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6 Bounded Rationality versus Standard Utility-Maximization: A Test of Energy Price Responsiveness

Lee S. Friedman

Introduction

Over the past decade, there has been a growing and fruitful debate over the applicability of various models of limited or bounded rationality to economic decision making. In particular, in a wide variety of situations the claim is frequently made that the standard model of utility-maximization (SUM) provides an inadequate explanation for observed behavior and that some alternative behavioral model provides a better explanation. However, SUM models continue to guide applied economic research in market settings. There have not been, to my knowledge, any empirical studies of actual market decision making that specify two competing models (one SUM and one based on an alternative behavioral model) and test their relative strengths. This study contributes such a test in the context of residential energy consumption.

The alternative behavioral models emphasize the difficulty or the impossibility of obtaining and processing the information required to maximize utility. Although some maintain the concept of utility-maximization, they impose information and transactional constraints that alter the predicted behavior. Other models reject the concept of utility-maximization and substitute some form of simplifying decision routine.[1] For short I shall refer to each class of models, respectively, as *limited utility-maximization* (LUM) and *bounded rationality* (BR). A full review of both classes of alternative models is beyond the scope of this study.[2]

I am grateful to the San Diego Gas and Electric Company for making its MIRACLE IV database available and to the University of California Energy Institute, whose support has made this research possible. I have benefited from the advice and assistance of many people, including Carl Blumstein, Karl Hausker, Ted Keeler, Daniel Khazzoom, John Quigley, Herb Simon, and Chris Weare.

Two of their attributes are particularly relevant to note here. First, the existing tests of the alternative models almost always rely on data that are not normally observable in market settings. Second, within the alternative models, it can be exceedingly difficult to test a LUM model against a BR model: The decision rules a consumer follows can often be thought of *as if* they are derived from LUM, even if they are not.[3]

Perhaps for these reasons, a surprising amount of the literature in economics relevant to this debate focuses on tests that can reject SUM but that cannot reject some alternative model. For example, there are many studies that show subjects in laboratory experiments behaving inconsistently with utility-maximization but that do not test any other specific theory.[4] To make intellectual progress, it is important to consider and test the relative strengths of alternative predictive models.

Furthermore, there are few tests that take place in actual market settings as opposed to in the laboratory or from the analysis of survey responses. Indeed, most of the chapters in this volume report on research based on the latter methods. Particularly in the case of the formal experiment, there is much to be said in favor of the methodology. I have already mentioned the ability to plan treatments (or, in the case of the survey, ask questions) and observe the responses to them that may be difficult or impossible to observe in natural market settings. The evidence concerning preference reversals is a good example.

But what about situations in which one can observe important evidence in the actual market? This is particularly relevant for public policy research because the effect of actual policies in the marketplace is paramount. Another important advantage of the experiment is the ability, through random assignment of subjects to experimental and control groups, to determine highly precise treatment effects. That is, the variation in decisions across groups is fully attributable to the designed treatment differences among the groups, save for some small statistical noise. By contrast, the use of natural (nonexperimental) decisions in the marketplace (like this study) requires the analyst to account for all of the factors that may explain systematic differences in choices among individuals. Such studies are always subject to the criticism that important factors besides the "treatment" of interest have not been sufficiently controlled, possibly leading to biased estimates of the treatment effect.

For example, suppose we wish to know how consumers respond to a price increase for a given product. The experimentalist will assign people randomly to a treatment group that will face the higher price and a control group that will not. The experimentalist will conclude, subject to normal statistical inference, that the price increase causes the difference in average consumption between the two groups.

The analyst who uses nonexperimental market data, however, will first have to make sure that the data include the consumption of both individuals who have and who have not experienced the price increase. Typically, this will involve time-series data from one geographic area, or geographic cross-sectional data within a given time period, or a combination. If, say, the price difference occurs across regions, then the analyst must make sure to control for nonprice regional factors that may cause differences in consumption (e.g., if studying home energy consumption, control for climate, wealth, and residence size differences). Similarly, there may be nonprice factors that cause changes in consumption over time (e.g., weather, occupancy changes). The list of nonprice factors may be large, and the ability to get data that measure each of these differences accurately may be limited. And, of course, the treatment studied – the size of the price increase – is limited to what has actually happened rather than chosen by experimental design.

Why, given the complication and imperfection of studying nonexperimental market decisions, would the researcher ever prefer to study them? There are several important reasons. If the alternative is a nonexperimental survey, then it is well recognized that *survey responses are not always reliable indicators of how people behave when making actual decisions.* This uncertainty makes it valuable to know if survey-based findings are consistent with what can be observed in actual market settings. Indeed, experimentalists value this as well, because *there are also varying degrees of undesirable artificiality in experiments.* To clarify this, let us note the important distinction between a laboratory experiment, which is the predominant mode for BR and LUM research, and a social experiment. The laboratory experiment may have as subjects university students who differ from the actual market decision makers, and it almost always takes place in an environment or setting that is quite unlike the actual market. The social experiment, by contrast, studies the actual market decision makers in an actual market setting. In principle, the earlier criticisms of the nonexperimental market study can be avoided by the social experiment.

But *few social experiments are conducted because they are expensive, difficult to arrange, and time-consuming.* If these costs were no object, almost all experimentalists would prefer to conduct a social rather than a laboratory experiment to understand the choices observable in the marketplace. However, given the limited resources available for research, it is possible to conduct social experiments only in rare circumstances.

These usually involve high public policy stakes that make the cost of the social experiment seem small in comparison.

Even when social experiments are conducted, important elements of artificiality often remain. For example, an experimental price increase is often regarded by participants as more temporary than a naturally occurring market price increase. This can affect the investment choices of subjects. In negative income tax social experiments, subjects whose real wage rates increased through lower taxes might have invested more in income-producing education if the increase was permanent. In our energy price increase example, fewer new energy-efficient furnaces will be bought under a temporary social experiment than under an actual market price increase of equal size.

Another source of artificiality in the social experiment is that the experimental population, although consisting of real market participants, may not be representative of the broader population to which the treatment may be administered. A rigorous social experiment that recruits volunteer participants who are randomly assigned to experimental and control groups may not tell us much about the effects of the same treatment when applied to those who did not volunteer. Similarly, the environment in which the social experiment takes place can have important effects: The response of participants in a suburb might be quite different from the response of an otherwise identical group located in a large city.

All of these sources of artificiality can, in principle, be removed (or at least reduced) by larger, more inclusive, and longer-duration social experiments. But then we run into the cost issue again. Once one recognizes that the costs prohibit us from routinely doing the ideal social experiment, we have several different ways of lowering costs. Some of them retain the experimental design, but they move from larger to smaller social experiments and then down to laboratory experiments, with each step increasing the artificiality and reducing the generalizability of the observed decision making. Alternatively, we can move away from the experiment but retain some of the comprehensiveness of time, place, and population studied by using the nonexperimental research design.

Imagine research efforts of both types that have equal (and relatively low) costs. It is not at all clear which is preferable. One must judge the extent of artificiality in the experiment against the quality and comprehensiveness of the data available for the nonexperimental design. Because each method has different strengths and weaknesses, it is valuable when possible to know if the findings are consistent across them.

The decisions that I study here would be difficult to simulate in a laboratory experiment. They involve consumer responses to energy price schedules, but also more than that. A key part of the actual decision environment is the long period of time, perhaps several years, during which the consumer forms a routine by making a series of (daily) decisions with infrequent and limited (monthly) feedback about the consequences. The lag between the decisions and feedback is (perhaps) long enough to forget important circumstances that framed the original decisions, and long enough so that the circumstances for the next series of decisions may have changed substantially from those of the prior series.

Smith (1989) noted that in the market consumers may learn their utility-maximizing choices by repetitive trials over time, even if they do not actually arrive at them by explicit maximizing calculations.[5] Although I remain open to the cleverness of experts in the design of laboratory experiments to test this in the home energy context, I believe that it is worthwhile to study the actual decisions with nonexperimental methods. This conclusion is reinforced by the unusual comprehensiveness of the available data, as well as the direct policy relevance of evidence on the effects of rates set by regulatory commissions.

This study is of a market decision by households concerning the consumption of natural gas. There are some good reasons why consumers might use simplified decision routines in this setting. I suggest that the use of one particular one with a common rate structure would cause a systematic departure from the conventional utility-maximizing choice.

I postulate a specific BR model (although the same systematic departure could be predicted by a LUM model, and I do not claim to distinguish these). Using only the type of data normally used to estimate SUM models, I estimate both and I pit the BR model against the SUM model. The results might be summarized as follows: The SUM model is not terrible, but the BR model is better. In the market examined, the welfare and policy implications are likely to be significant. Furthermore, the consumer decision routine specified may be applied with the same flaws (deviations from SUM) and similar implications in other contexts (and could be further tested in these settings). The rest of the chapter explains the basis for these conclusions.

The Two Competing Hypotheses for Residential Consumption of Natural Gas

The context I will focus on is that of short-run consumption choices, holding the stock of natural-gas-using appliances constant.[6] The equilibrium quantity of each model will be assumed to depend on the appliance stock (including characteristics of the dwelling unit itself), price of natural gas, household income, wealth and demographic features, and weather and climate conditions. When it comes to specification, the only difference between the two models will be the manner in which the rate structure affects the predicted equilibrium quantity. I will next lay the groundwork for this analysis.

