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CONSUMER CHOICE AND MARKET PENETRATION OF NEW TECHNOLOGIES: APPLICATION OF A DISCRETE CHOICE MODEL

Prepared for
Energy Division
Oak Ridge National Laboratory

ORNL/Sub-80/45734/1

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Final Report

CONSUMER CHOICE AND MARKET PENETRATION OF NEW TECHNOLOGIES: APPLICATION OF A DISCRETE CHOICE MODEL

Prepared for

Energy Division
Oak Ridge National Laboratory
Oak Ridge, Tennessee 37830

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Chapter 1
INTRODUCTION

Existing empirical models of market penetration utilize historical empirical regularities to model penetration of new technologies. Exponential, logistic, or skewed s-shaped curves are generally used to represent penetration of new technologies over time.[1] Parameters of the curve are related to variables such as relative costs of the new and old technologies. While these models represent a useful first step for evaluating the market penetration of new technologies, the heuristic approach does not explicitly represent many factors that are important determinants of market penetration (e.g., age distribution of the capital stock is often ignored), provides little information on the relative importance of the different elements that affect market penetration, and generates little confidence in situations that differ in circumstance from historical experience.

---

[1]For a review on this literature see Jerry R. Jackson and David L. Kaserman, *A Neoclassical Theory of Durable Good Diffusion*. ORNL/CON-37. Oak Ridge, Tenn.: Oak Ridge National Laboratory, October 1979.

These difficulties can be overcome by developing a disaggregate structural model based on economic theories of investment. Increases in the demand for durable goods, replacement decisions concerning existing equipment, and choice of equipment when one of the available goods is a new technology are all issues addressed by investment theory.

The purpose of this report is to demonstrate the feasibility of developing a full-scale disaggregate structural model of market penetration. An equipment choice model, which represents the most crucial and one of the most intractable components of the disaggregate model, is developed and estimated using data on residential space heating equipment.[1] This econometric model is incorporated, along with empirical representations of equipment replacement, depreciation, and capital stock growth, in a simulation model to represent a limited version of a disaggregate structural model of market penetration. The penetration of an example new technology is then evaluated to demonstrate the advantages achieved by pursuing a disaggregate structural approach to modeling market penetration.

The remainder of this report is organized as follows. Discrete choice modeling literature is briefly surveyed in the second chapter. Chapter 3 describes the data base used to estimate the model and Chapter 4 presents the estimation results. In Chapter 5 we combine the empirical discrete choice model with the optimal replacement relationships, a simple representation of the characteristics of the existing space heating equipment stock and assumptions

---

[1] Since equipment choice involves choosing among distinct alternatives, the discrete choice approach is the appropriate statistical technique for describing individuals' equipment choices.

concerning future stock growth to develop a limited version of the disaggregate structural model. This final chapter concludes with a short discussion of future research required to extend the components of the limited model version to yield a detailed policy-oriented model of market penetration.

Chapter 2
THE STATE OF THE ART IN DISCRETE CHOICE MODELING

Considerable effort has been applied to developing discrete choice models from propositions of economic theory and to estimating empirical formulations of these models by econometric methods. Individual choice of transportation mode, selection of one among several alternative models of a major consumer durable such as an automobile, residence location, and individual or family labor force participation decisions are among the economically important decisions that have been analyzed using discrete choice models estimated by econometric methods.[1] Development of applications of discrete choice models to choice among alternative energy-using appliances is

[1]Discrete choice models have been particularly widely applied to the analysis of transportation-related choices. See, for example, Thomas A. Domencich and Daniel McFadden, *Urban Travel Demand* (Amsterdam: North-Holland Publishing Company, 1975); Charles River Associates, *Disaggregate Travel Demand Models* (Cambridge, Mass.: CRA, 1976); and Eric Toder, N. Scott Cardell, and Ellen Burton, *Trade Policy and the U.S. Automobile Industry* (New York: Praeger Publishers, 1978).

in large part an outgrowth of the increased concern with efficient consumption of energy in the period since the 1973-1974 OPEC oil embargo and the accompanying and subsequent increases in prices of oil and other fuels.[1]

Discrete choice models, as developed in the economics literature, are approaches for modeling choice among a finite number of goods. As their name implies, discrete choice models apply to situations where choices are made among fundamentally separate alternatives and where the option to choose a partial amount of each of two or more alternatives, for example, is not feasible. Discrete choice models are thus well suited to analysis of the choice among alternative space conditioning systems.

Available discrete choice models share the underlying assumption that the relevant decision makers select the alternative that yields the highest level of well being from among the available alternatives.[2] The basic models among the discrete choice models that have been or are being developed are the multinomial logit model and the multinomial probit model. In addition, extensions of the multinomial logit and multinomial probit models as well as alternative discrete choice models are being developed. The available discrete choice models considered for use in the present study are the multinomial logit model, the multinomial probit model, and an extension of the multinomial logit model, the sequential logit model. These three models are the most promising candidates in terms of their theoretical

---

[1]For an example of a discrete choice model applied to air conditioner purchases, see Jerry A. Hausman, "Individual Discount Rates and the Purchase and Utilization of Energy-Using Durables," *Bell Journal of Economics* 10 (Spring 1979): 33-54.

[2]Consistent with classical economic theory, the decision-making unit is generally assumed to maximize utility in the case of households and to minimize cost for firms.

development and practicality of application.[1] The three models differ in their theoretical generality and their ease of computation. The multinomial logit is computationally easy but has a relatively restrictive specification, while the multinomial probit has a less restrictive specification but is computationally cumbersome. We have selected the sequential logit model for use in the present study because it avoids some restrictive assumptions of the multinomial logit and yet retains much of that model's attractive computational simplicity.

