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# Individual discount rates and the purchase and utilization of energy-using durables

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*This article presents a model of individual behavior in the purchase and utilization of energy-using durables. The tradeoff between capital costs for more energy efficient appliances and operating costs for the appliances is emphasized. Using data on both the purchase and utilization of room air conditioners, the model is applied to a sample of households. The utilization equation indicates a relatively low price elasticity. The purchase equation, based on a discrete choice model, demonstrates that individuals do trade off capital costs and expected operating costs. The results also show that individuals use a discount rate of about 20 percent in making the tradeoff decision and that the discount rate varies inversely with income.*

## 1. Introduction

■ Most demand for energy at the household level is a derived demand of other activities: transportation, services of household appliances, and heating and cooling provide examples. Thus, energy demand may be viewed usefully as part of a "household" production process in which the services of a long-lived consumer durable good are combined with energy inputs to produce household services. From this perspective, two important components of energy demand emerge. First, the technological design of the consumer durable determines required energy input per unit of household service output. Automobiles, home air conditioners, and home heating systems provide three examples where important differences exist across models in required energy inputs. The second aspect of energy demand is the utilization of the household capital stock. The number of automobile trips, summer and winter house temperatures, and utilization of other household appliances determine the demand for final services, and thus total household energy demand.

Both components of energy demand, the capital stock decision and the final services or utilization decision, determine household energy consumption. Also, varying substitution and conservation possibilities exist in each component.

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Some appliances, such as household stoves, offer little possibility of substitution between higher capital costs and lower operating costs. Stoves also provide an example where only a very limited possibility of altering final household utilization exists. On the other hand, home heating and cooling systems provide important examples where tradeoffs between capital costs and operating costs are substantial. In addition, household final demand for heating and cooling can be altered quite easily.

Separating household energy demand into capital-stock and final-services components tends to emphasize the potential differences in short-run and long-run reactions to changes in relative prices. In the short run, holding the capital stock fixed, only demand for final services will change. Possibilities for large changes are often limited at this stage; and, in fact, the given capital stock will not be efficient in an *ex ante* sense if relative prices have changed after the appliance was purchased. In the longer run as the capital stock adjusts, the possibility of substitution becomes correspondingly greater. If operating costs (energy input prices) have increased, consumers will trade off higher initial capital costs against a reduction in operating costs. Technological or engineering considerations will determine the range of these possible tradeoffs, and their effect on final energy demand may often be substantial.

If an econometric model of energy demand is to be successful, it must allow for the different nature of the adjustment of the two components of household energy demand. Econometric models which do not differentiate the capital-stock decision from the utilization decision cannot capture the interplay of technological change and consumer choice in determining final energy demand. Engineering models which do not allow for consumer choice but instead assume that the "least cost" design is adopted will fail to capture the diversity of consumer behavior. In this paper, I attempt to develop a model which allows for the possibilities of technical substitution and for consumer choice in the capital stock decision. I develop a model for household demand of the final output of energy-using appliances and apply it to the purchase and utilization of room air conditioners. As the paper will demonstrate, room air conditioners offer a wide range of capital cost-energy efficiency tradeoffs. Thus, the consumer can choose that unit which most closely meets his needs. Furthermore, a wide range of utilization is possible, since setting the thermostat determines the amount of cooling consumed by the household.

Besides providing an excellent example of both the durable capital stock and utilization features of energy use, room air conditioners are an important source of energy demand. In a national survey of appliance ownership and utilization, 41.6 percent of the households surveyed owned room air conditioners—a percentage which is exceeded only by refrigerators and clothes washers for major electric appliances.[1] Average energy use on room air conditioners is near 1000 KWH per year which is 11.6 percent of total household electricity use. For those households which own air conditioners, during the summer months air conditioners generate upwards of one third of total electricity demand. Thus, households will be aware of electricity usage by air conditioners and will presumably make informed choices about the efficiency of units they purchase and also about their utilization of these units. Finally, room air con-

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[1] These data are collected in the Midwest Research Institute (MRI) study (1978) on appliance utilization. The survey will be discussed further in Section 3.

ditioners provide an important possibility for technical advance in energy savings improvements. The model estimated in this paper permits evaluation of market demand for such proposed new models. Here, however, I explore the choice among existing models and leave the question of new technologies for a future paper.

The specific model used to depict the durable-purchase decision is a qualitative choice model of Hausman and Wise (1975) which builds on earlier work of McFadden (1974). The qualitative choice model is a disaggregate model of individual behavior which specifies the determinants of individual choice in terms of the characteristics or attributes of the different possible alternatives. As used by Hausman and Wise, it also permits differences in individual preferences and optimization behavior which might arise because of different intended utilization and other unobserved factors. For instance, energy efficiency is only one of many characteristics which differentiate automobiles. Size, acceleration, and price are other relevant attributes which affect consumer choice. Qualitative choice models are well-suited for such applications where choices are made from a discrete number of possibilities and the possibilities can be characterized by their different attributes. Much of the energy-using household capital stock has this form, so that the qualitative choice model may have an important range of applications in the area of energy demand.

The plan of the paper is as follows. Section 2 specifies the qualitative choice model and utilization model used in the empirical work in the context of the particular application to be studied—the demand for and use of home air conditioners. Section 3 considers the technological possibilities for substitution among air conditioners and discusses the range of models available in terms of an earlier literature on "hedonic" prices. In Section 4 I discuss the data and estimate a distribution of durabilities for air conditioners. The estimates of utilization and of the qualitative choice model are reported in Section 5 along with a consideration of the effect of different relative prices on consumer choice. Section 6 contains a rather speculative discussion on the advisability of government policy action in regard to the particular parameter estimates found which tend to indicate a high rate of time discount among many consumers.

## 2. Model specification

■ Two aspects of consumer demand need to be captured in a model of household energy use: the initial purchase price of the appliance and the operating cost which determines the units of final demand for the household. To determine the effect of initial purchase price, let $\rho$ be the initial purchase price of an air conditioner with an expected durability of $q$ years. Using real prices and assuming no growth factors, the present value of the cost of owning the air conditioner is

$$\sum_{i=0}^{\infty} \frac{\rho}{1+r} \frac{1}{(1+r)^{iq}} = \frac{\rho}{1+r} \cdot \frac{1}{1-(1+r)^{-q}}, \tag{1}$$

where $r$ is the individual discount rate and we assume that the air conditioner is purchased in year 0 and replaced every $q$ years thereafter. Hence, in annualized terms, the cost of owning the air conditioner is

$$\frac{r}{1+r} \cdot \frac{\rho}{1-(1+r)^{-q}}.$$

The operating cost per degree hour is a function of the price of electricity $p$ ($\$/KWH$), the capacity of the air conditioner $BTU$ ($BTU$/hr.), the efficiency of the air conditioner $EER$ ($BTU/KWH$) and the room characteristics. Assume that the $BTU$/hr. required to cool a room one degree is given by a constant $\mu$ representing room characteristics. Then the operating cost per degree hour is

$$\pi = p\mu BTU/EER. \tag{2}$$

Given a choice of thermostat setting $\tau$ and the proportion of time spent at home $\eta$, the planned degree hours of operation $H$ are determined. For one hour of operation the cost is $\pi(Tout - Tin)$, where $Tout - Tin$ is the difference between outside and inside temperatures, since we assume that cost is a linear function of the temperature difference.

Thus, in annual cost terms the sum of the annualized value of the initial purchase price and the operating costs equals

$$TC = \frac{\rho r}{1 + r} \cdot \frac{1}{1 - (1 + r)^{-q}} + \pi H. \tag{3}$$

Note that $\rho$, $q$, $BTU$, $EER$, and $\pi$ are determined by the particular air conditioner chosen while, given these characteristics, $H$ is determined by the utilization decision of the household.