The standard economic hypothesis is that the household will choose its utility-maximizing quantity of natural gas. With the SUM model, the household is assumed to be able to calculate this quantity and to select it. *The alternative BR hypothesis is that the household is characterized by a total bill sensitivity*, responding to the total monthly expenditure on natural gas (not the actual price) as well as the other nonprice factors mentioned earlier. This sensitivity is not assumed to be derived from any explicit calculation, but it parameterizes the household's adjustment function.

If the rate structure for natural gas consisted of a simple *uniform* price (independent of the quantity consumed), the BR model is assumed to have an equilibrium identical to that of the standard model.[7] This research focuses on the consumer response to a *nonlinear* rate structure. Almost all utility companies employ block rate structures, where the price per unit changes as the consumption level reaches the end of one specified block and begins another. With nonlinear rate structures for this good, the BR equilibrium will diverge from the SUM equilibrium.

Under the BR hypothesis, the household finds it easier to choose a sensitivity to the total natural gas bill rather than use a decision routine that has more explicit accounting for the price per unit consumed. Reasons why this might occur are as follows: (1) Consumers have imperfect information about the current rate structure (fuel cost adjustments, seasonal changes, and rate case decisions often cause frequent changes in price per block and in block sizes as well). (2) Even the information on a bill about the prior month is generally quite incomplete (many utilities simply list the total bill and the quantity consumed, without information on the block sizes or rates). (3) It is extremely difficult to purchase any particular quantity even if one was decided on (the actual quantity consumed results from a complicated interaction of exogenous weather conditions and daily household use of numerous natural-gas-using appliances like furnaces, hot water heaters, dryers, dishwashers, and swimming pool heaters).

Facing the previous decision difficulties, the household may simply consider if it is satisfied with its choice based on the prior month's outcome. If it feels that it overconsumed, for example, it can take a few actions to reduce consumption for the coming month (e.g., lowering the thermostat, closing the drapes at night, conserving on hot water usage, covering the swimming pool). Anthropologists Kempton and Montgomery (1982) provide some supporting evidence for this behavior based on interviews with householders.

To clarify the expected divergence in equilibrium between the SUM and BR models, I proceed in two steps. The first step is to define equilibrium and assume that under a *uniform* rate structure the equilibria of both models are the same. In the second step, the *nonlinear* rate structure will be introduced and shown to cause a systematic divergence between the equilibria. In addition, the BR equilibrium under nonlinear rates will be seen as identical to that of a particular LUM model, and thus the empirical tests that follow have the potential only for distinguishing SUM from the other two (BR and its LUM relative). I prefer the BR interpretation rather than LUM on grounds of a priori plausibility, but this is a matter of judgment and cannot be tested here.

Step One. The BR model of total bill sensitivity is described by an adjustment function:

$$Q_{t+1} = D(E_t, Z)$$

where Z represents a vector of all factors other than the total natural gas bill, E_t is total natural gas expenditures in time t, and Q_{t+1} is consumption quantity in time $t+1$. Except for relying on the total bill rather than the price, the adjustment function is assumed to be normal and well behaved. Let us define an equilibrium quantity as one from which the household would make no further adjustments (holding exogenous conditions constant):

$$Q_{t+1} = Q_t = D(E_t, Z)$$

Let us also define the total bill sensitivity α as the elasticity of equilibrium output Q with respect to E (dropping t subscripts since we are focusing on equilibrium):

$$\frac{\partial D}{\partial E} * \frac{E}{Q} = \alpha$$

Let us assume for a given household that in the *uniform* price case the BR equilibrium is identical to that of SUM.[8] In this case, total bill sensitivity α is equivalent to an ordinary price elasticity of $\alpha/(1-\alpha)$. I show this by making use of the chain rule. In the uniform case, total natural gas expenditure $E_t = P_t * Q_t$ by definition. Applying the chain rule to the equilibrium BR quantity:

$$\frac{\partial Q}{\partial P} = \frac{\partial D}{\partial E} * \frac{\partial E}{\partial P}$$

Note from the definition of total bill sensitivity that

$$\frac{\partial D}{\partial E} = \alpha * \frac{Q}{E} = \alpha * \frac{Q}{P * Q} = \frac{\alpha}{P}$$

Substituting this expression in the chain rule and differentiating $\partial E / \partial P$:

$$\frac{\partial Q}{\partial P} = \left(\frac{\alpha}{P}\right)\left(Q + \left[P * \left\{\frac{\partial Q}{\partial P}\right\}\right]\right)$$

Solving for $\partial Q/\partial P$ and multiplying both sides by P/Q results in the ordinary price elasticity:

$$\frac{\partial Q}{\partial P} * \frac{P}{Q} = \frac{\alpha}{1-\alpha}$$

Step Two. Imagine the household in equilibrium, and now let the rate structure change to be one of two or more blocks, but with the expenditure at the initial equilibrium quantity unchanged. The BR household, sensitive only to the bill total, remains in equilibrium and will make no adjustments.

The SUM household, however, is no longer in equilibrium. Its marginal rate of substitution of natural gas for other things equals the old uniform price (equal to the current average price), which is no longer the marginal price. If the marginal price exceeds the average price (as with increasing block rates), the SUM consumer will act to reduce consumption. If the marginal price is below the average price (as with decreasing block rates), the SUM consumer will increase consumption.

An interesting interpretation of the BR equilibrium under nonlinear rates can be offered. Note that by definition expenditure equals *average* price (P_A) times quantity. Then the same manipulation done earlier, replacing P with P_A, reveals that *the BR household is responding as if it is a faulty utility-maximizer, making the error of perceiving the marginal price as the average price*. It does not actually make this calculation, but it acts as if it does. Put differently, for any given E and Z the equilibrium of a BR household with bill sensitivity α will be identical to the equilibrium of an LUM household using average rather than marginal price and with price elasticity $\alpha/(1-\alpha)$.

Two important implications follow from the preceding illustration. First, the nature of the errors caused by this type of bounded rationality becomes clear: The household responding only to the total bill will overconsume if the average price at the true utility-maximum is below the marginal price and will underconsume if the average price at the true utility-maximum is above the marginal price.[9] In general, the BR household will overconsume with an increasing block rate structure and underconsume with a decreasing block rate structure (except when the true utility-maximum is in the first block). Second, empirical tests based on predicted equilibria cannot distinguish between the BR model and its LUM relative (since both predict the same equilibrium).

How common are the circumstances that may lead to behavior described? One characteristic important to the model here is a nonlinear budget constraint, and the other is consumer uncertainty about their locations relative to it. Similar situations characterize most other utility services: electricity, water, and telephones.[10] A quite different but important market concerns the labor–leisure choices of welfare recipients, particularly those qualifying for more than one assistance program (e.g., food stamps, Supplemental Security Income, Medicaid). The return on investment or savings decisions depends on the individual's income tax brackets, and many of these decisions may be made when the consumer is unaware of the relevant brackets. Similarly, depreciation and other rules governing net tax assessments may imply nonlinearities that are not clearly understood at the time of an investment.[11]

A more general application of this BR model, not requiring nonlinear prices, can be imagined. Suppose consumers follow common advice for household budgeting, with fixed proportions of income allocated to major expenditure categories (food, housing, etc.). The consumer's response to a price change for a specific item may occur only through its effect on the total expenditure for the category in which that item is a component. If the consumer's response is the same no matter which specific item prices in the category have increased, then that consumer is behaving in accordance with the same total bill sensitivity model described here. The plausibility of this situation increases with the difficulty of identifying the specific sources of change. For example, consumers may be less aware of the prices of specific items in a supermarket marked only for electronic scanning.

In short, there may be many areas of economic decision making where consumers adopt this type of simplified decision routine. The simplification is to make decisions based on an easy-to-utilize monetary total instead of its difficult-to-utilize components. A variety of cognitive difficulties, as illustrated in the preceding examples, trigger the use of this routine.

Let us summarize this discussion of the two hypotheses in a format that bridges the intuitive exposition and the formal econometric modeling to come. A SUM demand function relating the equilibrium quantity Q_U to the nonlinear rate structure with $i = 1, 2, \ldots, n$ segments and other factors may be represented as follows[12]:

$$Q_U = D_U(P_1, \ldots, P_N, B_1, \ldots B_N, Z)$$

where

P_i = the price per unit on segment i of the rate structure
B_i = the virtual budget size for segment i, where B_1 is the consumer's actual budget and B_i is B_1 plus the sum of the differences between P_i and the actual price for all units on preceding segments
Z = the vector of all nonrate structure variables that influence consumption

We have seen that the BR equilibrium may be described as if it results from faulty utility-maximizing with the error of using the average price P_A. That is:

$$Q_{BR} = D(E, Z) = D_U(P_A, \ldots, P_A, B_1, \ldots, B_1, Z)$$

Thus the equilibrium quantity under the BR hypothesis may be represented by the same functional form (but different rate structure variables) used to predict the SUM quantity. In the BR version, price and budget levels are represented as uniform over the segments and are equal to the average price and the actual budget level B_1, respectively. It remains an empirical question which of the two models is closer to the truth. We turn now to the empirical work of specifying the Z variables, selecting a functional form, and testing the relative strength of the two models.