The following section reviews the basic structure of the multinomial logit and multinomial probit discrete choice models. The purpose of the review is twofold: 1) to describe the fundamental similarity of the economic motivations assumed in the two models and 2) to outline the dissimilar assumptions about the process generating error terms in the empirical relationships to be estimated using the models. Differences in assumptions about the process generating the error terms give rise to the differences in restrictiveness of specification and ease of computation mentioned above. Following the review of the basic structure of the multinomial logit and multinomial probit models, we discuss the sequential logit model in general and outline a particular structure relevant to the present study.

---

[1]For a recent comprehensive survey of discrete choice models focusing on their basic structures, assumptions, and applicability to modeling the choice of energy-using appliances, see Charles River Associates, *Analysis of Household Appliance Choice* (Boston, Mass.: CRA, January 1979). Models reviewed therein, in addition to the multinomial logit, multinomial probit, and sequential logit, are as follows: the error components and simplified multinomial probit extensions to the multinomial probit model; the generalized extreme value model, which is an extension of the multinomial logit model; the Hedonic Demand Model being developed at Charles River Associates; maximum score estimation model; maximum model; elimination by aspects model; and a dichotomous choice model developed at the Electric Power Research Institute.

Basic Structure of Discrete Choice Models: Multinomial Logit and Multinomial Probit

Available discrete choice models developed for application to economic problems have in common certain underlying assumptions about the economic motivations and behavior of individual decision makers. In these models it is assumed that the decision maker, faced with the problem of selecting from a set of mutually exclusive alternatives, selects that alternative which maximizes his expected utility.[1] The individual (or household) is assumed to have a utility function that is linear[2] and depends on personal characteristics (e.g., income, size of area to be heated or cooled) and the attributes of the alternatives (e.g., operating cost, cost of purchase and installation, cleanliness). Interaction effects involving personal characteristics of the decision-making unit and the attributes of the alternatives can also occur. To summarize:

$$U_i = X_i\beta + \varepsilon_i \qquad (2\text{-}1)$$

where

U_i = the utility that the decisionmaking unit receives from alternative i;

X_i = the vector of measurable attributes of alternative i and their interactions with characteristics of the decisionmaking unit;

β = a vector of parameters to be estimated; and

ε_i = an error term representing the effects of unobservable attributes of alternative i and personal characteristics of the decision-making unit.

---

[1]Because our empirical application in this paper relates to household choice of equipment, we develop the discrete choice model structure against a background of the theory of consumer behavior. A nearly identical model can be developed, however, by basing equipment choice on the cost minimizing behavior of firms.

[2]The assumption of linearity is not restrictive. Rather, it can be viewed as an approximation to a more complicated functional form.

The two basic discrete choice models, the multinomial logit and the multinomial probit, assume that tastes are homogeneous in the population; that is, the parameter vector β in Equation (2-1) is assumed to be the same for all decision makers.[1] The two models are distinguished by the particular assumptions made about the error term (ε_i in Equation (2-1) above). In the multinomial logit model, the error terms for the alternatives are assumed to be independently and identically distributed Weibull variates.[2] In the multinomial probit model, the error terms for the alternatives available to an individual are assumed to be distributed as multivariate normal, and dependence between error terms is possible.

An attractive property of the multinomial logit model for computation purposes is that the probability of an individual

---

[1]Models under development that allow β to vary across decision makers include the CRA Hedonic Demand Model.

[2]That is, the probability that the error term associated with alternative i is less than or equal to a designated value, say α, can be written

$$P(\varepsilon_i \leq \alpha) = e^{-e^{-\alpha}}$$

and the probability that the error terms associated with a number of alternatives is each less than or equal to designated (not necessarily the same) values can be written

$$P(\varepsilon_1 \leq \alpha_1, \varepsilon_2 \leq \alpha_2, \ldots, \varepsilon_J \leq \alpha_J) =$$

$$P(\varepsilon_1 \leq \alpha_1)\ P(\varepsilon_2 \leq \alpha_2) \ldots P(\varepsilon_J \leq \alpha_J).$$

The Weibull distribution closely resembles the normal distribution except in the tails of the distribution, which are quite different. Also, the Weibull distribution is skewed.

choosing alternative i from among J mutually exclusive alternatives takes a simple, closed form:[1]

$$P_i = P(i \text{ chosen}) = \frac{e^{X_i \beta}}{\sum_{j=1}^{J} e^{X_j \beta}} \qquad (2\text{-}2)$$

In the multinomial probit model, on the other hand, the choice probability P_i cannot be written in a closed, analytic form without an integral.[2] Both models can be estimated by maximum likelihood methods, but it is considerably simpler and less costly to do so for the logit model. Software for maximizing the likelihood function for the logit model and its variates

---

[1]Mathematical treatments of the multinomial logit model are presented in Thomas A. Domencich and Daniel McFadden, *op. cit.*; Daniel McFadden, "Conditional Logit Analysis of Qualitative Choice Behavior," in *Frontiers of Econometrics*, ed. Paul Zarembka (New York: Academic Press, 1974); and Daniel McFadden, "Quantitative Methods for Analyzing Travel Behavior of Individuals: Some Recent Developments," Institute of Transportation Studies, University of California, Berkeley, March 1977.

[2]A mathematical treatment of the multinomial probit model is presented in Jerry A. Hausman and David A. Wise, "A Conditional Probit Model for Qualitative Choice: Discrete Decisions Recognizing Interdependence and Heterogeneous Preferences," *Econometrica* 46 (1978).

is widely available and computer costs of using this software are relatively low.[1] Software implementing the iterative maximum likelihood methods that must be used to estimate the likelihood function for the probit model is less developed and less widely available, and computer costs are higher than for the logit model.

The computational ease of the multinomial logit model resulting from the assumption of independence of error terms is bought at the price of restrictive properties thereby imposed on the model. In particular, the assumption of independence of error terms is consistent with a property of the model that has become known as the "independence of irrelevant alternatives." This property presents problems in projecting probabilities for newly available alternatives, as discussed below.