To model household decisions about purchase and utilization of an air conditioner we set up a utility model of the tradeoff between cost and a discomfort variable $z$ which represents dislike of high temperatures

$$u = u\left(y - \frac{\eta p \lambda H(\tau)}{EER} - \psi\rho,\ \eta z(\tau)\right). \tag{4}$$

The first term of the utility function represents income left from household income $y$ to spend on other goods, while the second term represents the discomfort of high temperatures. In writing the utility function in this manner, we assume that expenditure on air conditioning is sufficiently small that no income effect is present. In the specification in (4) $\eta$ is the proportion of time at home, $\lambda = \mu BTU$; and both degree hours of use, $H(\tau)$, and discomfort, $z(\tau)$, depend on the chosen thermostat setting $\tau$. The parameter $\psi$ represents the discount factor and the durability of the unit. $\psi = r/(1 + r)(1 - (1 + r)^{-q})$, where we have assumed durability $q$ is independent of $EER$'s of the model chosen and of its utilization.[2]

We now use the utility specification to determine purchase and utilization of room air conditioners. It is convenient to analyze the problem in reverse order, considering first the utilization for a given air conditioner. Then with optimal utilization given as a function of air conditioner characteristics, we solve for the optimal choice of air conditioner.

Suppose $F(t)$ is the (probability) distribution of number of hours per year with temperature less than or equal to $t$ and denote the associated density $f(t)$. Then degree-hours of utilization are

$$H(\tau) = \int_{\tau}^{\infty} (t - \tau)f(t)dt = \int_{\tau}^{\infty} tf(t)dt - \tau(1 - F(\tau)). \tag{5}$$

[2] In interpreting the results of the empirical analysis, this assumption will be relaxed somewhat. However, given that no durability data exist beyond what we have constructed in this paper, we are left with this assumption.

The derivative of degree hours with respect to temperature $H'(\tau) = -\int_\tau^\infty f(t)dt$. The discomfort measure $z(\tau)$ is defined by summing the degree-hours above 65°F (the point from which cooling degrees are measured) which the individual "suffers through:"

$$z(\tau) = \int_{65}^{\tau} tf(t)dt + \tau \int_{\tau}^{\infty} f(t)dt = \int_{65}^{\tau} tf(t)dt + \tau(1 - F(\tau)). \tag{6}$$

The derivative of the discomfort variable $z'(\tau) = \int_\tau^\infty f(t)dt$. For a given model of air conditioner the household chooses $\tau$ to maximize utility. The first-order condition is

$$\frac{\partial u}{\partial \tau} = u_1\left(-\frac{\eta p \lambda}{EER}\right)\left(-\int_\tau^\infty f(t)dt\right) + u_2\eta\left(\int_\tau^\infty f(t)dt\right), \tag{7}$$

where $u_i$ denotes the partial derivative of $u$ with respect to the $i$th argument. Setting the derivative equal to zero leads to the marginal condition:

$$-\frac{u_2}{u_1} = \frac{\eta p \lambda}{EER}. \tag{8}$$

Thus, the marginal rate of substitution between discomfort and the composite good is set equal to the marginal operating cost as expected.

To derive functional forms which can be used for purposes of estimation, we now specify the form of the temperature function $F(t)$ and the form of the utility function. In specifying the temperature function, it is convenient to use the complement of a cumulative distribution function. Thus, we define $G(T)$ to be the hours per year that the temperature is at $T$ *degrees or above* so that $-G'(T) = f(T)$ in terms of our previous derivation. The particular functional form we choose is the generalized exponential $G(T) = \gamma e^{-\alpha(T-T_0)}$ for $T > T_0$, where $T_0$ is taken to be 65°, the temperature origin for measuring cooling degree days. Then, the total number of yearly degree hours is

$$CDH = \int_{T_0}^{\infty} (t - T_0)g(t)dt = \frac{\gamma}{\alpha} \tag{9}$$

so that cooling degree days, $CDD = \gamma/24\alpha$. Let us now measure temperature in cooling degree units from $T_0$. It is straightforward to solve $H(\tau) = (\gamma/\alpha)e^{-\alpha\tau}$ and $z(\tau) = (\gamma/\alpha) - (\gamma/\alpha)e^{-\alpha\tau} = CDH - H(\tau)$. Thus, maximized utility with respect to utilization can be written as

$$u = u\left(y - \frac{\eta p \lambda H(\tau)}{EER} - \psi p,\ \eta(CDH - H(\tau))\right). \tag{10}$$

Total degree-hours of utilization $H(\tau)$ are not observable, but $KWH$/year are observed. We therefore choose a functional form for $u(\cdot)$ and solve for $KWH$/year to derive an equation which will form the basis for our utilization estimates. If $u$ is separable in its two arguments, the second-order conditions for a well-defined maximum will be met if $u_{11} \leq 0$ and $u_{22} < 0$. We thus choose to write the utility function in the linear form

$$u = y - \frac{\eta p \lambda H(\tau)}{EER} - \psi p - \eta m(z(\tau)), \tag{11}$$

where $m > 0$, and both $m'$ and $m''$ are positive.

We shall consider two forms of $m$ and choose between them on the basis of our estimation results. The first form is to let $m(z(\tau)) = (a/2)z^2$ with $a > 0$. The first-order condition from equation (8) is then $z(\tau) = p\lambda/(a \cdot EER)$ so that $H(\tau) = CDH - p\lambda/(a \cdot EER)$. Since $KWH$/year equal $H(\tau)$ times $\lambda$ divided by $EER$ and $\lambda = \mu BTU$, the utilization equation is

$$KWH = \frac{BTU}{EER}\left(\delta_1 CDH + \delta_2 \frac{pBTU}{EER}\right), \tag{12}$$

where the coefficients $\delta_1$ and $\delta_2$ represent $\eta$, $\mu$, and $a$. Note that we can estimate the price elasticity from this form. The second functional form we use is $m(z(\tau)) = be^{z(\tau)}$ with $b > 0$. Then, using similar calculations, we derive a partially log linear utilization equation,

$$KWH = \frac{BTU}{EER}\left(\delta_1' CDH + \delta_2' \log \frac{pBTU}{EER}\right). \tag{13}$$

Both of these utilization equations, (12) and (13), will be estimated in Section 5.

Once the utilization decision is given conditional on a specific type of air conditioner, we can derive the optimal model choice. Note that both capacity, $BTU$, and efficiency, $EER$, are choice variables. We shall assume that choice of capacity is determined exogenously—that is, without regard to price $\rho$ or utilization $H(\tau)$. Data exist which suggest that capacity is determined primarily by room size and climate conditions and not by a tradeoff between price and comfort.[3] The Consumer Reports Buying Guide (1978, p. 271) states

Sufficient cooling capacity is necessary to insure warm weather comfort. If you choose a unit that has too little capacity, it won't cool well. If it has too much, it may cool a room too fast to dehumidify adequately, leaving the room cool but clammy. . . . Any model you consider should have a cooling capacity, rated BTU/hr, within about 10% of your calculated needs.

The factors used to determine capacity are wall, ceiling, and floor areas, square feet of door and square feet of windows, and amount of sun through the windows. A multiplicative factor is then used for climate. The factor varies from 0.95 for Boston to 1.10 for Las Vegas. Thus, we take capacity as given and have individuals choose efficiency ($EER$) in their tradeoff between cost and discomfort.

The choice of air conditioner efficiency for a given size unit could be derived by differentiating equation (11) once we have chosen a form for $m(z(\tau))$. However, as our subsequent empirical work will demonstrate, the relationship between purchase price and $EER$ is rather complicated. Hence, instead of proceeding directly with equation (11), we use a qualitative choice formulation and assume that the individual chooses among low, medium, and high efficiency air conditioners.