Econometrics

This section describes the database and the procedures used to specify and estimate models based on the competing behavioral hypotheses.

The following section describes the estimation results and the tests made to evaluate the two models.

The San Diego Gas and Electric Company MIRACLE IV Database

The MIRACLE IV file contains usable monthly consumption and billing data from more than 6,863 households in the service area for 53 months beginning in February 1979 and ending in June 1983.[13] Each household in the file was randomly selected from the company's service area and surveyed in late 1979 or early 1980 to provide detailed microdata on the physical characteristics of the dwelling unit, the appliances in it, and socioeconomic characteristics of the household itself. The service area contains nine separate weather districts, and a weather tape with the daily high and low temperatures in each district for the 53-month period was used in constructing an observation set. During this period, the rate structure consisted of three blocks. The blocks were increasing in price: The second block price per unit was 15 to 51% above the first block price, and the third block price varied from 15 to 53% above the second block price.

For estimation purposes, a random 5% sample was drawn from these households. Observations were not used if they had important missing data (e.g., square footage) or contained detectable coding errors.[14] This left a sample with 11,775 monthly observations used for this study.

The rate structure during this period was one of increasing blocks, and there was substantial variation in it. In nominal terms, the rate on the first block was 19 cents per therm at the start of the period and rose to 51 cents per therm at the end. This represented a 238% increase in nominal rates, or 184% in real rates based on the Consumer Price Index. Thirteen discrete rate changes occurred during the period. The upper block rates changed at these times as well and relative block rates varied, with block two ranging from 15 to 51% above block 1 and block three ranging from 15 to 53% above block two. In addition, block sizes changed twice each year for seasonal reasons.

Consumption at the sample geometric mean was 44.3 therms. Such consumption does not lead to high average bills; in 1983, for example, the average winter bill was about $45 and the average summer bill was only $20. However, the average masks considerable variation. In winter months, the lifeline (first) block was 81 therms, and the top quartile of the sample consumed 94 therms or more. In any year, more than half of the households exceed the lifeline block for one or more months. If there is power to the BR hypothesis, it ought to be detectable with the variation in rates and consumption that characterizes this database.

Econometric Procedures

In this section, I discuss model specification procedures: variable definitions, simultaneity, pooling time series and cross-sectional data, and functional form.

Precise definitions of the variables used in this study are contained in Table 6.1. There are 35 nonprice and nontemporal variables used to describe the physical characteristics of the dwelling unit, the natural-gas-using appliances in it and other appliances that may substitute for them, weather and climate indicators, and socioeconomic characteristics of the household. I will describe these briefly.

Most physical characteristics of the dwelling unit affect energy consumption in conjunction with a specific appliance for space heating or space cooling. These characteristics include the square footage of the house, the presence of an attic, the amount of wall and ceiling insulation, and the age of the house. They enter the model in conjunction with a natural gas main heating system, and the latter four are defined as dummy variables in Table 6.1. The only house characteristic interacted with gas cooling is the house size.[15] I also include the overall size of the house as a noninteracted independent variable. This is because it may be the best proxy for the general wealth level of the household, as well as a correlate of other unmeasured gas-using appliances (e.g., the number of hot water outlets).

The basic gas-using appliances in a dwelling unit, other than main heating, are water heaters, stoves, and clothes dryers. Dishwashers and washing machines are also included as control variables if the water heater runs on gas. Additionally, some households have jacuzzis that use gas-heated water, and these, too, are included as control variables. Each of these appliance variables is interacted with the number of people in the household. Some households also report having an extra space heater that runs on natural gas, and this is included as a simple dummy variable.

Two nongas appliances are included as control variables: microwave ovens and extra space heaters. These secondary appliances permit some substitution of services from the main gas-using appliances by using alternative energy sources. However, they may also reflect general

Table 6.1. *Definition of Variables*

Dependent		
SGAS:		The monthly number of billed therms divided by the number of billing days multiplied by 365/12
SGASBC:		SGAS divided by its geometric mean, Box–Cox transformation (see XBC)
Demographic		
EDUC:		The educational background of the household head, scaled from 1 to 8 as follows: 1 = 0–7 years; 2 = 8 years; 3 = 9–11 years; 4 = 12 years; 5 = 12 + noncollege; 6 = college, no BS; 7 = college, BS; 8 = college advanced
PREBOOM:	= 1	if there are persons aged 35–44 in the household; = 0 otherwise
MIDDLE:	= 1	if there are persons aged 45–54 in the household; = 0 otherwise
MATURE:	= 1	if there are persons aged 55–64 in the household; = 0 otherwise
ELDER:	= 1	if there are persons aged 65 or more and if the preceding three variables = 0; = 0 otherwise
BABY:	= 1	if there are persons aged 5 or under; = 0 otherwise
NUM:	=	the total number of persons in the household is defined as follows: = 1 if one person; = 2 if two people; = 3.5 if three or four; = 5.5 if five or six; = 7.5 if seven or eight; = 10 if nine or more
INLAND:	= 1	if the climate zone is categorized as inland
	= 0	if the climate zone is categorized as maritime or coastal
SFHOME:	= 1	if the dwelling unit is single family;
	= 0	if apartment, duplex, triplex, condominium, or other
Temporal Terms		
JAN:	= 1	if the observation is from January; = 0 otherwise Similarly for FEB–DEC
YR79:	= 1	if the observation is from 1979; = 0 otherwise Similarly for YR80-YR83
Interaction Term with Some Appliances		
N		at the end of a variable name means that the variable is multiplied by NUM, defined under DEMOGRAPHIC
Appliances		
STOV:	= 1	if cooking range uses natural gas; = 0 otherwise
DRY:	= 1	if clothes dryer uses natural gas; = 0 otherwise
WAT:	= 1	if water heater uses natural gas; = 0 otherwise
JAC:	= 1	if there is a jacuzzi or hot tub; = 0 otherwise
WASH:	= 1	if WAT = 1 and there is a washing machine; = 0 otherwise
DISHWSH:	= 1	if WAT = 1 and there is a dishwasher; = 0 otherwise
EXHT:	= 1	if there is an additional room heater using natural gas; = 0 otherwise
SUBHEAT:	= 1	if main heating is natural gas and an additional room heater not natural gas; = 0 otherwise
MICRO:	= 1	if STOV = 1 and there is a microwave oven; = 0 otherwise
HEATDY:		if there is gas main heating and the month is November–May = the square footage of the dwelling unit multiplied times HMAX; = 0 otherwise

HEATNT:		if there is gas main heating and the month is November–May, = the square footage of the dwelling unit multiplied times HMIN; = 0 otherwise
POOLDY:		if there is a natural gas swimming pool heater, = the average daily high temperature for the month; = 0 otherwise
POOLNT:		if there is a natural gas swimming pool heater = the average daily low temperature for the month; = 0 otherwise
COOLDY:		if there is natural gas air conditioning and the month is May–October, = the square footage of the house multiplied times CMAX; = 0 otherwise
Interaction Terms with Main Heating and Swimming Pool Heaters		
HMAX:	=	the number of degrees by which 68 exceeds the average daily high temperature for the month; = 0 if 68 does not exceed the average daily high
HMIN:	=	the number of degrees by which 68 exceeds the average daily low temperature for the month; = 0 if 68 does not exceed the average daily low
CMAX:	=	the number of degrees by which the average daily high for the month exceeds 68; = 0 if the average daily high does not exceed 68
NWHTDY:	=	HEATDY if the dwelling unit age is 5 years or less; = 0 otherwise
NWHTNT:	=	HEATNT if the dwelling unit age is 5 years or less; = 0 otherwise
FA:	= 1	if gas main heating system is forced air; = 0 otherwise
AT:	= 1	if there is an attic; = 0 if no or partial attic
CI:	= 1	if at least 2 in. of ceiling insulation; = 0 otherwise
WI:	= 1	if wall insulation; = 0 if no or partial wall insulation
Economic Variables (All Prices Are Deflated to February 1979 Using the Monthly Consumer Price Index)		
SQFT:	=	the square footage of the dwelling unit
INCM:	=	total household income
PAP:	=	the predicted average price
PMP:	=	the predicted marginal price
PLS:	=	the predicted lump sum subsidy, which equals the minimum of \$1.00, or the sum of the differences between the prices of the marginal unit and each intramarginal unit minus the fixed connection charge
PAPHEAT:	=	the predicted average price if there is a gas main heating system; = 0 otherwise
PMPHEAT:	=	the predicted marginal price if there is a gas main heating system; = 0 otherwise
Transformation of Economic Variables		
XBC:	=	$(X^{\lambda} - 1)/\lambda$, where X is an economic variable and $0 < \lambda \leq 1$
PAPHTBC:	=	PAPBC if there is gas main heating and the month is November–May; = 0 otherwise
PMPHTBC:	=	PMPBC if there is gas main heating and the month is November–May; = 0 otherwise

wealth effects (the microwave) or an inefficient main gas-heating system (the extra nongas heater).