---

[1]For the logit model, the likelihood function for an individual (or household) can be written as the following product of individual choice probabilities, P_i, defined in Equation (2-2) in the text:

$$L = P_1^{Y_1} P_2^{Y_2} \ldots P_n^{Y_n} ,$$

where Y_i equals 1 if alternative i is chosen and 0 otherwise. Assuming that observations for different individuals are independent, the likelihood function for a sample (assuming that the set of available alternatives is the same for all individuals, which is unnecessarily restrictive) can be written as:

$$L = \prod_{h=1}^{H} \prod_{j=1}^{J} \left(\frac{e^{X_{ih}\beta}}{\sum_{j=1}^{J} e^{X_{jh}\beta}} \right)^{Y_{ih}} ,$$

where individuals (or households) are indexed with the subscript h and alternatives with j. In the probit model the expression in parentheses above would be replaced by a difficult-to-evaluate integral.

The probability that a newly introduced technology will be selected can be calculated using estimated parameters from a multinomial logit model. Because the newly introduced alternative has a nonzero selection probability, the selection probability of at least one of the initially available alternatives must be reduced. It is a characteristic of the multinomial logit model that addition of an alternative reduces the probabilities of selection associated with each of the originally available alternatives by the same percentage. That is, even if the characteristics of the new alternative are *identical* with the characteristics of one existing alternative, the model will not predict that the "popularity" of the identical existing alternative will be reduced by an amount greater than that of any *nonidentical* existing alternative. Similarly, the selection probability of two existing alternatives whose attributes are quite dissimilar will be reduced by equal amounts upon introduction of a new alternative, with attributes "close" to one but not the other of the existing alternatives.

The assumption of independence of the error terms in the multinomial logit model also implies certain relationships among existing alternatives that may not be intuitively pleasing. Specifically, the assumption implies that a change in an attribute of one among several alternatives which makes that particular alternative more desirable will result in an equal reduction in the individual selection probabilities for all other alternatives. For example, if the choice is among oil, gas, and electric heating systems and the price of gas increases by one percent, making gas heating less attractive, all else equal, a multinomial logit model would predict an equal percentage reduction in the individual choice probabilities for

oil heat and electric heat.[1] It is not intuitively obvious that this result should occur. Suppose the alternatives differ in an unmeasured attribute that is important to purchasers, say cleanliness of fuel. Then one might expect more purchasers to shift to electric systems as gas prices rise, all else equal, than to oil systems because electricity is a cleaner burning fuel than is oil. Such effects cannot be captured in a multinomial logit model.

The restrictiveness of the basic logit model and the attendant problems discussed are substantially overcome by the sequential logit model, however. The sequential logit model, which is a variant of the multinomial logit model, is discussed in the following section.

The Sequential Logit Model

The sequential or nested logit model structures a complicated decision-making process into a sequence of decisions.[2] For example, in the case of heating and cooling system combinations, the decision-making process might be factored conceptually into three levels: 1) selection of heating fuel; 2) selection of a heating system given that the choice of heating fuel has been made; and 3) selection of an air conditioning system once the choice of heating system and heating fuel have been made. Such a model is illustrated in Figure 2-1. The sequential logit model is estimated by applying the multinomial logit model to each of the component decisions in the conceptual decision-making process.