Suppose we use the quadratic form for $m(z(\tau))$. Then for a given household we can use equation (11) to determine utility for air conditioner model $i$

$$u_i = y - \beta_1 pKWH_i - \beta_2 \rho_i - \beta_3(pBTU_i/EER)^2 + \omega_i, \quad i = 1, 2, 3, \tag{14}$$

where the parameters $\beta_h$ correspond to $\eta$, $\mu$, $a$, and $\psi$. The stochastic term $\omega_i$ represents the effects of elements neglected in the analysis. This specification,

[3] A referee suggested that individuals might not totally insure against extremely hot weather. A temperature $T^*$ then exists so that for $T > T^*$ the room could not be kept at $\tau$. This possibility does not seem an important consideration. Engineering guides such as the ASHRAE handbook also choose size in a similar manner without any consideration of air conditioner "brownouts."

which is linear in the parameters, has proven quite successful in applications of qualitative choice models to other problems.

We have now specified the utility $u_i$ of alternative $i$ and need to specify the model of individual choice from the choice set $i = 1, 2, 3$. Rewrite equation (14) as $u_i = x_i\beta + \omega_i = \bar{u}_i + \omega_i$, where $\bar{u}_i$ represents the nonstochastic part of the model. Then the probability that the individual consumer will choose alternative $i$ from a choice set $i = 1, \ldots, I$ is:[4]

$$
\begin{aligned}
s_i &= \mathrm{pr}\ [u_i > u_j \quad \text{for all} \quad j \neq i] \\
&= \mathrm{pr}\ [\bar{u}_i - \bar{u}_j + \omega_i > \omega_j \quad \text{for all} \quad j \neq i] \\
&= \mathrm{pr}\ [\bar{u}_{ij} + \omega_i > \omega_j \quad \text{for all} \quad j \neq i] \\
&= \int_{-\infty}^{\infty} \int_{-\infty}^{\bar{u}_{i,1}+\omega_i} \cdots \int_{-\infty}^{\bar{u}_{i,j}+\omega_i} \cdots \int_{-\infty}^{\bar{u}_{i,I}+\omega_i} f(\omega_1, \ldots, \omega_I) d\omega_1 \ldots d\omega_j \ldots d\omega_I d\omega_i, \quad (15)
\end{aligned}
$$

$j \neq i,$

where $\bar{u}_{ij} = \bar{u}_i - \bar{u}_j$ and $f$ is the joint density of the random variables $\omega_i$. This rather formidable appearing probability statement merely represents the probability that the individual chooses alternative $i$ because his utility from this choice exceeds that of any alternative choice $j$. The nonstochastic parts of the probabilities, the $\bar{u}_{ij}$'s, represent the tradeoffs in utility terms between the attributes of the different alternatives. As $\bar{u}_{ij}$ increases for a given $i$, note that the probability of its being chosen increases, since the limits of the integral in equation (15) increase. The stochastic term represents unobserved factors with $E\omega_i = 0$ for all $i$ by assumption.

We now extend our specification of individual choice to choice by a population of individuals. Consideration of equation (11) indicates that even for individuals facing identical choice sets, the utility specification of equation (14) may differ, since the individual parameters $\eta$, $\lambda$, $a$, and $r$ may all differ across individuals. Thus, for individual $k$ we write the utility from alternative $i$ as

$$u_{ik} = y - \beta_{1k} p_k KWH_{ik} - \beta_{2k}\rho_i - \beta_{3k}(p_i BTU/EER_{ik})^2 + \omega_{ik}, \qquad i = 1,2,3, \quad (16)$$

where $p_k$, the marginal price of electricity, varies across individuals as does their intended utilization, $KWH_{ik}$. But we assume they face the same price $\rho_i$ for a particular air conditioner model.

The question then arises of how the parameters $\beta_{hk}$ might be distributed in the population. Following Hausman and Wise (1978) we assume a normal distribution with $\beta_{hk} \sim N(\bar{\beta}_h, \sigma^2_{\beta_h})$ so that the $\beta_h$'s are distributed independently of each other and $\sigma^2_{\beta_h}$ is the variance in the population of $\beta_h$.[5] We also assume that $\omega_{ik} \sim N(0, \sigma^2_\omega)$.[6] Given this stochastic specification, we rewrite equation (16) as

$$u_{ik} = y + \bar{\beta}_1 p_k KWH_{ik} + \bar{\beta}_2\rho_i + \bar{\beta}_3(p_k BTU_k/EER_{ik})^2 + \epsilon_{ik}, \quad i = 1, 2, 3, \quad (17)$$

---

[4] The possibility of equality of utility is neglected, since it is an event of negligible probability.

[5] This covariance probit specification of Hausman and Wise eliminates the independence of irrelevant alternatives assumption of logit qualitative choice models. The independence of irrelevant alternatives assumption seems improper in the consumer durables context, given the close substitution possibility of the different choices.

[6] For a specification and estimation scheme that relaxes both independence assumptions on the $\beta_{hk}$ and $\omega_{ik}$, see Hausman (1977).

where $\epsilon_{ik} = \omega_{ik} + x_{ik}(\beta_k - \bar{\beta})$ using notation introduced earlier. Note that the expectation of $\epsilon_{ik}$ is zero. Now the probability that person $k$, when faced with a choice set $j_k$ consisting of alternatives $i = 1, \ldots, I_k$ will choose alternative $i$ is

$$\begin{aligned} s_{ik} &= \mathrm{pr}\,[u_{ik} > u_{jk} \quad \text{for all} \quad j \neq i \quad \text{in} \quad j_k] \\ &= \mathrm{pr}\,[\bar{u}_{ijk} + \epsilon_{ik} > \epsilon_{jk} \quad \text{for all} \quad j \neq i] \\ &= \int_{-\infty}^{\infty} F_{ik}(\bar{u}_{i1k} + \epsilon_{ik}, \ldots, \epsilon_{ik} \ldots, \bar{u}_{iI_k k} + \epsilon_{ik})d\epsilon_{ik}, \end{aligned} \tag{18}$$

where $F_{ik} = \partial F/\partial \epsilon_i$ and $F_k$ is the joint multivariate normal distribution of the $\epsilon_{ik}$'s. Thus, differences among individuals are reflected in differences in the parameters $\beta_{hk}$ in equation (16).

Once the specification of individual choices in a population is completed, we are ready to write the likelihood function from which we shall derive the estimates of the unknown parameters. Since $\sigma_\omega^2$ is normalized at unity because only the outcome of utility differences is observed, the unknown parameter vector $\theta$ consists of six elements. These six elements are $\bar{\beta}_1, \sigma_{\beta_1}^2, \bar{\beta}_2, \sigma_{\beta_2}^2, \bar{\beta}_3, \sigma_{\beta_3}^2$, and they represent the parameters of the tradeoff among operating costs at optimal utilization, the initial cost, and the discomfort variable. Since these parameters are assumed to vary in the population, both the means and variances of the distribution are estimated. Then given a random sample of $N$ individuals, each of whom purchases one unit of the good from his choice set $j_k$, we have the log likelihood function

$$L(\theta) = \sum_{k=1}^{N} \sum_{i=1}^{3} y_{ik} \log s_{ik}, \tag{19}$$

where $y_{ik} = 1$ if person $k$ chooses alternative $i$ and $y_{ik} = 0$ otherwise. The probabilities $s_{ik}$ follow a multinomial distribution and are computed from equation (18). Maximization of this likelihood function leads to parameter estimates with favorable large sample properties. These parameter estimates will allow us to assess the possibility of conservation in the population and indicate the degree of tradeoff between total cost of operation and discomfort.

To summarize, in this section we specified a statistical model at the individual level which attempts to indicate the important economic factors involved in the optimal choice among energy-using durable goods. With this optimization assumption, we derived an estimable utility function and the probability of individual choice of alternative $i$ from a given choice set followed. An equation indicating the utilization of the durable was also derived. The specification at the individual level was then extended to the population so that the choice specification might differ among individuals. Finally, we specified a likelihood function which permits the estimation of unknown parameters.

## 3. The market for home air conditioners

■ Before proceeding to estimate the model, we consider the market for home air conditioners. Our goal is to determine the degree of purchase price/operating cost substitution available for air conditioners in the market.