Three of the gas-using home appliances are expected to be heavily dependent on weather conditions: main heating, main cooling, and swimming pool heaters. Given the general climate of the area, it is reasonable to constrain the main heating to be off from June through October and the main cooling to be off from November through April. In other months, indices of heating and cooling requirements with reference to a 68°F base are constructed. Because the daily temperature variation may be large, averaging 20°F differences between high and low for some months, we construct one index based on the average daily high (daytime requirements) and another based on the average daily low (nighttime requirements).

The day heating requirement index is defined as zero if the average daily high exceeds 68°F for that month, and equals the difference between the average daily high and 68°F otherwise. The night heating requirement is defined similarly, substituting the average daily low for the average daily high. The day cooling requirement index is defined analogously: zero if the average daily high is below 68°F and the difference between the high and 68°F otherwise.[16]

Finally, the gas space heating and cooling indices are defined as the relevant temperature index times the square footage of the house whenever the dwelling unit contains gas main heating or cooling (and the month is not one in which the appliance is constrained to be off). The day and night space heating indices are included independently and in interaction with several other dummy variables: the type of gas heating (forced air or other) and the house insulation variables mentioned earlier. The swimming pool heating indices are defined simply as the average daily high and low temperatures for the month whenever a gas pool heater is present.

The additional control variables in the model can be simply described. A regional dummy variable is included to discriminate between inland and coastal or maritime areas. Another dummy variable is included to distinguish single-family dwellings from others. Dummy variables are also used to indicate the age brackets (e.g., 45–54 or 55–64) of the adults and whether a young child (5 years of age or less) is present. Additional variables representing socioeconomic characteristics are included: the number of people in the household, the educational level of the head (measured on a scale of 0 through 8), and the income level of the head. The last was estimated by using the midpoints of the first 9 income brackets identified by the survey, and through an auxiliary regression based on Pareto's Law to estimate the mean income in the 10th and highest bracket of $50,000 and over.[17]

Let us turn now to the econometric procedures. One problem is how to deal with the simultaneity problem. There are both demand and supply functions that relate price (or cost) and quantity. The demand function is observed with errors, whereas the supply function is not. This suggests that ordinary least squares (OLS) estimates will be biased toward the supply parameters. To deal with this, I use an instrumental variable approach used by Hausman and Wise (1976) for labor supply and later used by Hausman, Kinnucan, and McFadden (1979) for residential energy demand.[18] An unbiased estimate of predicted quantity is made by regressing all of the exogenous variables on actual quantity. This predicted quantity is then used with the known rate schedule to determine the predicted average price (for the BR hypothesis), as well as the predicted marginal price and predicted lump sum subsidy (the latter two for the SUM hypothesis).[19] These series are then used with the other model variables to estimate the structural demand equations associated with each of the two behavioral hypotheses.

Another econometric problem to contend with concerns the pooling of time series and cross-sectional data. Using a Cobb–Douglas functional form, the data determine temporal groupings through a series of structural homogeneity (Chow) tests. I sought the fewest equations possible in order to reduce the chances for ambiguous results of the main tests of the behavioral hypotheses. I began with one equation (for each hypothesis) using all 53 months of data with month and year temporal dummies, and tested it for homogeneity against two equations in which the 6 summer months per year and 6 winter months per year were estimated separately. Structural homogeneity was rejected, and I continued the process (next testing each of the 6-month equations against two 3-month equations, etc.). The result was four stable monthly groupings, each including all years, as shown at the top of Tables 6.2 and 6.3.

An important finding of this testing is that there is a great deal of stability over the years: All of the monthly equations are stable (i.e., homogeneity cannot be rejected) over the 4.5-year period. Relative to 1979, consumption in the later years either decreased or changed insignificantly; there is only one case (May–June 1980) where consumption increased significantly. This suggests that any uncontrolled changes

Table 6.2. *Bounded Rationality Model Estimates (Asymptotic t-Statistics in Parentheses)*

Variable	Feb.–Apr.	May–June	July–Oct.	Nov.–Jan.
INTERCEPT	−2.11226	−2.47123	−1.74154	−1.25908
	(5.66)	(5.34)	(7.45)	(4.13)
EDUC	−.02145	−.02527	−.01075	−.00917
	(4.58)	(4.26)	(2.22)	(1.66)
PREBOOM	−.05342	−.01433	.02341	−.04248
	(2.28)	(.48)	(.98)	(1.53)
MIDDLE	.08394	.07120	.13947	.13699
	(4.24)	(2.82)	(6.74)	(5.79)
MATURE	.15355	.09504	.04671	.24057
	(6.90)	(3.41)	(2.07)	(9.01)
ELDER	.15081	.11203	.10218	.15858
	(5.02)	(2.97)	(3.28)	(4.46)
BABY	−.03487	.04212	.15286	.03389
	(1.12)	(1.06)	(4.75)	(.91)
NUM	−.03640	−.04482	−.02615	−.03479
	(2.78)	(2.73)	(1.90)	(2.20)
INLAND	.08967	.10305	−.00499	−.03109
	(3.84)	(3.46)	(.21)	(1.12)
SFHOME	.11598	.01768	−.00178	.11746
	(3.91)	(.49)	(.06)	(3.40)
STOVN	.00957	.03034	.05940	.01291
	(1.54)	(3.83)	(9.33)	(1.74)
DRYN	.03202	.02817	.03878	.02576
	(6.00)	(4.15)	(7.10)	(4.08)
WATN	.02517	.06408	.03229	.01984
	(1.52)	(3.08)	(1.90)	(1.00)
JACN	.02021	.00729	.02760	.02496
	(1.82)	(.53)	(2.53)	(1.90)
WASHN	.03070	.00913	.00295	.05119
	(2.45)	(.58)	(.23)	(3.46)
DISHWSHN	.00429	.00690	.02302	.00035
	(.68)	(.86)	(3.59)	(.05)
EXHT	.29875	−.25303	−.41563	.17326
	(3.42)	(2.29)	(4.57)	(1.66)
SUBHEAT	.03038	−.00554	−.06352	−.01754
	(1.62)	(.24)	(3.46)	(.78)
MICRO	.04715	.07874	.11806	.08560
	(1.75)	(2.32)	(4.36)	(2.67)
HEATDY	−.10052	−.05048	—	.14588
	(.72)	(.12)		(.87)
HEATNT	.00297	−.02023	—	−.01247
	(.18)	(.62)		(.67)

Variable	Feb.–Apr.	May–June	July–Oct.	Nov.–Jan.
NWHTDY	−.07330	.28229	—	−.05798
	(.62)	(.87)		(.44)
NWHTNT	−.04953	−.05825	—	−.04623
	(6.00)	(3.00)		(5.57)
FAHEATDY	.57262	.44781	—	.36238
	(4.21)	(1.10)		(2.40)
FAHEATNT	.01351	−.00292	—	.01427
	(1.57)	(.13)		(1.60)
ATHEATDY	.04167	.08997	—	.16969
	(.38)	(.27)		(1.46)
ATHEATNT	−.00210	−.00355	—	−.02192
	(.29)	(.20)		(2.88)
CIHEATDY	−.34138	.64391	—	−.42346
	(2.52)	(1.63)		(2.91)
CIHEATNT	.00852	.05385	—	.02371
	(.88)	(2.28)		(2.33)
WIHEATDY	−.05285	−.15612	—	−.04512
	(.48)	(.48)		(.36)
WIHEATNT	.03630	.04234	—	.01066
	(4.98)	(2.37)		(1.41)
POOLDY	.01403	.00810	.02131	.01925
	(2.82)	(1.84)	(6.33)	(4.13)
POOLNT	−.02655	−.01507	−.03122	−.03568
	(3.75)	(2.57)	(6.87)	(4.93)
COOLDY	—	.08888	.06307	—
		(3.06)	(4.11)	
YR80	−.17285	.14516	−.07638	−.10879
	(4.41)	(2.93)	(3.32)	(3.58)
YR81	−.19917	−.06206	−.14163	−.25568
	(3.77)	(.80)	(5.70)	(7.80)
YR82	−.13535	.05382	−.04660	−.10263
	(2.11)	(.55)	(1.08)	(1.82)
YR83	−.11774	.24893	—	−.10905
	(.99)	(1.53)		(1.21)
JAN.	—	—	—	.21508
				(5.23)
FEB.	.28879	—	—	—
	(13.02)			
MAR.	.13812	—	—	—
	(7.10)			

(continued)

Table 6.2 *(continued)*

Variable	Feb.–Apr.	May–June	July–Oct.	Nov.–Jan.
MAY	—	.11402	—	—
		(2.11)		
JULY	—	—	.02044	—
			(.78)	
AUG.	—	—	−.04845	—
			(2.09)	
SEP.	—	—	−.07977	—
			(3.52)	
NOV.	—	—	—	−.47429
				(17.92)
SQFTBC	.02986	.01824	.01854	.03500
	(9.95)	(9.11)	(12.32)	(9.32)
INCBC	.00454	.00235	.00178	.00412
	(8.72)	(5.97)	(5.66)	(6.73)
PAPBC	−.43923	−1.20395	−.70913	.45076
	(1.32)	(2.75)	(2.73)	(1.40)
PAPHTBC	−.10008	−.04493	—	−.17153
	(2.06)	(.74)		(2.72)
n	3163	2263	3599	2750
λ	.35	.40	.40	.35

over the time of the sample are an unlikely source of bias. This would apply, for example, to changes in the appliance stock of households over this period. Furthermore, a bill formatting change implemented during 1981 to provide some additional information (but not the complete rate structure) seems to have had an insignificant impact (one would expect consumption to increase if the BR hypothesized here was reduced; the trend, however, was in the opposite direction).