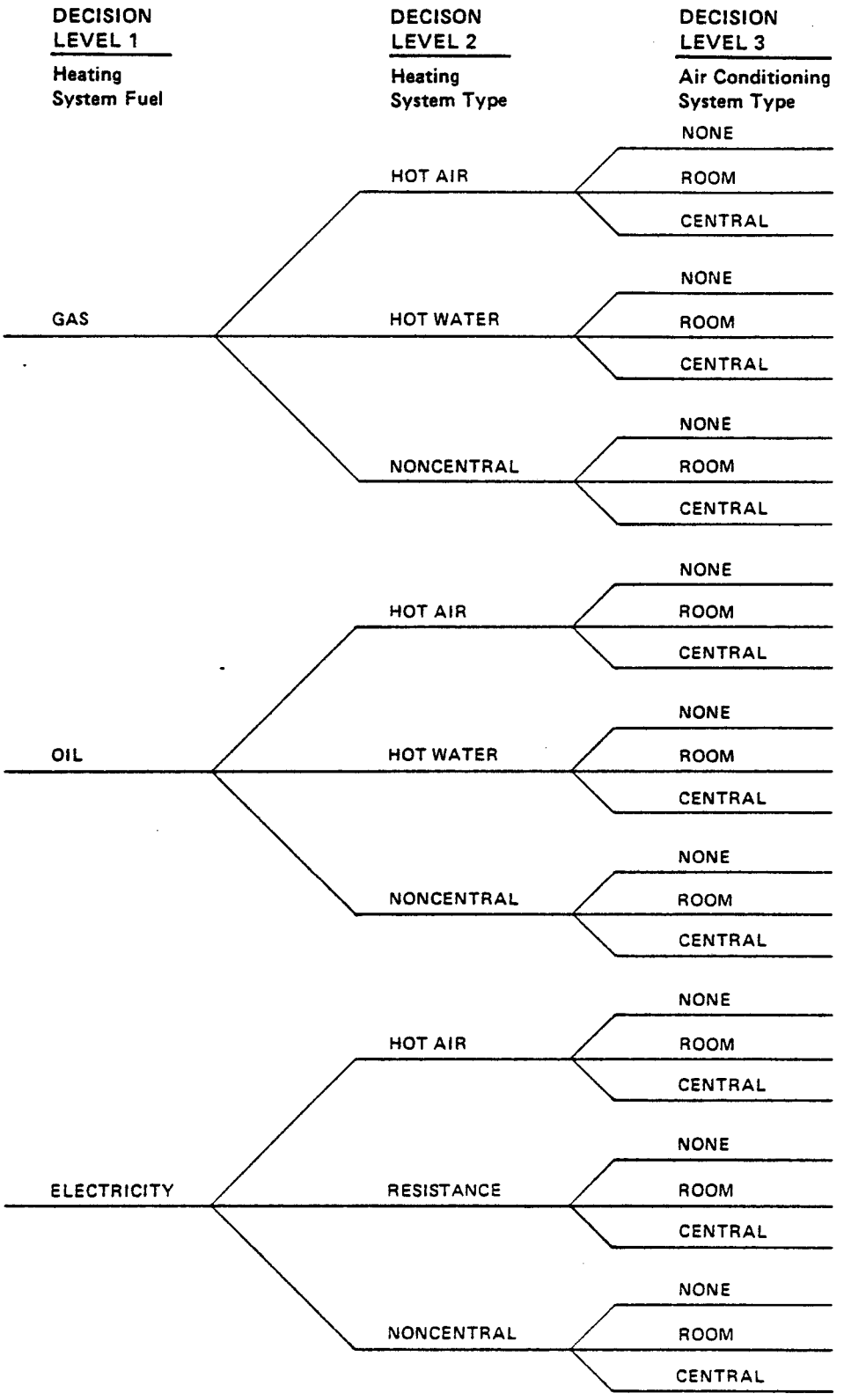
---

[1]That is, at the individual level, the multinomial logit model exhibits equality of cross-partial elasticities of the choice probabilities with respect to attributes of alternatives.

[2]Domencich and McFadden base this approach on an assumption that the individual utility function is weakly separable in the attributes of each decision stage. If this is true and the error terms satisfy the multinomial logit assumptions, then the decision process is separable. (See Thomas A. Domencich and Daniel McFadden, *op. cit.*)

Figure 2–1

A CONCEPTUAL STRUCTURE FOR A SEQUENTIAL LOGIT MODEL OF INDIVIDUAL CHOICE AMONG CONVENTIONAL HEATING AND COOLING SYSTEM COMBINATIONS



SOURCE: Charles River Associates Incorporated, 1979.

Factoring the decision-making process into levels in the sequential logit model has two important benefits. One is that the computation required for complicated problems involving many alternatives is thereby reduced. Thus, in the example just presented, separate multinomial logit models would be estimated for the choice of an air conditioning system from among n alternatives, the choice of a heating system from among m alternatives, and the choice of a heating fuel from among l alternatives, rather than estimating a single multinomial logit model of the choice of a heating and cooling system combination from among up to $n \times m \times l$ alternatives.[1]

A second benefit, and one which is particularly important in predicting acceptance of a new technology, is that the sequential logit model reduces the problem presented by the "independence of irrelevant alternatives" property of the multinomial logit model. The sequential logit model retains the independence of irrelevant alternatives property within each level of the factored decision-making process but not between levels. For example, introduction of a new air conditioning alternative would, under the assumptions of the sequential logit model, reduce the selection probabilities of all existing air conditioning alternatives by an equal percentage in the above example. However, the relative odds of choosing between the new air conditioning alternative in combination with, say, a gas hot air heating system and any one of the combinations of the original air conditioners with a gas hot air heating system would change. Thus, when specifying a sequential logit model,

---

[1]The number of alternatives for the combined systems would be less than $n \times m \times l$ if some combinations of the separate heating and cooling systems and heating fuels were not technically feasible or were not observed to be selected in available data sets. In Figure 2-1 there are an equal number of alternatives at each decision "node" within each decision level. This is not required in general, and software is readily available to handle more complicated models.

it is important that the conceptual decision-making process be specified so that the independence of irrelevant alternatives property is plausible within each decision step. Another way of stating this point is that there should be more "comparability" in the characteristics of alternatives relevant to one decision step than between any of these alternatives and the alternatives considered in the following conceptual decision step.

The steps of the decision-making process as modeled by sequential logit are linked together by the use of variables sometimes called "inclusive prices" in the literature. The concept of an inclusive price variable is most easily explained by example. Consider again the example given above in which the choice by a household of a combined heating and cooling system is factored conceptually into, first, a choice of heating fuel, then a choice of heating system given that heating fuel has been selected, and finally, a choice of air conditioning system given that the heating fuel and heating system have been selected. The criterion for selection of the heating system is its impact on expected utility of the household. However, the impact on utility of choosing a particular heating system alternative also depends on the air conditioning option selected. To represent the impact of air conditioning on utility, the sequential logit model used in estimating the choice of heating system includes as a variable an "average utility" for air conditioning, i.e., the inclusive price variable, which is defined

as the exponential average of the utilities that would result from selection of each of the air conditioning alternatives.[1]

Finally, it should be noted that the order of factorization of the decision-making process in empirical applications of the

---

[1]Using Equation (2-1) in the text, utility is:

$$U_i = X_i\beta \ ,$$

where X is the vector of relevant attributes of alternative i and β the vector of coefficients of those attributes. Assume there are three air conditioning alternatives. Then the inclusive price is:

$$I = e^{X_1\beta} + e^{X_2\beta} + e^{X_3\beta} \ .$$

Note that the inclusive price is the denominator of the expression (Equation (2-2) in the text) for the individual choice probability for any of the available alternatives in the multinomial logit model. (For a mathematical treatment of the sequential logit model, see Daniel McFadden, "Modeling the Choice of Residential Location," (1978, unpublished); for further review see Charles River Associates Incorporated, *Analysis of Household Appliance Choice, op. cit.*)

sequential logit model is essentially arbitrary.[1] There is no way to test that one way of factoring the process is more valid than another, although, for many applications, technical characteristics of alternatives provide a valuable guideline. In Chapter 4 an elaborated version of the sequential logit model presented in Figure 2-1 is developed and an empirical application is tested. The empirical application utilizes the data selected on the basis of a review of available data discussed in the following chapter.