Product differentiation is an important aspect of the markets for almost all consumer durables. Different models of a consumer durable usually differ in their characteristics or attributes. Suppose a particular product $j$ can be described in terms of a vector of $n$ observable characteristics $R^i = R_1^i, \ldots, R_n^i$. Then in the market we observe the whole spectrum of available models $R^i$, $i = 1, \ldots, I$ as well as their associated prices $p^i$. Since in buying a particular model of the consumer durable $i$, the consumer buys the "package" of attributes $R^i$, we might be interested in estimating the implicit price $q_j^i$ of each quantity of attributes. Then the total price of the model is decomposed into the sum of its attribute costs: $p^i = \sum_{j=1}^{n} q_j^i R_j^i$. This idea underlies the analysis of "hedonic prices" pioneered by Court (1941) and later revived and extended by Griliches (1971) and Rosen (1974). In general, neither the production technology nor the consumer preferences can be recovered by using only observable market data; but as a description of market data, hedonic price analysis is useful in characterizing the available range of market choice.

In 1976 there were 41 companies producing over 500 models of room air conditioners.[7] The characteristics $R^i$ we use to describe room air conditioners are: cooling capacity reported as *BTU*/hour, electric voltage which is either 115 volts or 230 volts, electric amperes, and electric wattage. The last three characteristics all are associated with electricity consumption, and they are conveniently summarized in a measure called *EER*—the energy efficiency ratio. This value is obtained by dividing *BTU*/hr. by the electric wattage input during cooling. *EER* represents the relative electrical efficiency of room air conditioners, and its inverse is a measure of a model's relative operating costs.

Complete information was obtained for 409 models of 1976 air conditioners. *BTU*/hr. and *EER* are used in the hedonic regression as the attributes of the different models. The specification preferred in the hedonic price literature is log linear, so that specification is used here. This simple specification does rather well in describing the market data with the standard error approximately 16 percent of the market price and very precise parameter estimates. The results are given in Table 1. Thus a definite and substantial tradeoff exists between initial purchase price and operating costs. Since the inverse of *EER* is a measure of electricity consumption, a higher *EER* leads to lower operating costs, but as the results show, it also means a higher initial purchase price. For instance, an increase in *EER* from 7.5 to 8.0, which is approximately the mean of the sample, leads to a 6.4 percent decrease in electricity consump-

TABLE 1

PARAMETER ESTIMATES FOR LOG PRICE REGRESSION

| | PARAMETER ESTIMATE | STANDARD ERROR |
|---|---|---|
| CONSTANT | 4.6986 | 0.04720 |
| BTU (1000's) | 0.05597 | 0.001916 |
| EER | 0.07081 | 0.006130 |
| $R^2$ = 0.7248 | S.E. = 0.1611 | NO. OF OBSERVATIONS = 409 |

[7] These data are in directories published by the Association of Home Appliance Manufacturers (AHAM). Price data are contained in the Home Appliance Blue Book. A subject that has always raised problems in the hedonic literature is the difference between list price and traded price owing to the substantial discounts at which consumer durables are often sold. The publication from which the data are taken attempts to report the traded price.

tion and a 3.5 percent increase in the purchase price. As discussed in Section 2, consumer choice of a particular model depends on this tradeoff as well as on an individual's personal characteristics, tastes, intended utilization and the price of electricity in his area.

To test whether the log-linear specification is an adequate description of the market data, a separate regression was run for 5000 BTU air conditioners. This is a very popular size unit with 34 different models available in 1976. The coefficient for *EER* in Table 2 is significantly different from the corresponding coefficient in Table 1 which was computed by using data on all BTU sizes. Now an increase in *EER* from 7.5 to 8.0, which leads to a reduction of 6.4 percent in electricity consumption, leads to a rise of 6.3 percent in initial purchase price. This result indicates that one would expect to see fewer high efficiency models for low BTU air conditioners in the market since the initial price versus operating cost tradeoff is less favorable.

The finding of a significant difference between the efficiency parameter for 5000 BTU models and the efficiency parameter in Table 1 indicate that the original log-linear specification in Table 1 is inadequate to describe the market data. Thus, a log-quadratic specification was used which also allows for interaction between *BTU*'s and *EER*. The results are presented in Table 3. The standard error of the regression falls from 16 percent to 14 percent; and all the coefficients except the $EER^2$ term are estimated relatively precisely. A strong nonlinearity is indicated by this regression. The results demonstrate that the original linear specification was inadequate to describe the market data. An *F*-test comparing the regression of Table 1 with the specification of Table 3 has the value $F(3,403) = 31.94$, which is significant at the 1-percent level.

Perhaps of more interest is the nonlinearity created for the tradeoff between initial purchase price and operating costs. For an increase in *EER* from 7.5 to 8.0 with an associated decrease of 6.4 percent in operating costs, the initial purchase price rises 3.8 percent for a 5000 BTU model. For a 10,000 BTU model this price rise is 2.99 percent while for a 15,000 BTU model the price rise is only 2.15 percent. Since the higher BTU models consume more electricity per hour when in use, we would expect more efficient, large BTU models to be bought than efficient, small BTU models given that the initial purchase price/operating cost tradeoff is also more favorable. This expectation is verified in our sample of consumers: for air conditioners with 8000 BTU's and an *EER* greater than 8.0 none were purchased, while for the larger models such high *EER* units comprised about 20 percent of consumer choices.

Having summarized the market data using the hedonic price regression, we question whether data on individual consumer demand can be used to estimate consumer demand for the different models. In a very interesting paper Rosen (1974) suggests using the estimated gradient which defines implicit

TABLE 2

PARAMETER ESTIMATES FOR LOG PRICE REGRESSION OF 5000 BTU AIR CONDITIONERS

| | PARAMETER ESTIMATE | STANDARD ERROR |
|---|---|---|
| CONSTANT | 4.4969 | 0.2044 |
| EER | 0.1268 | 0.03181 |
| $R^2 = 0.3324$ | S.E. = 0.1614 | NO. OF OBSERVATIONS = 34 |

TABLE 3

PARAMETER ESTIMATES FOR LOG PRICE REGRESSION

| | PARAMETER ESTIMATE | STANDARD ERROR |
|---|---|---|
| CONSTANT | 4.0064 | 0.2317 |
| BTU (1000's) | 0.1702 | 0.01383 |
| EER | 0.1172 | 0.05469 |
| $BTU^2$ | −0.003935 | 0.0004336 |
| $EER^2$ | −0.001546 | 0.003514 |
| BTU • EER | −0.003344 | 0.001548 |
| $R^2$ = 0.7776 | S.E. = 0.1453 | NO. OF OBSERVATIONS = 409 |

marginal prices $P_j(R^i)$ for each attribute and then estimating the demand and supply equations for the attributes. However, unless "arbitrage" or complete repackaging of attributes is permitted, in general the prices are nonlinear, so that the consumer budget set is not a straight line. In fact, it need not even be convex. As Burtless and Hausman (1978) demonstrate for nonlinear budget sets created by tax and transfer programs, because of the nonlinearity of prices, the consumer demand function is unlikely to exist in closed form when both the income effects and substitution effects are taken into account. Therefore, estimating the derived demand for attributes could be a complicated econometric problem when the marginal price of an attribute depends on the quantity of the attribute in the particular model.

The qualitative choice model of Section 2 seems better suited to the task of estimating the determinants of consumer demand in this situation. Instead of attempting to estimate the derived demand for attributes, the qualitative choice approach compares the utility of each model in terms of its attributes through a random utility function specification. The implicit consumer tradeoff between attributes can still be evaluated, but the derived demand for the attributes need not be specified explicitly.

## 4. Individual data on purchases and utilization and durability

■ To estimate the utilization equations (12) and (13) and the qualitative choice specification of equations (17) and (18), data on individual households are required. While many samples exist which record total household electricity consumption, currently only the MRI (1978) survey records electricity consumption for individual appliances. The MRI survey was conducted in early 1976 and consists of a random sample of 1985 households in sixteen cities across the United States. Appliance holdings for each household were recorded along with brand name, year of purchase, and model characteristics for the appliance. In addition, socioeconomic data for each household were collected. Monthly electric bills and gas bills from August 1976 to July 1977 were also collected.[8] A subsample of 150 households had some of their individual appliances metered. In this subsample 51 room air conditioners were metered.