The Goldfeld–Quandt tests were used to check for heteroskedasticity, and the hypothesis of homoskedasticty was maintained. Finally, the Box–Cox technique was used to determine a precise functional form. The dependent variable (divided by its geometric mean for normalization) and those identified as the economic variables in Table 6.1 were subjected to the Box–Cox transformation, choosing the minimum sum of squared errors (SSE) within the range for the transformation parameter λ of $0 < \lambda \leq 1$. The transformation parameters were estimated at .35 for two equations and .40 for the other two (the same across the competing behavioral specifications); since the 95% confidence interval in each

Table 6.3. *Utility-Maximization Model Estimates (Asymptotic t-Statistics in Parentheses)*

Variable	Feb.–Apr.	May–June	July–Oct.	Nov.–Jan.
INTERCEPT	−1.34111	−1.00308	−1.14238	−1.70339
	(2.83)	(3.94)	(4.78)	(6.17)
EDUC	−.02228	−.02708	−.01209	−.00907
	(4.74)	(4.58)	(2.49)	(1.64)
PREBOOM	−.05977	−.01734	.02197	−.04268
	(2.55)	(.58)	(.92)	(1.54)
MIDDLE	.08896	.07452	.14837	.13417
	(4.45)	(2.95)	(7.14)	(5.71)
MATURE	.16220	.10012	.05147	.23698
	(7.11)	(3.58)	(2.28)	(8.96)
ELDER	.15923	.11842	.10110	.15999
	(5.23)	(3.13)	(3.22)	(4.47)
BABY	−.04146	.04594	.16218	.03164
	(1.32)	(1.16)	(5.04)	(.86)
NUM	−.03735	−.04616	−.02984	−.03319
	(2.85)	(2.80)	(2.17)	(2.10)
INLAND	.09514	.12557	.00199	−.03198
	(4.09)	(4.32)	(.08)	(1.14)
SFHOME	.12077	.03032	.00145	.10928
	(4.15)	(.84)	(.05)	(3.19)
STOVN	.00973	.03062	.06025	.01305
	(1.56)	(3.85)	(9.28)	(1.76)
DRYN	.03391	.03031	.03916	.02546
	(6.34)	(4.48)	(7.13)	(4.04)
WATN	.02636	.06971	.03607	.01776
	(1.59)	(3.37)	(2.13)	(.89)
JACN	.02178	.01037	.02643	.02595
	(1.96)	(.75)	(2.42)	(1.97)
WASHN	.03266	.00695	.00366	.05142
	(2.59)	(.44)	(.29)	(3.46)
DISHWSHN	.00507	.00688	.02376	.00029
	(.80)	(.85)	(3.68)	(.04)
EXHT	.32296	−.23120	−.46814	.16801
	(3.68)	(2.09)	(5.26)	(1.61)
SUBHEAT	.03096	−.00253	−.06343	−.01791
	(1.65)	(.11)	(3.44)	(.80)
MICRO	.05095	.08999	.12220	.08312
	(1.89)	(2.66)	(4.45)	(2.61)
HEATDY	−.09356	−.12221	—	.13114
	(.67)	(.29)		(.79)

(continued)

Table 6.3 *(continued)*

Variable	Feb.–Apr.	May–June	July–Oct.	Nov.–Jan.
HEATNT	.00288	−0.2387	—	−0.1430
	(.17)	(.73)	—	(.78)
NWHTDY	−.08008	.24248	—	−.04544
	(.68)	(.75)		(.35)
NWHTNT	−.05135	−.05776	—	−.04696
	(6.19)	(2.91)		(5.62)
FAHEATDY	.57013	.47852	—	.36594
	(4.20)	(1.17)		(2.43)
FAHEATNT	.01482	.00104	—	.01437
	(1.72)	(.05)		(1.61)
ATHEATDY	.04501	.12329	—	.16931
	(.41)	(.36)		(1.46)
ATHEATNT	−.00137	−.00291	—	−.02105
	(.19)	(.16)		(2.77)
CIHEATDY	−.35015	−.64429	—	−.42761
	(2.58)	(1.63)		(2.93)
CIHEATNT	.00861	.05147	—	.02347
	(.89)	(2.18)		(2.31)
WIHEATDY	−.03755	−.12527	—	−.05346
	(.34)	(.39)		(.42)
WIHEATNT	.03704	.04110	—	.01154
	(5.09)	(2.27)		(1.53)
POOLDY	.01397	.00836	.02321	.01843
	(2.81)	(1.90)	(7.01)	(4.02)
POOLNT	−.02688	−.01589	−.03409	−.03432
	(3.79)	(2.71)	(7.68)	(4.84)
COOLDY	—	.08953	.06109	—
		(3.08)	(3.93)	
YR80	−.25741	.02636	−.07173	−.09960
	(6.13)	(.69)	(3.03)	(3.22)
YR81	−.33014	−.28920	−.16539	−.23402
	(5.09)	(5.90)	(6.61)	(6.82)
YR82	−.28987	−.25233	−.14442	−.03070
	(3.62)	(3.90)	(3.69)	(.57)
YR83	−.40709	−.26249	—	.00531
	(2.68)	(2.96)		(.07)
JAN.	—	—	—	.175220?
				(5.59)
FEB.	.31350	—	—	—
	(15.05)			
MAR.	.14556	—	—	—
	(7.37)			

Variable	Feb.–Apr.	May–June	July–Oct.	Nov.–Jan.
MAY	—	.16266	—	—
		(3.03)		
JULY	—	—	−.05342	—
			(2.27)	
AUG.	—	—	−.03934	—
			(1.69)	
SEP.	—	—	−.07956	—
			(3.50)	
NOV.	—	—	—	−.45977
				(18.66)
SQFTBC	.03162	.01969	.01970	.03491
	(10.82)	(10.15)	(13.43)	(9.57)
INCBC	.00477	.00244	.00184	.00416
	(8.92)	(6.11)	(5.763)	(6.70)
PLSBC	−.03410	−.01420	.02311	.00893
	(1.14)	(.50)	(.59)	(.39)
PMPBC	.27396	.18203	−.02136	.01549
	(.73)	(.92)	(.11)	(.07)
PMPHTBC	−.10956	−.05857	—	−.16157
	(2.43)	1.05)		(2.93)
n	3163	2263	3599	2750
λ	.35	.40	.40	.35

case is approximately ±.04, both Cobb–Douglas ($\lambda = 0$) and linear ($\lambda = 1$) forms must be rejected.[20]

Estimation Results

The estimates of the resulting structural demand equations are shown in Table 6.2 (for the BR hypothesis) and Table 6.3 (for the SUM hypothesis), and the regression means of the variables are shown in Table 6.4. For the noneconomic variables, there are only minor differences in the estimated coefficients and asymptotic standard errors across the behavioral models.[21] Among the demographic variables, education has the expected negative sign, and is clearly significant in three equations and marginally significant ($t = 1.65$) in the other. To illustrate its effect, an increase from 5 to 6 in education level (to some college beyond high school) implies just over a one therm reduction from the February–April

Table 6.4. *Means of Variables*

Variable	Feb.–Apr.	May–June	July–Oct.	Nov.–Jan.
SGASBC	.05730	.06963	.07112	.07683
EDUC	5.78185	5.76491	5.78327	5.78182
PREBOOM	.21499	.21167	.21756	.21455
MIDDLE	.29592	.29386	.29536	.29709
MATURE	.24850	.24967	.24979	.24727
ELDER	.12646	.12638	.12170	.12655
BABY	.10117	.10164	.10169	.09964
NUM	2.83070	2.82346	2.83857	2.82782
INLAND	.15839	.15952	.16088	.15891
SFHOME	.86374	.86213	.86079	.86073
STOVN	1.35093	1.36036	1.36774	1.36436
DRYN	1.31552	1.30137	1.32870	1.31236
WATN	2.63468	2.62329	2.66032	2.63636
JACN	.22321	.21807	.22048	.22218
WASHN	2.41827	2.40544	2.44248	2.42054
DISHWSHN	1.61650	1.60384	1.62656	1.61727
EXHT	.00885	.00884	.00889	.00873
SUBHEAT	.36390	.36058	.35621	.36073
MICRO	.13405	.13257	.13365	.13455
HEATDY	.07969	.01622	—	.08657
HEATNT	2.58693	.84917	—	3.01011
NWHTDY	.02120	.00471	—	.02453
NWHTNT	.59913	.19452	—	.69472
FAHEATDY	.07969	.01280	—	.06754
FAHEATNT	2.58693	.62565	—	2.22417
ATHEATDY	.05599	.01168	—	.06014
ATHEATNT	1.76510	.57727	—	2.05753
CIHEATDY	.05893	.01192	—	.06521
CIHEATNT	2.04061	.66683	—	2.39086
WIHEATDY	.02948	.00644	—	.03153
WIHEATNT	.82451	.27293	—	.95553
POOLDY	5.85686	6.41361	6.97102	6.03764
POOLNT	4.09583	4.79992	5.18052	3.88838
COOLDY	—	.04067	.07319	—
YR80	.21530	.19841	.24535	.25382
YR81	.21530	.20415	.25507	.24582
YR82	.21562	.19973	.25452	.25018
YR83	.21910	.20548	—	.08364
JAN.	—	—	—	.33636
FEB.	.28612	—	—	—
MAR.	.35694	—	—	—

Variable	Feb.–Apr.	May–June	July–Oct.	Nov.–Jan.
MAY	—	.50155	—	—
JULY	—	—	.25035	—
AUG.	—	—	.24423	—
SEP.	—	—	.25063	—
NOV.	—	—	—	.32982
SQFTBC	33.64066	43.49570	43.53626	33.61666
INCBC	92.31331	135.01849	135.20256	92.10303
PAPBC	−1.01527	−.97226	−.93193	−.98888
PAPHTBC	−.94061	−.45895	—	−.91583
PLSBC	.50407	.03297	−.09317	−.06892
PMPBC	−1.01698	−1.00041	−1.01942	−1.06751
PMPHTBC	−.93909	−.48308	—	−.98618

monthly mean of 55 therms. From this same mean, the difference between the least and most educated households is 8.6 therms.