---

[1]If the coefficients of the inclusive price variables are equal to unity (they do not have to be), then the assumptions of the basic multinomial logit model are satisfied and the decision-making problem can be factored in any order. Also, if the coefficients of the inclusive prices do not decrease in value as one moves up the decision tree (e.g., from decision level 3 to level 2 to level 1 in Figure 2-1), then, as McFadden has shown, the sequential logit model is consistent with individual utility maximization under more general assumptions about the error terms than those of the basic logit model. (Daniel McFadden, "Quantitative Methods," *op. cit.*)

Chapter 3
DATA FOR A DISCRETE CHOICE MODEL FOR HEATING AND COOLING SYSTEMS

There are a number of publicly available data sets that might be used to estimate a model of the discrete choice of heating and cooling system combinations. From among these we have selected for use a survey of household appliance ownership and energy use conducted by the Midwest Research Institute (MRI) in 1976. The MRI data set offers certain advantages over alternative disaggregate data sets containing information on appliance ownership and household characteristics. However, it shares with the available alternatives a fundamental shortcoming for the purposes of this study. The data sets reviewed in this chapter contain information on the *stock* of appliances, while the discrete choice model for heating and cooling system combinations developed in this study requires information on *purchases* of equipment for installation in a new housing unit or for replacing a system in an existing unit.

Information on the stock of heating and cooling system combinations can be used to estimate a discrete choice model of system purchases under either of two sets of assumptions. First, using information on current fuel prices and equipment costs, the shares of alternative heating and cooling systems in the stock of all such systems can be interpreted to be the purchase choice a consumer would make if it can be assumed that all households are in long-run equilibrium. This is equivalent to assuming that a household making a purchase would select the system it is observed to own, an unreasonable assumption if fuel or equipment prices have been changing or can be expected to change in real terms, or if there have been significant advances in heating or cooling technology.

Alternatively, if information on fuel prices and equipment costs at the time a system was installed is available, then the shares of alternative systems in the total stock will represent the selection probabilities for purchases if it can be assumed that all household characteristics relevant to the choice did not change significantly between the time the purchase was made and the time the survey was taken. Indexes could probably be used to update some household information if the age of the heating and cooling system were known. Because of dramatic changes in fuel markets in recent years, the second of the above two sets of assumptions seems to us most reasonable.

None of the available data sets reviewed below contains all the information necessary to estimate a discrete choice model for heating and cooling system combinations. The MRI data set can be most easily augmented with supplemental data. However, because the MRI survey did not collect information

on age of heating equipment or age of the dwelling unit, and because fuel prices have changed dramatically in recent years, we have selected from the MRI data set a subsample of observations that can reasonably be believed to describe heating and cooling systems installed in new housing units constructed between 1974 and 1976, that is, after the OPEC embargo. We use this subsample to estimate the empirical discrete choice model presented in Chapter 4 below. Prior to describing the MRI data base and the subsample selected from it, we briefly review data requirements of a discrete choice model for heating and cooling system combinations and summarize available data sets.

Data Requirements and Available Data Sets

The general types of variables affecting household[1] choice of heating and cooling system combinations are as follows: 1) cost of purchasing and installing a particular system combination in the housing unit; 2) expected future operating and maintenance costs of the system in the housing unit; 3) household characteristics affecting ability to pay or preferences among alternative systems; and 4) fuel availability. A minimum information requirement for our purposes consists of data on system type, fuel type, residence size,

[1]We abstract from the problem that it may be the developer rather than the purchaser of the housing unit who makes the space conditioning system decision. This is a serious problem for purposes of model development for policy analysis applications because the developer may be expected to make a different trade off between costs of purchasing and installing the equipment versus future operating costs than the trade off the home owner or renter would make. However, available data do not allow us to resolve this issue.

normal weather conditions, and system efficiency, as well as fuel prices and costs of alternative systems at the time a system was purchased. Household income should also be included. Variables that might be useful for refinement of a model of heating and cooling system choice include information on whether the household owns or rents, number of occupants, and age of occupants.

Available data sets containing information on heating and cooling systems in the housing stock are summarized in Table 3-1.[1] In addition to the MRI data set collected for the Electric Power Research Institute and the Federal Energy Administration, Table 3-1 contains information on data sets collected for the Federal Energy Administration (FEA) or for the FEA and others, a survey by A. C. Nielsen for the Division of Energy of the State of Illinois, a data set collected by the Washington Center for Metropolitan Studies (WCMS), and a data set collected by San Diego Gas and Electric. In addition, characteristics of the Census 5 percent and 15 percent samples are summarized. While Table 3-1 is not exhaustive because new data sets are being collected regularly, it does summarize information on the major, readily accessible data sets.

The MRI data set is discussed in the following section. We conclude this section with comments on critical features of the other data sets that affect their usefulness for the purposes of this study. Each FEA pricing experiment is for a single region. In addition to the experiments summarized in Table 3-1, experiments have been conducted or planned for

---

[1]For further review of these data sets, see Charles River Associates, *Analysis of Household Appliance Choice* (Boston, Mass.: CRA, January 1979).

Table 3-1

SUMMARY OF SELECTED DATA ELEMENTS IN VARIOUS DATA SETS[1]