[8] Only households paying for their electricity usage were included in the sample, so that problems of electricity demand when payment is only indirect (through rent) do not arise.

From the 51 room air conditioners that were metered, we derived a sample of 46 observations that are used in the utilization regressions. Five observations were deleted because they arose in multi-air-conditioner households so that it was impossible to ascertain which air conditioner the meter was attached to and impossible to avoid the possibility of interconnection between air conditioner usage. Our sample of 46 households represented eight of the 16 cities. For these eight cities we collected individual cooling degree day data for each month of the year as well as humidity data. The marginal price of electricity was derived from the monthly electric bills. These data were used to estimate the utilization equation.

For the qualitative choice model, a sample of sixty-five households which had bought room air conditioners in 1975 and 1976 was constructed. These years were used since they were post-oil embargo years when individuals were presumably more concerned with electricity consumption both because their electric bills were rising rapidly and because of national attention focused on the "energy crisis." In these years almost all air conditioners sold had a tag attached giving consumer information according to standards established by the Association of Home Appliance Manufacturers and the U.S. Department of Commerce. This information included BTU/hr, voltage, amperes, and EER (and the definition of EER). Furthermore, for the given BTU size of air conditioner, the EER range of all models of that size was listed. Thus, the consumer had the necessary information to calculate the cost of operation, given the additional information of the electricity price he faced. When he included expected utilization he could, in principle, make the economic calculation to choose the best model for his situation. We do not assume that all consumers made the calculation, but an individual certainly had enough data to make an informed choice.

Purchase price of the appliance was taken from AHAM publications and the Home Appliance Blue Book. As mentioned in footnote 7, the divergence of traded price from list price is a problem for consumer durables, but our data sources attempt to collect average traded price. A five-year average of yearly cooling degree day data was used for each city to attempt to capture long-run climate conditions. Electricity prices pose a problem since they depend on total quantity consumed. They might also be expected to grow faster in the future than other prices. However, with no apparent solution to the expectations problem, we used marginal prices constructed from "normal" electricity consumption for each household.

The other data we constructed concern durability of room air conditioners. While the U.S. government has attempted to estimate durability for other household appliances, it does not seem to have done so for room air conditioners. In Section 6, we shall use the durability estimates to calculate discount rates.

To estimate durability we collected data on air conditioner sales for the period 1963–1976.[9] From the MRI survey we know the number of room air conditioners purchased in each year which were still in operation when the survey was constructed, $S_t$. We first form the ratio of sample air conditioners bought in year $t$ and still operating, $S_t$, divided by total air conditioners sold

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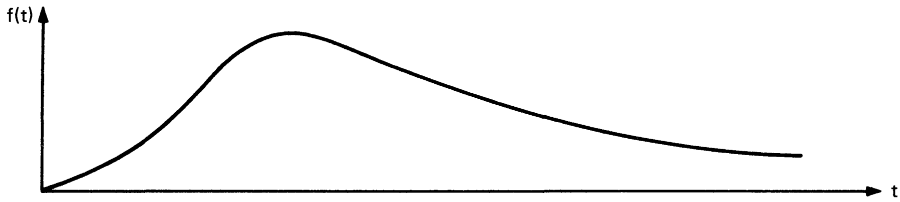
[9] These data were collected by the Association of Home Appliance Manufacturers (AHAM), who were very helpful in the course of this research. Two problems exist with the data: they represent shipments rather than sales and, of course, are not divided into household and office use. Durability might differ in the two categories.

FIGURE 1

WEIBULL PROBABILITY DENSITY




in that year, $n_t$. Now these two numbers do not give us the desired probability of survival $\pi_t$. Instead, we form the ratio $l_t = (S_t/n_t)/(S_{1975}/n_{1975})$ which allows us to calculate durability so long as the MRI survey represents a random sample of air conditioners purchased.

A sample of 1101 surviving air conditioners was used. To estimate average durability the survival function must be chosen. The Weibull distribution is used since it is often used in reliability testing.[10] The cumulative distribution has the form

$$F(x) = 1 - \exp\left[-\left(\frac{x}{\alpha}\right)^c\right], \qquad c > 0, \qquad \alpha > 0, \tag{20}$$

which leads to a general form of density function for failing at $t$ years of age as shown in Figure 1. Minimum $\chi^2$ estimation was used on the observed $l_t$ for 1963–1976 to estimate the parameters $\alpha$ and $c$. The estimates of the parameters with associated asymptotic standard errors are shown in Table 4.

The value of $\chi^2$ indicates that the Weibull distribution fits the data quite well. Using the estimated parameters, we calculate the mean lifetime to be 9.94 years with a median lifetime of 8.49 years. The 25th percentile is 4.61 years while the 75th percentile is 13.74 years. These results are further supported by the fact that in the MRI data, seven air conditioners still exist from 1955 and eight from 1956. The existence of 20-year-old room air conditioners further indicates that air conditioners may be relatively long-lived durables.

In this section we have described construction of the data which are used in our study. We have also done some approximate durability calculations which indicate that the average lifetime of an air conditioner is around ten years. In the next section, these data and the models from Section 2 are used to estimate the unknown parameters in the utilization equation and the model choice equation. The results will enable us to attempt to measure the tradeoff between cost and efficiency of air conditioners and the tradeoff between cost and comfort in their utilization.

TABLE 4

ESTIMATES OF PARAMETERS FOR DURABILITY CALCULATION

| | | | |
|---|---|---|---|
| $\hat{\alpha}$ = 10.95 (2.28) | $\hat{c}$ = 1.45 (0.32) | $\chi^2$ = 2.29 | t = 1,...,13 YEARS |

[10] Since we are looking for a convenient distribution to summarize the data, other choices of distribution are possible. A gamma distribution provided very similar results.

## 5. Model estimation

■ In this section we first estimate the utilization equations (12) and (13) for the sample of 46 air conditioners which were individually metered in the MRI survey. With our utilization results we then estimate the qualitative choice model for the purchase of new air conditioners. As is often the case in econometrics, we have little prior knowledge about the correct stochastic specification of an equation. Thus, the first equation we estimate is (20), which is a simple linear form of equation (12) with an additive error term[11]:

$$KWH_k = \delta_1(BTU_k \cdot CDD_k/EER_k) + \delta_2(p_k BTU_k^2/EER_k^2) + \epsilon_k, \qquad k = 1, \ldots, 46. \tag{21}$$

Recall that $p_k$ is the *marginal* price of electricity faced by household $k$.

Since the theoretical development of Section 3 indicates that the $EER$ chosen will be a function of intended utilization, we estimate equation (21) using nonlinear two-stage least squares. The original price of the air conditioner and $BTU_k$, $p_k$, $CDD_k$, and $BTU_k^2$ are used to form instruments. The results of this estimation are given in the first column of Table 5, where $KWH_k$ and $CDD_k$ are measured on a per day basis while $BTU_k$ is in 1000's and $p_k$ is measured in ¢/$KWH$.