Among the other demographic variables, household consumption generally increases with the age of the head. The negative coefficient on the number of people in the household is a bit misleading; the number of people is also interacted with most of the natural-gas-using appliances, all of which have the right sign and some of which all households have. Increases in number at the mean have the expected positive effects on consumption. Those households located inland generally use more energy than others, and single-family homes generally use more energy than other dwellings.

All of the appliances have the correct signs with two minor exceptions. Having an extra (natural-gas-using) heater seems to reduce consumption in May through October, and having a microwave oven (assumed to be a substitute for a natural-gas-using appliance) is associated with increased gas consumption.[22]

The effects of the main home heating appliance are not transparent because they work through 12 complex variables. Nevertheless, new homes are more efficient than older ones, and insulation does reduce consumption. For example, dwelling units with attics enjoy an average reduction of consumption of between 3 and 4 therms per month during the November–January period, or about 7% of mean consumption.

Swimming pool heaters do not have strong effects in this sample; the two variables measuring high and low temperatures for residences with pool heaters are each significant but together largely offsetting.

Nevertheless, the estimates suggest, as expected, that higher temperatures (e.g., a 1°F increase in both the high and the low temperature) tend to reduce consumption. Finally, homes with air conditioners powered by natural gas do have substantially higher consumption in May through October.

To sum up, the estimated effects of the noneconomic variables are in accord with expectations. Almost all of them are significant, with the expected signs and coefficients of plausible magnitudes.

The economic variables represent wealth, income, and price factors. The square footage variable, interpreted here as a wealth proxy, is strongly significant in all equations. The elasticity of consumption with respect to wealth is approximately constant across the estimated equations from .34 in the July–October period to .38 in February–April. The income elasticity is also positive and significant in all equations, from .10 in July–October to .15 in February–April. Both of these are quite inelastic, as one should expect when the appliance stock is being held constant.

Turning to the price variables, it now becomes important to consider the estimates from the competing models separately. Under the BR hypothesis, there are seven price variables in the four equations. Four of these variables are negative and significant, two are negative but not significant, and one is positive but not significant. The elasticities associated with these estimates at the sample geometric means are shown in Table 6.5. Over a year, the average short-run elasticity is −.25 for residences with natural gas heating and −.19 for those without natural gas heating. These estimates certainly are close to what one would expect a priori.

Table 6.5. *Summary of Price Elasticity Estimates from the Box–Cox Estimations*

Period	Residences w/o Gas Heating		Residences with Gas Heating		Therms at Sample Geometric Means
	BR	*SUM*	*BR*	*SUM*	
Feb.–Apr.	−.28	+.08	−.34	+.10	55.12
May–June	−.72	+.11	−.74	+.07	31.16
July–Oct.	−.43	−.01	−.43	−.01	21.59
Nov.–Jan.	+.29	+.01	+.18	−.09	49.20
Monthly average	−.19	+.08	−.25	+.02	44.32

Under the SUM hypothesis, there are seven marginal price variables analogous to the average price variables discussed previously. Five of the seven variables are not significant, two with negative signs and three with positive signs. Two are negative and significant. Table 6.5 shows the implied elasticities at the means. Over the year, the average short-run elasticity is slightly positive, .02 for gas-heated residences and .08 for others. These estimates are somewhat disappointing if the underlying theory is valid; they imply that consumers are simply not detectably sensitive to price in the short run. Although some consumers may in fact be insensitive, one would hope that in a sample as detailed as this one, with the length of time and magnitude of price changes covered, a detectable negative response would be identified.

In addition to the seven marginal price variables of this specification, there are four lump-sum subsidy variables. These are all insignificant, two with negative signs and two with positive signs. Although a strict interpretation of the theory implies that these variables should have effects identical to those of the income variables, I do not find the insignificance disturbing. After all, the size of the lump-sum subsidy is almost always under $20, and the expected effect of this on therm consumption (given the sample incomes and income elasticities reported earlier) is so small that it would strain credulity to believe it could be reliably detected.

Finally, I note that there may be an interpretable seasonal pattern to the BR price elasticity estimates reported in Table 6.5. Bills are highest in the February–April period, which may heighten sensitivity in the following May–June period. As bills decrease due to seasonal factors, price sensitivity decreases with a lag. Responding to the lowest bills in July–October, consumers display the least price sensitivity during November–January. But then bills increase sharply, and price sensitivity grows again in February–April. One cannot offer this interpretation under the SUM hypothesis, where the estimates suggest a constant insensitivity.

Hypothesis Testing

There are three types of tests I use to evaluate the two competing hypotheses. The first one is not really a formal test and has already been described: the plausibility of the estimated price effects under each hypothesis. Although this "test" is by its nature and with respect to actual results hardly definitive, the only plausible inference is that the results discussed earlier favor somewhat the BR hypothesis. The degree to which it is favored depends on the strength of convictions concerning the detectability of small, negative price effects. Virtually all prior econometric studies of home energy consumption in the short run, unconcerned with the hypotheses under examination here, have maintained the expectation of detecting small, statistically significant negative price effects. By extension, one ought to maintain that expectation here as well, and therefore the results favor the BR hypothesis.

The second and third tests are more formal. The second test consists of a series of *J*-tests on the estimated demand equations. The *J*-test is appropriate when there are two competing models and one data set used to explain the same dependent variable. It essentially adds to the model being tested an additional right-hand-side variable of predicted consumption based on the alternative model; if this additional variable is significant based upon its *t*-statistic, then one rejects the model being tested in favor of the alternative (see Ram, 1986, for another example).

Column 2 of Table 6.6 reports the results of the tests with the null hypothesis that the BR model is true and the SUM model is false. Column 3 reports the results of testing the reverse null hypothesis that SUM is true and BR is false. Columns 4 and 5 summarize the results. At the 1% level, the BR hypothesis is supported in two of four periods (the lower consumption periods), and SUM is not supported in any period. This unambiguously favors BR. At the weaker 5% level, however, some ambiguity is introduced: There is no additional support for BR, but SUM is now supported in three of the four periods (the higher-consumption

Table 6.6. *J-Tests of Estimated Equations (T-Ratios)*

Period	H_0: BR Is True and SUM Is False	H_0: SUM Is True and BR Is False	Supported Hypothesis (Level = .01)	Supported Hypothesis (Level = .05)
Feb.–Apr.	2.42*	.34		SUM
May–June	2.54*	3.91**	BR	BR, SUM
July–Oct.	1.95	3.39**	BR	BR
Nov.–Jan.	2.06*	.54		SUM

*$t > 1.97$, the 5% level.
**$t > 2.60$, the 1% level.

periods). Since it is difficult to argue that there is one "right" testing level for making the comparison, I conclude that the *J*-tests by themselves do not show which hypothesis should be preferred.

These results may not be very surprising. It is tempting to offer the interpretation that consumers pay more attention to their bills in the higher-consumption months (i.e., behave closer to SUM) and less in the lower-consumption months (i.e., behave closer to BR). If one relates these tests to the estimated price elasticities, this conclusion is reasonable for November–January. It is the one period in which the elasticities from both models for gas-heated residences are insignificant, with the wrong sign for BR and the right sign for SUM. However, the results for February–April do not really support this interpretation. The *J*-test offers weak support for the SUM model with an insignificant but positive price elasticity of .10 for gas-heated residences, but not for the BR model with a significant and negative elasticity of −.34.

The third test is designed to be the most important: comparing the predictions of the two models on an independent sample. A new 1% sample was drawn from the master tape, with the restriction that only residences with square footage exceeding 1,050 be selected. This restriction served two purposes: (1) it ensured that the distribution of the random sample would not be identical to the distribution of the estimating sample; and (2) recalling that the two hypotheses had the greatest predictive difference for households with consumption exceeding the lifeline amount, it tilted the test sample toward those households.