Data Elements	MRI	FEA Pricing Experiments: Connecticut	Wisconsin	Los Angeles	Ohio	New Jersey	Vermont	Arkansas	San Diego	Nielsen	Arizona	Census 5%	Census 15%	WCMS
Weather		Y							Y					Y
Fuel prices:														
Electric	Y	Y							Y					Y
Gas	P								Y					P
Oil														P
Household: number	Y	Y	Y	Y		Y	Y	Y	Y	Y	Y	Y	Y	Y
Ages	Y	Y	Y	Y		Y		Y	Y	Y	Y	Y	Y	Y
Income	Y	Y	Y	Y		Y		Y	Y	Y	Y	Y	Y	Y
Own/rent		Y	Y	Y		Y		Y	Y	Y		Y	Y	Y
Pay utilities	P	Y	Y	Y				Y			P	Y	Y	Y
Dwelling: house/apt.	Y	Y	Y	Y	Y	Y		Y	Y	Y	Y	Y	Y	Y
One/multiple family	Y	Y	Y	Y	Y	Y		Y	Y	Y	Y	Y	Y	Y
Number of rooms	Y	Y	Y	Y				Y		Y	Y	Y	Y	Y
Square feet	Y		Y			Y			Y	Y	Y			
Storm windows/doors	Y	Y	Y					Y		Y	Y			Y
Floor/attic/wall ins.	Y								Y	Y	Y			
Construction type			Y		Y	Y		Y		Y	Y			Y
Age		Y	Y			Y			Y	Y	Y	Y	Y	Y
Heating: system type	Y	Y	Y		Y			P	Y	Y	P	P	P	P
Fuel type	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y		Y
Thermostats		Y			Y									Y
Water heating: fuel	Y	Y	Y	Y	Y	P	Y	Y	Y	Y	Y	Y		Y
Capacity	P	Y	Y			P		Y			Y			
Age	P	Y	Y	Y										
None	Y	Y	Y	Y							Y			
Cooking: fuel	Y	Y	Y	Y	Y	P		P	Y		Y	Y		Y
Age	P	Y	Y	Y				P			Y			
Central Air Con.: fuel	P	Y	Y	Y	P	Y	Y	Y	Y	P	P			Y
Age	P	Y	Y	Y				Y			Y			
None		Y	Y	Y	Y	Y	Y	Y	Y		Y		Y	Y
Room air con.: age	Y	Y	Y	Y				Y			Y			
Number	Y	Y	Y	Y	Y	Y		Y	Y	P	Y		Y	Y
Clothes dryer: fuel	Y	Y	Y	Y	Y	P	Y	P	Y		Y	Y		Y
Age	Y	Y	Y	Y				P			Y			
None	Y	Y	Y	Y	Y		Y		Y		Y	Y		Y
Availability: gas	Y	Y		Y										
Oil	Y													

[1]Y = Yes, complete information; P = Partial.

SOURCE: Adapted from Charles River Associates Incorporated, Analysis of Household Appliance Choice (Boston, Mass.: CRA, January 1979), p. 4-8.

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Michigan, New York, California, Puerto Rico, North Carolina, Edmond (Oklahoma), Washington, and Rhode Island. Different, but generally similar, questionnaires have been used for each of the pricing experiments. Several of these surveys would have to be combined to be potentially useful for estimating a discrete choice model for space conditioning choice because any one survey covers a single region in which there is little or no variation of fuel prices or weather variables and thus little variation in system operating costs.

The data set collected by the Washington Center for Metropolitan Studies is a national sample. It contains the data from a 1973 survey of 1,455 households and from a 1975 survey of 3,149 households. About 1,000 households appear in both surveys. The data set contains considerable information on household and structural characteristics and on ownership of appliances, including air conditioners. Information on space heating systems is more limited. The 1975 survey collected data on fuel choice and system type, but the system type data are incomplete. The 1973 survey only collected information on fuel choice. Neither survey asked about fuel availability. Information on fuel bills was collected. However, fuel prices for fuels not used by a particular household were not collected. Because households are identified only by state and type of metropolitan area, augmenting the data set with fuel price data would be difficult.

The San Diego Gas and Electric Miracle 2 data set contains information from questionnaires mailed to customers. This data set, which may or may not be made available for public use, contains information on electricity and gas rates, heating system type and fuel, and age of building. Information on heating system or appliance age and on fuel availability is not available. This data set is potentially useful for estimating

a discrete choice model. It would have to be combined with other data sets, which would require determining its sampling properties. The data set resulting from a survey taken by the A. C. Nielsen Company for the state of Illinois could also prove useful, providing its sampling properties were determined and it was augmented with fuel price data. This latter data set contains information only on single-family dwellings, but it does specify whether the household owns or rents and the age of the dwelling (but not the age of the heating system or major appliances).

Finally, disaggregate U.S. Census data available in Public Use Samples, while potentially useful in some discrete choice modeling applications, are not likely to be useful in estimating a discrete choice model for heating and cooling system combinations. Both the 15 percent and the 5 percent samples of the U.S. Census of Housing contain information on household income, ownership or renter status, residence age, size of the housing unit, and type of heating system. However, the breakdown of heating system types is not sufficiently detailed for our purposes. In particular, heat pumps are not distinguished from other hot air systems. Also, information on air conditioning choices is inadequate.

The MRI Data Base and the Subsample Used for Discrete Choice Model Estimation

The MRI data base contains information collected in a 1976 survey of approximately 2,000 households in 16 cities throughout the United States and in a follow-up survey in early 1977 of about 1,500 of these households.[1] The MRI data base

[1]The questionnaires for MRI's patterns of energy use by electrical appliance study are *Appliance Energy Survey 1976* and *Heating Energy Questionnaire - 1977*. (For a discussion of the survey results, see R. D. Harper, D. McDonald, M. Sharp and M. G. Bennett, *Patterns of Energy Use by Electrical Appliances*, Prepared by Midwest Research Institute for Electric Power Research Institute, EPRI Report EA-682, 1979.)

provides information on fuel prices and availability as well as general household and building characteristics. Specifically, the data base includes information on gas and electric rates, the availability of gas and oil, and a description of primary and supplementary heating and cooling systems. It also provides information on household characteristics such as income (by category), size of household, and age distribution of occupants and on building characteristics such as number of rooms, square footage, and amount of insulation.

There are certain deficiencies for our purposes and also some apparent errors in the MRI data base. No information on building age is available; nor is there information on heating system age. The basic information on air conditioners only concerns the existence of either electric central or room air conditioning; no information on gas central air conditioners is available. The survey did not identify home owners versus renters and contained only households that pay their own fuel bills. Finally, the data base contains no information on oil prices, weather, system efficiencies, or system acquisition and installation costs.