The estimates are quite precise with 0.486 of the variance explained. At the mean of the sample the price elasticity is computed to be 0.0447. This elasticity corresponds to the short-run elasticity holding the capital stock fixed and indicates that higher electricity prices will have a small but significant effect on utilization. However, no large decrease in utilization would occur unless electricity price were raised greatly, say by a time-of-day price system where the marginal price has risen by as much as a factor of 16 in the Connecticut time-of-day demonstration. Another interesting aspect of equation (21) is the implied elasticity of $KWH$ with respect to $EER$. Theory indicates that utilization should increase with $EER$, other things being equal, but since $\hat{\delta}_1$ and $\hat{\delta}_2$ have

TABLE 5

ESTIMATES OF AIR CONDITIONER UTILIZATION EQUATION (ASYMPTOTIC STANDARD ERRORS IN PARENTHESES)

| | EQ. (21) | CONSTANT ADDED | CITY DUMMIES | EQ. (22) | EXPONENTIAL |
|---|---|---|---|---|---|
| $\delta_1$ | 0.436<br>(0.050) | 0.406<br>(0.056) | 0.300<br>(0.112) | −0.00948<br>(0.064) | 0.440<br>(0.063) |
| $\delta_2$ | −0.300<br>(0.125) | −0.355<br>(0.134) | −0.260<br>(0.213) | −0.0187<br>(0.208) | −0.768<br>(0.432) |
| $\delta_0$ | | 4.342<br>(3.864) | | | |
| S.E.E. | 16.27 | 16.23 | 17.21 | 5.66 | 16.72 |
| $R^2$ | | 0.545 | 0.584 | | |

[11] Note that we are disregarding the income effect induced by declining block prices. However, it is apt to be very small, and we keep to our utility specification which allows for no income effect. Cooling degree days ($CDD$) are used in this section instead of cooling degree hours ($CDH$), but the result is simply a rescaling of the coefficients.

opposite signs we need to check. At the point of means, the elasticity turns out to be 0.265 so that people do utilize higher efficiency air conditioners more. In evaluating new technology, high-efficiency air conditioners, this higher utilization must be included.

We now attempt to check the specification of the utilization equation. First, a constant is added to see whether the quadratic form is adequate. The results presented in column 2 of Table 5 show that the estimated constant is not statistically significant. More importantly, the estimates of $\delta_1$ and $\delta_2$ remain close to the previous estimates. Next, we included dummy variables for each of the eight cities in the sample. This specification attempts to capture partly the possible influence of humidity. The results are presented in column 3 of Table 5. Here both $\delta_1$ and $\delta_2$ decrease in absolute magnitude, both by about one-third. However, the (asymptotic) $F$-test, $F(8,35) = 0.546$, indicates that when tested jointly, the city coefficients are not significant. Furthermore, none of the individual asymptotic $t$-statistics for the city dummies exceeds 1.35. Last, an alternative stochastic specification was used, estimating $KWH$ in logarithmic form:

$$\log KWH_k = \log\left[\delta_1(BTU_k CDD_k/EER_k) + \delta_2(p_k BTU_k^2/EER_k^2)\right] + \epsilon_k. \quad (22)$$

The estimates are inferior to the linear estimates in terms of precision. Also, the sign of $\delta_1$ has changed. Nevertheless, the price elasticity is now 0.164, which is consistent with the low price elasticity our linear results indicate.

The other specification that we estimated is equation (13) which was derived by using the exponential rather than the quadratic specification of discomfort in the utility function. The results in column 5 of Table 5 are quite good, making it difficult to decide between the two specifications. The price elasticity is again quite small, estimated at 0.0413, very close to the estimated value in the specification of equation (21). Results from adding either a constant or city dummies were as before—neither yielded differences of statistical significance. Since the fit of equation (21) is marginally better (with more precise estimates of the coefficients) than the fit using the exponential specification embodied in equation (13), we shall only present results using the quadratic specification of discomfort when we turn to the air conditioner purchase model. Again, the results using the exponential specification in the purchase model were quite similar. Thus, although we cannot distinguish between the two specifications in terms of fit, they tell similar economic stories from the data.

We now turn to the consumer's model-choice decision. The hedonic price specification discussed in Section 3 demonstrated the significant degree of substitution available among air conditioner models. Lower operating costs are possible to achieve, but only at the expense of higher initial capital costs. We shall now utilize the qualitative choice model of Section 2, and in particular the utility specification of equation (14), to estimate the parameters of consumer choice in selecting among the different models of air conditioners. The parameters to be estimated from the utility function of equation (17) and the likelihood function of equation (19) are the parameters associated with the tradeoff between initial capital cost and operating costs and a parameter which values discomfort above 65°. We also estimate the dispersion of these coefficients in the population.

As discussed earlier, the BTU size is taken to be exogenous, and the choice among efficiencies is divided into low-efficiency, medium-efficiency, and high-efficiency models. The empirical results turn out to be insensitive to the exact limits used to define the efficiency classes. The price, $p_i$, for each of the two models not chosen was predicted by an instrumental variable procedure using the hedonic price regression reported in Table 3. Likewise, $KWH_{ik}$ was predicted using the estimates of equation (21) given in Table 5. We have seen that individuals with higher efficiency air conditioners utilize them more, so the instrumental variable procedure used here in the choice equation will imply that individuals with higher intended utilization will buy more efficient models if $\bar{\beta}_1$ of equation (17) is estimated to be negative.

Parameter estimates were obtained by maximum likelihood estimation and are given in Table 6.

The first column of Table 6 gives the estimates from equation (17). The estimated parameters have the correct sign, and $\bar{\beta}_1$ and $\bar{\beta}_2$, the coefficients corresponding to operating cost and initial purchase price, are estimated relatively precisely. The estimated standard deviations indicate significant variation in the population of preference although the estimates are much less precise. To give some indication of the explanatory power of the model, we evaluated its log likelihood value for $\theta = 0$, where $\theta$ is the vector of unknown parameters. The specification $\theta = 0$ assumes equal probability of choice among all three models of a given BTU size. Thus we are comparing the model with estimated means and standard deviations of the parameters $\beta$ to a model which assumes that consumer choice is equiprobable among models. A large value of the likelihood ratio test statistic indicates that our model has significant explanatory power, while a small value indicates failure of the model specification in explaining consumer choice. The likelihood with $\theta = 0$ is $-71.40$ so that the likelihood ratio test calculated as

TABLE 6

ESTIMATES OF THE INDIVIDUAL CHOICE MODEL FOR AIR CONDITIONER DEMAND*

| | EQ. (17) BASIC SPECIFICATION | MODEL–SPECIFIC DUMMIES | DURABILITY DIFFERENCES ALLOWED |
|---|---|---|---|
| $\bar{\beta}_1$ OPERATING COST | –0.194 (0.110) | –0.182 (0.125) | –0.191 (0.142) |
| $\bar{\beta}_2$ INITIAL PURCHASE PRICE | –0.0449 (0.0170) | –0.0357 (0.0096) | –0.0333 (0.0054) |
| $\bar{\beta}_3$ DISCOMFORT | –0.0151 (0.0127) | –0.0153 (0.0246) | –0.0157 (0.0328) |
| $\sigma_{\beta_1}$ STANDARD DEVIATION OF $\beta_1$ | 0.0183 (0.0065) | 0.0148 (0.0106) | 0.0167 (0.0123) |
| $\sigma_{\beta_2}$ STANDARD DEVIATION OF $\beta_2$ | 0.0167 (0.0088) | 0.0236 (0.0191) | 0.0148 (0.0182) |
| $\sigma_{\beta_3}$ STANDARD DEVIATION OF $\beta_3$ | 0.124 (0.202) | 0.111 (0.232) | 0.131 (0.258) |
| $\gamma_2$ | | 0.0305 (0.0421 | 0.0031 (0.0016) |
| $\gamma_3$ | | 0.0396 (0.0685) | 0.0037 (0.0023) |
| LOG LIKELIHOOD FUNCTION | –46.58 | –44.59 | –41.59 |

NO. OF OBSERVATIONS = 65

*ASYMPTOTIC STANDARD ERRORS ARE ADJUSTED FOR THE INSTRUMENTAL VARIABLE PROCEDURE USED.

twice the difference of the log likelihood is 49.64, which is distributed as $\chi^2$ with six degrees of freedom, a highly significant value.

Another possible test is to calculate the likelihood value using the sample proportions purchased of low, medium, and high-efficiency air conditioners. The likelihood value computed in this way is 62.68, again much worse than the qualitative choice model is able to achieve. Last, we compare the likelihood value to that of independent probit, which closely corresponds to the logit qualitative choice specification.[12] The independent probit specification does not permit the tradeoff parameters $\beta_1$, $\beta_2$, and $\beta_3$ to vary in the population. Its log likelihood value is $-49.95$ so that the likelihood ratio test is 6.74, which is distributed as $\chi^2$ with three degrees of freedom. Thus, the independent probit specification is rejected at the 10-percent significance level.