There are 2,738 monthly observations in this sample, and the results of the prediction tests are shown in Table 6.7. For each of the structural equations, predicted consumption is compared with actual consumption and the root mean square is calculated. In three of the four equations,

Table 6.7. *Prediction Accuracy on New Sample with SQFT > 1,050 (Root Mean Squares)*

Period	*n*	BR	SUM	Supported Hypothesis
Feb.–Apr.	732	27.88	28.76	BR
May–June	528	21.83	22.07	BR
July–Oct.	845	13.65	13.84	BR
Nov.–Jan.	633	26.74	26.49	U-Max
Total	2738	22.86	23.16	BR

Table 6.8. *Summary Table of Three Tests*

Period	Significant Negative Price Effects	*J*-Test .01 Level	*J*-Test .05 Level	Predictive Accuracy
Feb.–Apr.	BR		SUM	BR
May–June	BR	BR	BR, SUM	BR
July–Oct.	BR	BR	BR	BR
Nov.–Jan.	SUM		SUM	SUM
Overall	BR	BR	?	BR

BR has lower root mean squares and is thus more accurate than SUM. SUM does better only in the November–January period, and recall that it is the one period for which a comparison of the estimated price effects does not favor BR. For the overall prediction test, shown in the last row of Table 6.7, the BR model is more accurate.

In Table 6.8, I attempt to summarize the results of each test for each structural equation. Each cell in the table reports the hypothesis favored by a particular test. Column 2 reports the favored hypothesis based on the expectation of negative price effects, columns 3 and 4 based on the *J*-test, and column 5 based on predictive accuracy. The first four rows represent the four structural equations, and the final row is an overall assessment. It is clear that in three of the four periods, and overall, the preponderance of the evidence favors the BR model.

Concluding Observations

The tests reported here are designed to answer one question about residential energy consumption under block rate pricing structures. The question is: If we are to choose one of two alternative behavioral models to represent household behavior, which one is best? For this study, the answer is the Bounded Rationality (BR) model: Household behavior is better explained and predicted by the model, assuming that households respond simply to the total bill, compared to the SUM model, which assumes that households maximize utility subject to the actual block rate structure.

What other questions are raised by the results reported here? Just how poorly does the SUM model fare? In the November–January period, the standard model works better. This makes one wonder if perhaps consumers put more effort into their decision making as the stakes go up. Perhaps, by extension, consumers in the San Diego area, due to its moderate climate, are not typical of consumers living in less moderate climates. This is certainly worth exploring, although the results reported here do not fully support this idea: The stakes here are highest in February–April, and in this period the BR model generates more plausible price elasticities and better predictions.

The preceding idea sticks with the notion of households characterized by identical decision-making processes; the precise routine used for any particular situation varies with the importance of the situation. Of course, households need not all be characterized by the same type of decision making. It is certainly possible that one could better explain and predict behavior (holding the decision-making environment constant) by classifying each household into one of the two models and using both. That is, one could imagine concluding that the SUM model works best for, say, 30% of the population and the BR model is best for the other 70%. Again, this is certainly worth exploring, but it does work against the objective of model simplicity that has characterized economic research heretofore.

Are the welfare implications of these results important for energy allocation? I believe the answer is yes, primarily because it is so common to observe large price differences (of 50 to 100%) across blocks, and under BR such differences create large errors. Take the example of a household with short-run price elasticity of −.25 facing a rate structure with a 50% price increase for the second block and consuming a modest 20% above the first block size (such a household is near the average in northern California). If this consumption choice is due to BR, then the overconsumption is about 8%, the overexpenditure is about 12%, and the net loss from the consumer's perspective is about 2% of expenditure.[23] These figures become substantially larger if the behavior extends to long-run decision making, where price elasticities are thought to be in the elastic range. Thus it is certainly worthwhile to consider whether or not there are cost-effective policies by which one might reduce these errors.

One can imagine trying to reduce the errors through two types of strategies: information provision and changes in the rate structure. For example, each bill might include a message of the following sort: "10% less consumption would have saved you $8.20." However, if such information provision has effects similar to those generally reported in studies of information provision, it is unlikely to eliminate the majority of errors and thus a substantial problem will remain.[24]

Thus one might consider alterations in the rate design itself. Of course, economists have long advocated changes to bring rates more in line with marginal costs. It is interesting to note that the two-part tariff idea, with rates uniform at marginal costs and a fixed customer charge assessed to raise the rest of the utility's revenue requirement, has good potential for solving the BR problem as well. If the fixed charge could be assessed separately from the monthly consumption charges, substantial efficiency gains would be predicted (for different reasons) by both models compared to the block rate structures now in common use.

Finally, the results reported here raise the issue of whether similar behavior may be found in other areas. It would, of course, be natural to explore the BR hypothesis for other difficult consumption choices subject to block rate structures, like that of commercial and even industrial energy customers, or for other services like telephones or water delivery. More intriguing still is the question of whether this behavior characterizes other choices made under nonlinear price structures, like the labor-leisure choices of those eligible for income-support programs, or choices made nonlinear by complex tax rules such as child-care expenditures or many investments. And the possibility exists, as suggested by the earlier example of household budgeting in general, that this behavior may characterize certain difficult choices under normal price structures.

Notes

1 Herbert Simon has been a long-time proponent of these models. See, for example, Simon (1959, 1979). More recently, Richard Thaler (1980, 1985) has made numerous modeling contributions in this vein.

2 A good discussion of these is contained in Lesourne (1977). See also Machina (1987, 1989) and Camerer and Kunreuther (1989). Much of the debate has focused on individual responses to uncertainty, particularly low-probability events like the reliability of electricity (see Hartman, Doane, & woo, 1991), or insurance purchases in earthquake- or flood-prone areas (see Kunreuther, 1976, and Brookshire, Thayer, Tschirhart, & Schulze, 1985). Sometimes the debate in this context is described as relevant only to utility-maximization, although Grether and Plott (1979) and Tversky, Slovic, and Kahneman (1990) make it clear that the debate extends to utility-maximization more generally.

3 For a discussion of testing difficulties, see Roth (1989).

4 See Smith (1989) for an introduction to and a summary of this literature. The same generalization can be applied to the public goods literature studying actual preference revelations more "honest" than those expected by conventional theory; see, e.g., Marwell and Ames (1981).

5 The effect of repetitive trials has also been considered in the public goods literature; see, e.g., Isaac, McHugh, and Plott (1985).

6 In the long run, the appliance stock would itself change in response to fuel prices. The short-run focus here avoids this issue.

7 In such a case, one still might be interested in the difficult problem of understanding the adjustment process. This research tests the central tendencies rather than the nature of adjustment around them. Research to test the nature of the adjustment process itself can potentially be useful for distinguishing LUM from BR models, which this research does not attempt. Such research would examine trial-and-error learning, and might distinguish between optimal and suboptimal trials.

8 Most BR models do not have a unique equilibrium, but rather a set of outcomes that satisfice and adjustments triggered only by outcomes outside of the satisficing range. Further assumptions would be required to specify such behavior here, and the main testable implication of a divergence in equilibrium between BR and SUM would be the same: The shift to a nonlinear rate structure has no effect on the midpoint of the set of satisficing points, although it does affect the SUM equilibrium.

9 *Overconsumption* and *underconsumption*, as used here, refer to deviations from the utility-maximizing choice, not to a social perspective. Evaluating the latter requires linking actual rates to true social costs, which is beyond the scope of this study.

10 Little attention has been given to the possibility of this type of consumer in the empirical literature on utility services. For electricity, there was an early debate (reviewed in Bohi, 1982) on the use of average versus marginal prices, but this was motivated by an entirely different issue: how to represent a block rate structure when each observation was an *aggregate* of consumers (many facing different marginal prices and each assumed to be utility-maximizing). Similarly, Taylor (1975) considered the use of average price to represent the income effect of intramarginal tiers relevant to a utility-maximizing consumer, although Nordin (1976) pointed out that this is incorrect and that the lump-sum subsidy must itself be calculated. Parti and Parti (1980) did use the average price as perceived by each household rather than the marginal price. However, the focal point of their work was not to debate or theorize about consumer behavior or price specification, but to construct their conditional demand model, which allows separate demand equations for each appliance to be inferred from the overall household demand equation. Keane and Aigner (1982) considered the possibility of bounded rationality in a different way. Using aggregate data with cities as the unit of observation they tested whether jointly billed customers (i.e., those with one bill for both natural gas and electricity) responded differently to price than other customers and found no significant differences. An interesting debate at the theoretical level occurred in the journal *Land Economics*, in which several authors raised the possibility that water consumers (facing block rates) respond to average price and discussed possible tests. See, for example, Opaluch (1984).

11 An excellent survey by Moffitt (1990) of estimation problems with nonlinear budget constraints did not discuss the type of bounded rationality problem under consideration here.

12 Nordin (1976) describes the theoretical treatment of the nonlinear rate structure.

13 The original tape contains an unfortunate but detectable compilation error that corrupts the consumption and billing data for 45% of the original 12,379

households. I am grateful to Steve Slezak for calling this to my attention. No important differences were found between the included and excluded observations in terms of demographics or physical characteristics of the dwelling unit; there are concentrations of excluded observations in a few geographic portions of the service area. The error was detectable because in each case the household time series had a few missing observations and then continued by repeating identically the earlier consumption and billing data.

14 Coding errors were presumed if the reported quantity combined with the rate structure for that time was inconsistent with the reported billing amount.