To adapt the MRI data base to the purposes of this study, we found it necessary to: 1) make certain assumptions about anomalous or ambiguous survey responses; 2) augment the "corrected" data base with supplemental data on fuel prices, weather, system efficiencies, and cost of equipment acquisition and installation; and 3) select from the corrected and augmented data base a subsample of observations that, because they refer to new homes, provide information on purchases of new heating and cooling system combinations. This selected subsample is the data base used to estimate the empirical discrete choice model for heating and cooling system combinations presented in Chapter 4.

Of the 2,000 households surveyed by MRI, 1,428 responded to the questions concerning heating fuel and system type. Of these, 33 claimed to have gas heat pumps and 1 claimed to have an oil heat pump. Because these systems were not commercially available at the time of the study, we assumed these households had gas or oil hot air systems. The surveys were confusing with respect to their treatments of air conditioning. There is no way to ascertain from the survey whether evaporative coolers are room or central air conditioning units or whether electric heat pumps are heat-only units. We assumed that all households with evaporative cooling systems had central units and that all households with electric heat pumps had central units with cooling capability. Also, if households indicated that they had any form of central air conditioning, we ignored their responses to questions about room air conditioners. Finally, because we restricted our interest in this study to the three major fuel types (i.e., electricity, gas, oil) we eliminated all households from the sample who heated with minor fuels (e.g., coal, wood, bottled gas).

Having made the adjustments to the MRI data base described above, we supplemented the resulting data base with data on fuel prices, costs of equipment acquisition and installation, and normal weather conditions in the 1975-1976 period and with data on system efficiencies. (These data are presented in the Appendix). We collected supplemental fuel price data because the MRI data base did not contain information on oil prices and because responses to the questions about electricity and gas rates were incomplete.

Finally, we selected from the corrected and augmented data base a subsample of 44 observations on homes that we believe were newly constructed in the 1974-1976 period. The subsample, which is described in Table 3-2, was selected for two reasons.

Table 3-2

SUMMARY OF HEATING AND COOLING SYSTEM COMBINATIONS, SUBSAMPLE SELECTED FROM THE MIDWEST RESEARCH INSTITUTE (MRI) DATA BASE
(Number of Observations)

Heating System	Cooling System				Total
	No Air Conditioning	Room Air Conditioning	Central Air Conditioning	Evaporative Cooler	
Gas					
Hot Air	10	8	16	2	36
Hot Water	1	0	1	a	2
Noncentral	1	0	0	1	2
Oil					
Hot Air	0	1	1	a	2
Hot Water	0	0	0	a	0
Noncentral	0	0	0	a	0
Conventional Electric					
Hot Air	0	0	2	a	2
Resistence	0	0	0	a	0
Noncentral	0	0	0	a	0
Electric Heat Pump	a	a	0	a	0
TOTAL	12	9	20	3	44

a = Not a feasible combination.

SOURCE: Compiled by Charles River Associates Incorporated, July 1979.

First, dramatic changes in fuel prices that have occurred between the pre-1974 and post-1974 periods make it unreasonable to assume that the fuel prices from the 1974-1977 period reported in the MRI survey represent real fuel prices at the time a particular heating or cooling system was purchased. Second, because the MRI survey did not ask about age of the housing unit or heating system, it is not possible to collect or infer, by the use of fuel prices indexes, the fuel prices that pertained when the heating and cooling system combination was purchased.

The MRI subsample representing new homes was developed by inferring the age of dwelling units from the ages of two or more major appliances in the dwelling units. Major appliances are defined here as refrigerator/freezers, water heaters, range/ovens, dishwashers, and central air conditioning systems. Of the forty-four observations, six are characterized as having water heaters and central air conditioners of identical and appropriate ages (1974-1976), twenty had central air conditioners and at least one major appliance of the appropriate ages, two had water heaters and one or more major appliances, five had three or more major appliances of identical ages, and the remaining eleven observations had two or more appliances of identical and appropriate ages. In addition to the criterion described above, each individual observation was examined to remove any suspicious observations that met the original criteria. For several observations, two or more major kitchen appliances had identical manufacturing years in the 1974 to 1976 period, but several other major appliances had identical manufacturing ages prior to 1974. We removed these observations, assuming that they represented kitchen remodeling efforts.

Chapter 4
A MODEL OF CHOICE OF HEATING AND COOLING SYSTEM COMBINATIONS

The conceptual model of choice of heating and cooling system combinations in this study is based on the assumption that the decision maker selects from among the technically feasible combinations that combination which yields the highest level of utility or well-being. A system combination is purchased not because it directly increases the well-being of the purchaser but rather because, when combined with fuel, it produces heating and cooling services that directly increase the well-being of the purchaser.[1] The utility yielded by a particular heating and cooling system combination is assumed to depend primarily on the initial cost of the system and on normal operating costs. Normal operating costs depend on fuel price, system efficiency, and weather. Noncost attributes such as cleanliness and perceived safety of the system may also

[1] In terms of the economic theory of the consumer, the demand for heating and cooling equipment is a derived demand. In terms of the economic theory of household production, equipment is a purchased input into a household production process producing heating and cooling services.

affect utility, and some systems may not be selected because of unavailability of fuel.[1]

The empirical formulation of the utility function that is used in this study to describe the impact of choice of alternative heating and cooling system combinations on utility of individual decision makers is as follows:

$$U_i = \alpha_1 K_i + \alpha_2 OCC_i + \alpha_3 OCH_i + \alpha_4 \sqrt{R_i} \cdot CDD + \alpha_5 DRAD_i \cdot HDD + \alpha_6 DNCH_i \cdot HDD \tag{4-1}$$

where:

α = parameter to be estimated;

i = index of heating and cooling system alternatives;

K_i = installed cost of system i;

OCC_i = annual cost of cooling those rooms that system i will cool;

OCH_i = annual cost of heating residence with system i;

$\sqrt{R_i} \cdot CCD$ = measure of cooling comfort of air conditioning subsystem in system i;

$DRAD_i HDD$ = measure of comfort, relative to hot air heating systems, provided by the even heat distribution characteristic of radiant (i.e., hot water, steam, or electric baseboard) heating systems; and

$DNCH_i HDD$ = measure of discomfort, relative to hot air heating systems, provided by the uneven heat distribution of noncentral (i.e., space heaters) heating systems.