To explore for possible omitted factors, two additional specifications were estimated.[13] The first specification allowed for "model-specific dummies," which attempt to capture features of the medium- and high-efficiency air conditioners such as lower noise or less yearly maintenance on which we have no data. These results are presented in column 2 of Table 6. The estimates of $\gamma_2$ and $\gamma_3$, corresponding to medium- and high-efficiency models, respectively, indicate that individuals do value medium- and high-efficiency air conditioners more than low-efficiency air conditioners, but not by a large amount. For instance, a charge of \$1 of initial purchase price is valued about the same as the model-specific effect that we estimate. The likelihood ratio test of 3.98 does not reject the hypothesis that the effects of these model-specific features are zero at the 10-percent test level.

The last specification that we estimated in this section attempted to allow for higher durability among medium- and high-efficiency air conditioners. Note that from its definition $\beta_2 = r/(1 + r)(1 - (1 + r)^{-q})$, where $q$ is expected durability. In Section 2 we assumed that $q$ was independent of the EER of the model chosen. To test this assumption we rewrite the utility function of equation (16):

$$u_i = y - \beta_1 pKWH_i - (\beta_2 + \gamma_i)\rho_i - \beta_3(p_i BTU_i/EER_i)^2 + \omega_i, \quad i = 1, 2, 3, \tag{23}$$

where the $\gamma_i$ parameters allow $q$ to be different for different efficiencies. The coefficient $\gamma_1$ is normalized at zero, and we estimate $\gamma$'s for medium- and high-efficiency models, $\gamma_2$ and $\gamma_3$, respectively. The results are presented in column 3 of Table 6. Again we find some indication that medium- and high-efficiency models are valued differently. For instance, for medium-efficiency air conditioners the coefficient $\bar{\beta}_2$ is about 10 percent smaller in absolute value than it is for low-efficiency air conditioners, which may indicate that medium-efficiency models are expected to last longer. Note that the effects are estimated relatively precisely and that the likelihood ratio is 9.98 distributed as $\chi^2_2$. Thus,

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[12] For a further discussion of the similarity of the independent probit specification and the logit specification, see Hausman and Wise (1978).

[13] An additional specification which allowed for correlation among the taste parameters was tried. Thus, three additional parameters were included. Unfortunately, convergence problems were encountered, so that final results were not obtained. However, the estimates of $\bar{\beta}_h$ had not changed much nor had the likelihood function increased significantly by the time we terminated the calculations.

the effects are statistically significant. Additional data which would allow calculation of durabilities of different models would be helpful.

In this section we have estimated both the utilization model and the model of consumer choice of new air conditioners. The models seem to be in accord with economic theory and to explain a significant proportion of individual behavior. In the concluding section of the paper we shall draw out the implications of the parameter estimates in the choice model. In particular, we use the estimates of the tradeoff between operating cost and initial purchase price to calculate implicit discount rates. These discount rates have important implications for consumer acceptance of new appliances which conserve energy. If energy conservation programs are to succeed, higher efficiency appliances need to be adopted. Yet if consumers find the operating cost-initial cost tradeoff unacceptable, adoption of the new technology will not take place unless consumer choice is mandated by law.

## 6. Individual discount rates and energy policy

■ Using the estimates of the qualitative choice model in Section 5 and the durability calculations in Section 4, we now compute individual discount rates and explore their implications for energy policy. The estimates of $\bar{\beta}_1$ and $\bar{\beta}_2$ along with their standard deviations allow us to assess the individual tradeoff between operating cost and initial purchase price, that is, between future vs. present costs. To simplify, we consider only the mean individual and solve for his discount rate.

The mean discount rate is computed by solving for the value of $r$ in $\beta_2$ after finding the change in operating costs which keeps utility constant for a one-dollar change in the initial purchase price. Thus, by taking the ratio of $\bar{\beta}_2$ to $\bar{\beta}_1$ and solving the implicit equation for $r$, since $\beta_2 = r/(1 + r)(1 - (1 + r)^{-q})$, we can, for a given value of $q$, estimate the intertemporal utility tradeoff.[14] In calculating the discount value in this manner, we are assuming that the air conditioner is expected to last $q$ years and then to have no scrap value. At that time, the individual is expected to purchase a new air conditioner. Also assumed in the calculation is lack of economic deterioration over time and absence of differential expected inflation rates of purchase price and electricity price. Neither of these factors can be explicitly considered here, but introducing either effect would change the calculation only slightly and leave the essential results intact.

Using the results from the first column of Table 6, that $\bar{\beta}_1 = -0.194$ and $\bar{\beta}_2 = -0.045$, at the mean durability of room air conditioners calculated in Section 4 to be 9.94, the discount rate is calculated to be 26.4 percent per year. At the median estimate of durability, $q = 8.49$ years, the discount rate is calculated to be 24.1 percent per year. Both of these estimates indicate a substantial rate of time discount in the population. An estimated discount rate of around 25 percent substantially exceeds values used in "engineering calculations" to determine so-called life-cycle costs for evaluating the tradeoff between increased energy conservation and lower operating costs against higher initial capital costs. A clear implication of these estimates is that previous estimates

[14] We cannot estimate $r$ directly from $\beta_2$ because in qualitative choice models only the ratio of parameters matters, since utility is unobserved. The normalization $\sigma_\omega^2 = 1$ provides the cardinal measure of the utility function, but provides no natural measure for the coefficients of the utility function.

of consumer demand for energy-saving appliances, which are usually characterized by higher initial purchase price, may be overly optimistic. Energy conservation through improved technology may have difficulty succeeding if consumers do have such a high discount rate. Thus the low rates used in the engineering calculations suffer from two shortcomings: from a positive standpoint they are too low to forecast accurately consumer behavior, while from a normative standpoint they are too low for the individuals involved.

Before embarking on a further discussion of policy issues, several caveats are in order. First, we have calculated these discount rates from observed consumer behavior in the purchase and utilization of one energy-using appliance, room air conditioners. Further study of the choice of other energy-using appliances, e.g., home heating systems, is clearly necessary. The estimated discount rates might well be different. Second, the calculation assumes that $q$ is independent of appliance efficiency. Yet the results in column 3 of Table 6 indicate that this assumption does not hold exactly. The results from that model, where $\bar{\beta}_1 = -0.191$ and $\bar{\beta}_2 = -0.033$, indicate a discount rate of 14.8 percent per year if we assume that air conditioners sold in the past had the same estimate of $\gamma_2$ and $\gamma_3$ found in Table 6. This second calculation of a discount rate of around 15 percent per year, while considerably lower than our previous estimate, still gives the same result of a substantial discount rate in the population. The last caveat is that an argument can be made that anyone who is doing positive saving should have a discount rate no higher than the interest rate received. By decreasing monetary savings now, the consumer can achieve returns in energy savings later which should be equated with his return to monetary savings now. On the other hand, a substantial amount of credit is obtained through credit cards which charge a rate of 18 percent in most states. This 18 percent interest rate lies between our two discount rate calculations of 15 percent and 25 percent. Other factors such as uncertainty and the possibility of technological change do not seem sufficient to explain the high discount rate which we found.

Yet this finding of a high individual discount rate does not surprise most economists. At least since Pigou, many economists have commented on a ''defective telescopic faculty.'' A simple fact emerges that in making decisions which involve discounting over time, individuals behave in a manner which implies a much higher discount rate than can be explained in terms of the opportunity costs of funds available in credit markets. Since this individual discount rate substantially exceeds the social discount rate used in benefit-cost calculations, the divergence might be narrowed by policies which lead to purchases of more energy-efficient equipment. Tax subsidies are a possibility, since they lower the initial capital cost and make the tradeoff toward lower operating costs more favorable. This type of tax credit policy has been adopted for home insulation in the recent U.S. energy legislation.