15 There are a small number of air conditioning systems run centrally on natural gas (1.7% of households in the master file), and potentially the insulating characteristics would also affect the energy required for cooling. However, in the sample we use here, such air conditioners are negligible in number and thus do not permit these interaction terms.

16 The sample had no positive observations with an analogously defined night cooling index, so no variable for it was included.

17 Pareto's Law states that the number of households (N) with incomes (Y) greater than the mean income of the population may be approximated as

$$N = \alpha Y^{\beta}$$

with parameters $\alpha > 0$ and $\beta < 0$. From this we may derive a simple expression for the total income contributed by households with income greater than \$50,000. First, note that the (negative) change in the number of households as Y increases can be expressed as the derivative:

$$\frac{\partial N}{\partial Y} = \beta\alpha Y^{\beta-1}$$

The contribution of this incremental group to total income is simply the negative of the preceding expression multiplied by Y:

$$-Y\left(\frac{\partial N}{\partial Y}\right) = -\beta\alpha Y^{\beta}$$

The integral of the preceding expression from $Y = \$50,000$ to $Y = \infty$ is the total income contributed by households with incomes in excess of \$50,000.

$$\int_{Y=\$50,000}^{Y=\infty} -\beta\alpha Y^{\beta} dy = \frac{\beta\alpha(50,000)^{\beta+1}}{\beta+1}$$

This expression can be used with the sample data to estimate the mean income level in the \$50,000 and up bracket. The mean income in the original survey was reported as \$21,800. In a preliminary sample drawn from the master tape, there were 90 households with income greater than \$30,000, 28 households exceeding \$40,000 in income, and 17 households reporting income in excess of \$50,000. These four observations were used to estimate the parameters α and

β from the basic Pareto equation by regression in logarithmic form (t-statistics in parentheses):

$$\begin{aligned}\ln N &= \ln\alpha + \beta \ln Y\\ &= \underset{(36.90)}{29.31977444} - \underset{(-32.26)}{2.44917816} \ln Y \qquad R^2 = .998\end{aligned}$$

Taking the antilog of the first term to solve for α, and then plugging the estimates of α and β into the equation for the value of the integral, we estimate that households with incomes of \$50,000 or greater have a total income of \$1,417,980.12 among them. Since there were 17 such households in the sample, we estimate the mean income for this group at \$83,411.

18 An alternative method with two error components, introduced by Burtless and Hausman (1978) and reviewed by Moffitt (1990), has advantages for dealing with observations at the kink points. This method is not used here for several reasons. First, one of the error components represents optimization error, which implies that observed behavior cannot be taken as utility-maximizing and is thus inconsistent with the purpose of this study. Second, the observations in this sample are very widely dispersed over the budget constraint, and do not cluster at the kink points where the alternative method gains its advantages.

19 A utility-maximizing equilibrium with a nonlinear constraint is described in terms of two effects: the effect of the marginal price and the income effect of the lump-sum subsidy caused by not charging the marginal price for the intramarginal units. See Nordin (1976).

20 An approximate 95% confidence interval for λ is found by solving for the two values of λ for which $\ln SSE(\lambda) - \ln SSE(\lambda) = 3.84/\text{d.f.}$, where 3.84 is from the chi-square distribution table with 1 degree of freedom and $p = .05$. See, e.g., Box and Draper (1987, pp. 289–291).

21 Tables 6.2 and 6.3 report asymptotic t-ratios: those approached as error due to the use of price instruments, estimated G's, and uncontrolled household preference effects vanish.

22 These are minor because it is, of course, possible to use the extra heater as a substitute for the main heating and to use the microwave as a complement to other gas cooking appliances.

23 It is important to distinguish this net loss calculation from the standard measures of relative efficiency. Due to the nature of utility regulation, there is no reason to assume that the actual marginal price faced by a consumer has any relation to the social cost of providing the marginal unit. This calculation is simply a measure of the importance of the household's error from its own perspective. The importance of these errors to efficiency depends on the relationships between actual rates and marginal social costs of electricity. The calculations are approximations made using a constant elasticity demand function and are similar for a linear function.

24 See, for example, the discussion of this point in Friedman and Hausker (1988) and the studies on energy consumption reviewed in Stern (1986). I have argued elsewhere (Friedman, 1991) that the effectiveness of other rate design policies in electricity pricing, such as interruptible service and time-of-day rates (and

its extension to continuous or real-time pricing), depends on the information provided about them and the ease with which consumers can understand and respond to them.

References

Bohi, D. (1982). Price elasticities of demand for energy: Evaluating the estimates. EPRI EA-2612. Palo Alto, CA: Electric Power Research Institute.

Box, G. E. P., & Draper, N. R. (1987). *Empirical model-building and response surfaces.* New York: Wiley.

Brookshire, D. S., Thayer, M., Tschirhart, J., & Schulze, W. (1985). A test of the Expected Utility Model: Evidence from earthquake risks. *Journal of Political Economy, 93,* 369–389.

Burtless, G., & Hausman, J. (1978). The effect of taxation on labour supply: Evaluating the Gary negative income tax experiment. *Journal of Political Economy, 86,* 1103–1130.

Camerer, C. F., & Kunreuther, H. (1989). Decision processes for low probability risks: Policy implications. *Journal of Policy Analysis and Management, 8,* 565–592.

Friedman, L. S. (1991). Energy utility pricing and customer response: The recent record in California. In R. Gilbert (Ed.), *Regulatory choices: A perspective on developments in energy policy* (pp. 10–62). Berkeley: University of California Press.

Friedman, L. S., & Hausker, K. (1988). Residential energy consumption: Models of consumer behavior and their implications for rate design. *Journal of Consumer Policy, 11,* 287–313.

Grether, D. M., & Plott, C. R. (1979). Economic theory of choice and the preference reversal phenomenon. *American Economic Review, 69,* 623–638.

Hartman, R. S., Doane, M. J., & Woo, C. K. (1991). Consumer rationality and the status quo. *Quarterly Journal of Economics, 106,* 141–162.

Hausman, J., Kinnucan, M., & McFadden, D. (1979). A two-level electricity demand model: Evaluation of the Connecticut time-of-day pricing test. *Journal of Econometrics, 10,* 263–289.

Hausman, J., & Wise, D. (1976). The evaluation of results from truncated samples: The New Jersey income maintenance experiment. *Annals of Economic and Social Measurement, 5,* 421–445.

Isaac, R. M., McHugh, K. F., & Plott, C. R. (1985). Public goods provision in an experimental environment. *Journal of Public Economics, 26,* 51–74.

Keane, D., & Aigner, D. J. (1982). Testing the joint billing effect hypothesis. *The Energy Journal, 3,* 113–128.

Kempton, W., & Montgomery, L. (1982). Folk quantification of energy. *Energy, 7,* 817–827.

Kunreuther, H. (1976). Limited knowledge and insurance protection. *Public Policy, 24,* 227–261.

Lesourne, J. (1977). *A theory of the individual for economic analysis.* New York: North-Holland.

Machina, M. J. (1987). Choice under uncertainty: Problems solved and unsolved. *Journal of Economic Perspectives, 1,* 121–154.

Machina, M. J. (1989). Dynamic consistency and non-expected utility models of choice under uncertainty. *Journal of Economic Literature, 27*, 1622–1668.

Marwell, G., & Ames, R. E. (1981). Economists free ride, does anyone else? Experiments on the provision of public goods, IV. *Journal of Public Economics, 15*, 295–310.

Moffitt, R. (1990). The econometrics of kinked budget constraints. *Journal of Economic Perspectives, 4*, 119–139.

Nordin, J. A. (1976). A proposed modification of Taylor's demand analysis: Comment. *Bell Journal of Economics, 7*, 719–721.

Opaluch, J. J. (1984). A test of consumer demand response to water prices: Reply. *Land Economics, 60*, 417–421.

Parti, M., & Parti, C. (1980). The total and appliance-specific conditional demand for electricity in the household sector. *Bell Journal of Economics, 11*, 309–321.

Ram, R. (1986). Government size and economic growth: A new framework and some evidence from cross-section and time-series data. *American Economic Review, 76*, 191–203.

Roth, T. P. (1989). *The present state of consumer theory*. Lanham, MD: University Press of America.

Simon, H. (1959). Theories of decision-making in economics and behavioral science. *American Economic Review, 49*, 223–283.

Simon, H. (1979). Rational decision making in business organizations. *American Economic Review, 69*, 493–513.

Smith, V. L. (1989). Theory, experiment and economics. *Journal of Economic Perspectives, 3*, 151–169.

Stern, P. (1986). Blind spots in policy analysis: What economics doesn't say about energy use. *Journal of Policy Analysis and Management, 5*, 200–227.

Taylor, L. D. (1975). The demand for electricity: A survey. *Bell Journal of Economics, 6*, 74–110.

Thaler, R. H. (1980). Toward a positive theory of consumer choice. *Journal of Economic Behavior and Organization, 1*, 39–60.

Thaler, R. H. (1985). Mental accounting and consumer choice. *Marketing Science, 4*, 199–214.

Tversky, A., Pal Slovic, P., & Kahneman, D. (1990). The causes of preference reversal. *American Economic Review, 80*, 204–217.