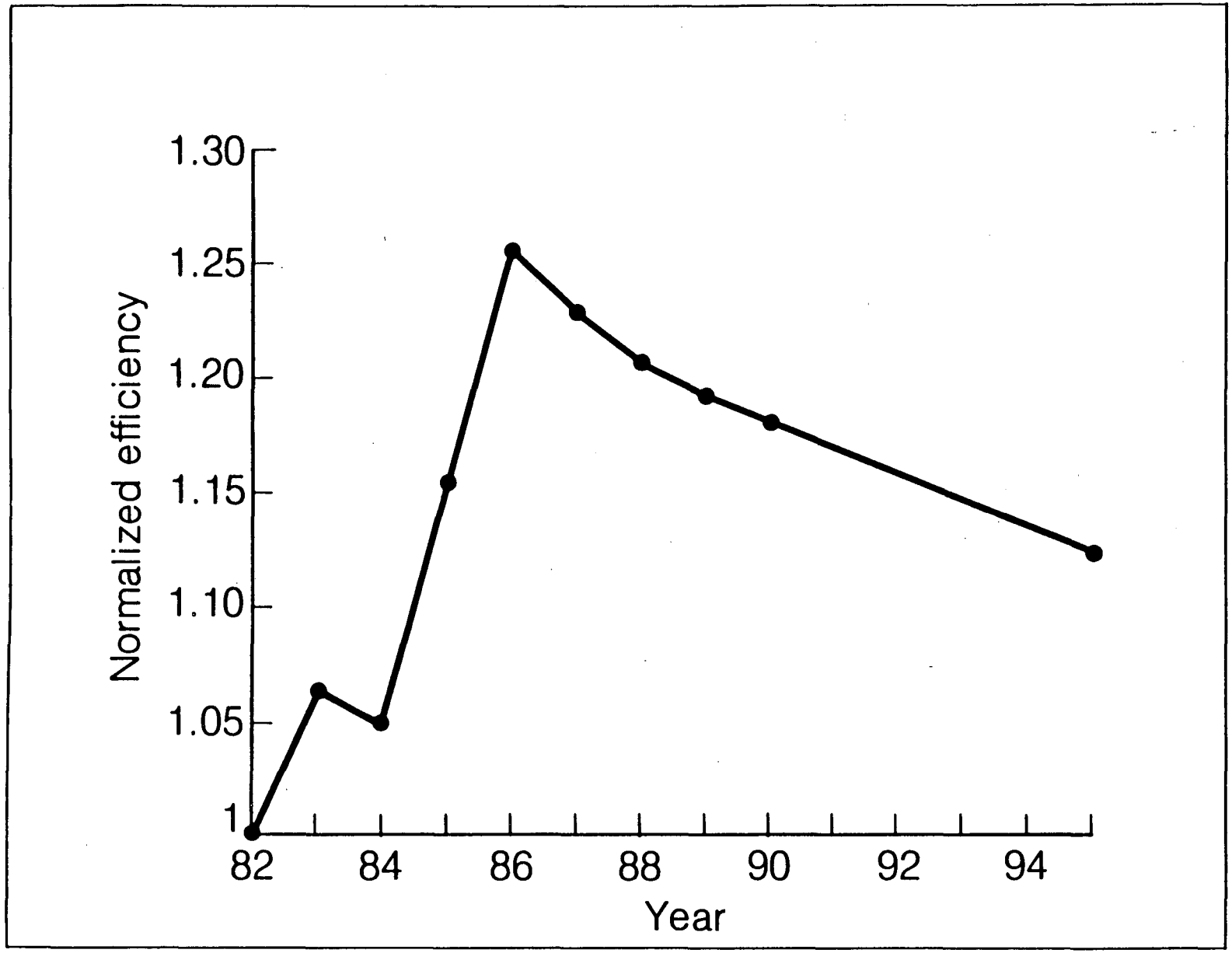
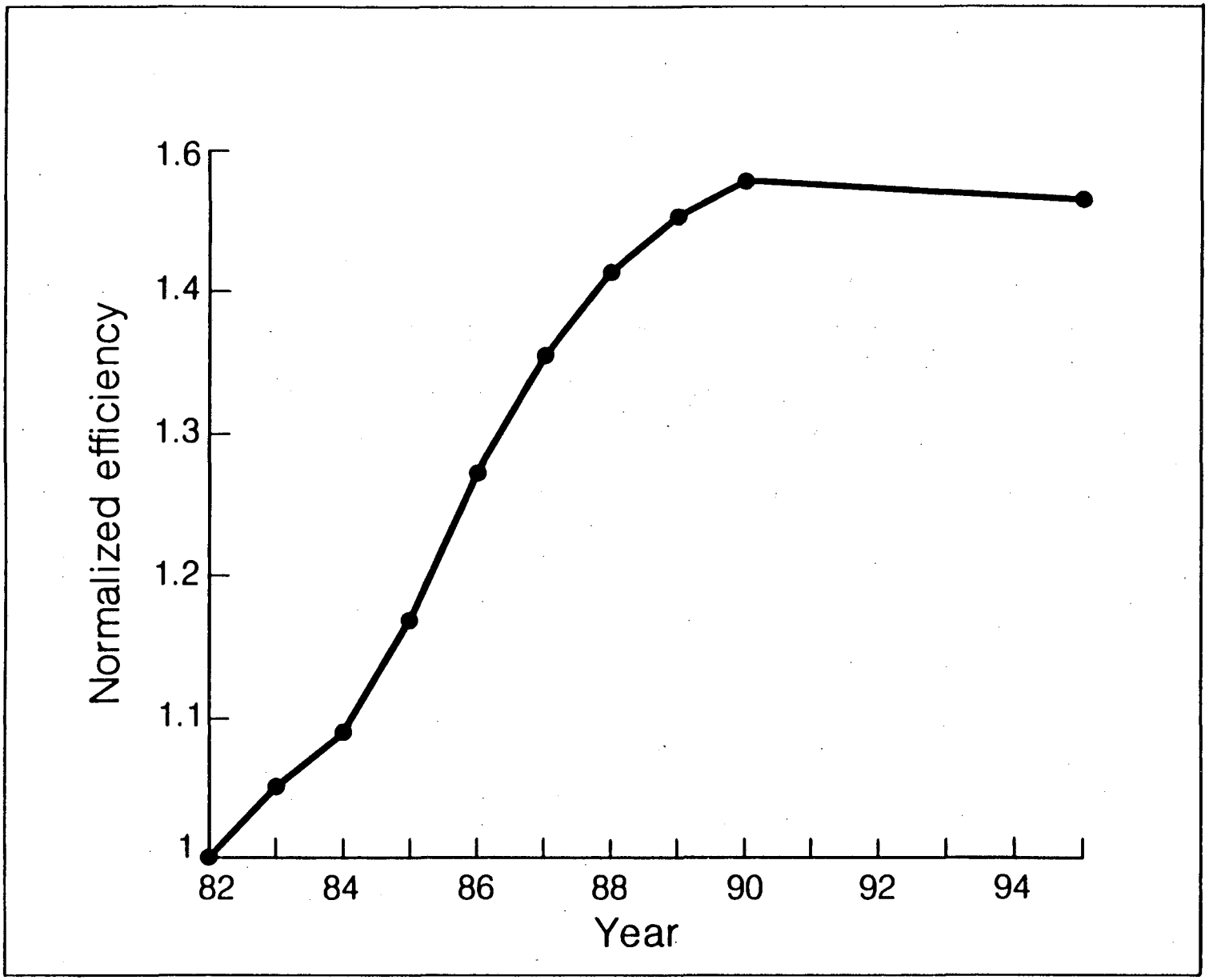
YEAR



Projected Efficiency of New Central Air Conditioners

XBL 8310-607



Projected Efficiency of New Refrigerators

XBL 8310-608

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LAWRENCE BERKELEY LABORATORY
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BERKELEY, CALIFORNIA 94720