Another possible type of market solution would be to have utility companies purchase appliances and lease them to their customers. Presumably utilities would be willing to engage in such profitable activity, since they could borrow money to finance the more energy-efficient appliances and then charge a rental rate which would leave the consumer better off.[15] Utilities could develop

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[15] This type of arrangement might also overcome one supposed reason for high unobserved discount rates, the short mean length of occupancy of a house by U.S. families. It is often claimed that capital improvements which lead to savings over time are not fully reflected in the sale price of a house.

expertise in choosing the optimal efficiency model in terms of climate and intended utilization and help their customers make a better choice. However, a clear incentive problem exists because more efficient models might lead to a decreased electricity demand, which is the primary product of those same companies. Thus, implementation of such a plan might be difficult.

Our findings also suggest that the government might undertake an educational campaign to help consumers better understand the tradeoff between initial purchase price and energy savings in the future. Both our utilization results and our choice model results indicate that individuals do take this tradeoff into account to some extent. Better information might lead to an even more informed choice.

The last policy choice to be discussed is the setting of government efficiency standards. By reducing or even eliminating the consumer tradeoff decision, energy savings could be accomplished. The first problem with such standards is they would need to be quite complex. Our utilization results from Table 5 demonstrate that the price of electricity and the climate both need to be taken into account. Furthermore, intended utilization would also enter an optimal efficiency schedule. But then the standards would become very difficult to enforce except at the individual level, which would require much administrative effort and thereby generate a number of economic and bureaucratic problems. In particular, a result of such standards is to place an implicit tax on those individuals who are thought to have the highest discount rates: the less well off. Thus efficiency standards can have an adverse income distribution effect.

To determine the interaction of the income distribution and consumer choice, we now expand the model specification to allow income to play a role. Even if all other factors are identical, discount rates should vary with income class owing to the progression of the income tax which causes intertemporal marginal rates of substitution to differ.

In the utility function specification of equation (14), $\beta_1$ and $\beta_2$ are the parameters which measure the tradeoff between operating costs and initial purchase price. A reasonable hypothesis might be that $\beta_2$ depends on income, since the availability of credit as well as the marginal rate of substitution influence the observed discount rate. Therefore, instead of our earlier specifications, $\beta_{2k} = \bar{\beta}_2 + \tilde{\tau}_{2k}$, where $\tilde{\tau}_{2k}$ was a normal random variable, we specify $\beta_{2k} = \alpha_0 + \alpha_1 \log y_k + \tau_{2k}$, where $\tau_{2k}$ is again assumed to be a normal random variable and $y$ is family income. Therefore $\beta_{2k} \sim N(\alpha_0 + \alpha_1 \log y_k, \sigma^2_{\beta_2})$. If we find $\alpha_1 = 0$, then the specification reduces to our earlier model and the tradeoff does not depend on family income. The results are presented in Table 7 where the income variable is taken from the MRI survey, and we grouped individual income into six classes up to a maximum of \$50,000. The parameter estimates again demonstrate that a substantial tradeoff exists between initial purchase price and operating costs. Note that the discount rate decreases with increased income as expected. A hypothesis test of $H_0$: $\alpha_1 = 0$ yields an asymptotic $t$-test (Wald test) of 2.71 with the associated likelihood ratio test taking a value of 10.90. Both tests indicate that income plays a substantial role in determining the discount rate. Also note that $\sigma_{\beta_2}$ has decreased from 0.0167 in Table 6 to a value of 0.0036 in Table 7, which indicates that income is an important variable in the distribution of discount rates in the population.

Economic theory implies that the discount rate should decrease as income rises, even with perfect capital markets, since the marginal tax rate rises with income while the services of consumer durables are untaxed. We now use these

TABLE 7

ESTIMATES OF THE INDIVIDUAL CHOICE MODEL WITH INCOME ADDED

| | PARAMETER ESTIMATE | ASYMPTOTIC STANDARD ERROR |
|---|---|---|
| $\alpha_0$ — PARAMETERS OF PURCHASE PRICE VARIABLE | –0.162 | 0.055 |
| $\alpha_1$ | 0.0636 | 0.0235 |
| $\bar{\beta}_1$ OPERATING COSTS | –0.2486 | 0.0575 |
| $\bar{\beta}_3$ DISCOMFORT | –0.0038 | 0.0083 |
| $\sigma_{\beta_1}$ STANDARD DEVIATION OF $\beta_1$ DISTRIBUTION | 0.0371 | 0.0236 |
| $\sigma_{\beta_2}$ STANDARD DEVIATION OF $\beta_2$ DISTRIBUTION | 0.0036 | 0.0048 |
| $\sigma_{\beta_3}$ STANDARD DEVIATION OF $\beta_3$ DISTRIBUTION | 0.143 | 0.161 |
| LOG LIKELIHOOD FUNCTION = –41.13 NO. OF OBSERVATIONS = 65 | | |

estimates to calculate the discount rate for different income classes. The results are shown in Table 8. While the estimates at the extreme classes should be taken as very uncertain both because of the small number of people in each of those classes and because of the log linearity of the specification, the results do indicate that the discount rate varies markedly with income. For instance, the discount rate falls from 39 percent for households with under $10,000 of income to 8.9 percent for households between $25,000 and $35,000 of income.

It is interesting to note that the top income classes have an implied discount rate much closer to the interest rate prevailing in credit markets. The high discount rate of the poor has received much previous notice, and our results indicate this high discount rate in a striking manner. Given the uncertainty of their income streams and their lack of savings, we would expect a high discount rate for this part of the population. These results indicate that setting efficiency standards would have a much greater impact on lower income households, since they would find the increased purchase price of the more efficient air conditioners more onerous than persons with a lower discount rate.[16]

TABLE 8

ESTIMATED DISCOUNT RATES USING MEAN POPULATION ESTIMATES

| INCOME CLASS | NUMBER OF OBSERVATIONS | $\beta_2$ | IMPLIED DISCOUNT RATE |
|---|---|---|---|
| 1. $6,000 | 6 | –0.118 | 89% |
| 2. $10,000 | 15 | –0.075 | 39% |
| 3. $15,000 | 16 | –0.061 | 27% |
| 4. $25,000 | 17 | –0.049 | 17% |
| 5. $35,000 | 8 | –0.039 | 8.9% |
| 6. $50,000 | 3 | –0.031 | 5.1% |

[16] To the extent that income is a proxy for education in this specification, an educational campaign by the government to help make a more informed choice by consumers would help low income people more.

We have discussed the divergence between the private discount rate implied in our results and the social discount rate and suggested policy measures which would encourage the purchase of more energy-efficient consumer durables. The question might arise whether instead we should take the calculated private discount rate and use it as a type of social time preference rate (STP) in regulatory hearings. I think not. Another approach to choosing the discount rate to be used in investment projects is the social opportunity cost of capital (SOC) approach. If a regulated utility can borrow money at a given rate, the market interest rate seems the appropriate basis on which to make its investment decision rather than the discount rates implicitly used by its customers. The margin on which the regulated utility operates is given by its opportunity cost of capital, and it cannot affect the borrowing-lending margin of its customers. The two margins differ, but there exists no reason for the regulated utility to attempt to operate on the intertemporal margin used by its customers.

In conclusion, further research might try to develop more complete models of consumer choice to account for other factors, such as the type of heating system installed. A more complete model would also address the problem of when individuals decide to purchase air conditioners. The qualitative choice specification seems a useful model when goods are characterized by different attributes. It provides a coherent model of individual choice and yields parameter estimates that can be used to assess policy measures such as tax subsidies. For instance, a subsidy on high-efficiency air conditioners is straightforward to include in the model. The model would forecast the change in consumer choice and predict the amount of shifting from low- and medium-efficiency air conditioners to high-efficiency models. The utilization model would then forecast the change in KWH demand owing to the lower operating cost. Using the two models would thus allow us to calculate the change in the demand for electricity by considering both the capital stock decision and the utilization decision which are the important factors in models of energy demand.

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