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[1]Availability of natural gas, which is dependent on access to a pipeline, has been a major determinant of home heating system choice for new homes in the past. Distillate fuel oil (usually number 2) is available in almost all parts of the country, although, because actual availability depends on the interaction of supply and demand, it may not be observed to be supplied in certain areas where prices of other fuels are sufficiently lower.

Variables and components of variables included in Equation (4-1) are defined as follows:

HDD = annual heating degree days;

CDD = annual cooling degree days;

R_i = percent of rooms air conditioned with system i;

$$OCC_i = \frac{PC_i \cdot R_i \cdot SIZE \cdot CDD}{EC_i}, \text{ where}$$

PC_i = price of fuel used to cool with system i,

EC_i = fuel efficiency of cooling with system i (annual utilization efficiency), and

$SIZE$ = number of rooms in the residence;

$$OCH_i = \frac{PH_i \cdot SIZE \cdot HDD}{EH_i}, \text{ where}$$

PH_i = price of fuel used to heat with system i, and

EH_i = fuel efficiency of heating with system i (annual utilization efficiency);

$DRAD$ = a dummy variable equal to 1 if system i is a radiant system and 0 otherwise; and

$DNCH$ = a dummy variable equal to 1 if system i is a noncentral system and 0 otherwise.

Certain simplifying assumptions underlie the utility function in Equation (4-1). It is assumed that the utility

function is additive in cost and convenience elements.[1] Decision makers purchasing a heating and cooling system combination are assumed to have the same desires regarding realized indoor temperatures irrespective of system type. It is further assumed that a household will maintain each air conditioned room at the same temperature. The difference between outdoor temperature and desired indoor temperature is approximated in the relevant variables of Equation (4-1) by measures of heating and cooling degree days. Finally, it is assumed that the utility derived from a cooling system is a weighted average of utilities for the rooms cooled and the rooms not cooled, that the utility derived from cooling (or not cooling) a room is a function of temperature, and that each additional room air conditioned makes a lesser impact on the utility achieved by air conditioning.[2]

We estimated a sequential logit model of choice of heating and cooling system combinations using the variables in Equation (4-1). The choice problem was factored as follows: 1) air conditioning system choice given heating system and heating

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[1]The functional form of Equation (4-1) is consistent with the assumption that household discount rates are independent of the level of household income. There is theoretical support for the alternative hypothesis that household discount rates decline as income increases -- e.g., that well-to-do households can better afford to save future operating costs by purchasing more efficient but more expensive equipment -- as well as some supporting empirical evidence. (See, in particular, the results for the choice among models of room air conditioners in Jerry A. Hausman, "Individual Discount Rates . . .," *op cit.*) Attempts to estimate functional forms consistent with this alternative hypothesis did not yield promising results. One possible explanation is that the sample reflects a mixture of system choices made by households and by builders, the latter of which are likely to install less efficient but less costly systems in order to keep the house sales price as low as possible.

[2]This final simplifying assumption justifies the use of a nonlinear function of percent of residence cooled (i.e., $\sqrt{R_i}$) in Equation (4-1).

system fuel choices; 2) heating system choice given heating fuel choice; and 3) heating fuel choice. The model was calibrated on the new homes sample selected from the MRI Energy Appliance Survey, as described in Chapter 3, supplemented by data on delivered fuel prices, installed system costs, system fuel efficiency, and heating and cooling degree days. These supplemental data are presented in the Appendix. The heating and cooling systems contained in the sample are all "conventional" systems; there are no electric heat pumps in the sample though some appeared in the MRI survey. In estimating the model, certain system combinations were considered technically infeasible, either in general or in particular climates. Specifically, evaporative coolers, a fourth air conditioning option appearing in the MRI survey in addition to no air conditioning and electric room and central air conditioning options, appeared only in combinations with gas hot air or gas noncentral heating systems and were assumed infeasible with other systems. Also, evaporative coolers were assumed to be feasible only in low humidity climates because they are very inefficient in other climates.[1]

It is important to note that, due to the data limitations discussed in Chapter 3, the model discussed here is calibrated on a sample in which all households have access to natural gas. This limits the applicability of the model to locations where natural gas is available. Thus, development of a data base on system purchases that includes information on households for which gas in not available, in addition to information on households for which gas is available, is a priority research task if the model developed in this project is to be made applicable to the analysis of space conditioning choice nationwide.

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[1]No estimation problems are presented by having differing numbers of air conditioning alternatives available depending on the choice of heating system made. Similarly, available software can handle the case in which certain system options are considered infeasible for a household because of its location.

Sequential logit estimates of the parameters of variables affecting choice among four air conditioning systems -- none, electric room, electric central, and evaporative cooler -- conditional on heating system and heating fuel are presented in Table 4-1.

Estimates of the parameters of variables affecting choice among three heating system types -- hot air, hot water/steam, and noncentral -- conditional on heating fuel choice are shown in Table 4-2.

The estimates for choice of heating fuel among gas, oil, and electricity for use in conventional heating systems are shown in Table 4-3.

The estimates from the sequential logit model have the expected signs with one exception, noted below. Cost variables reduce utility and variables representing increased comfort levels increase utility. The two normal operating cost variables, OCC_i in the air conditioning choice estimation and OCH_i in the fuel choice estimation, have negative coefficients, indicating that in the sample an increase in the normal operating cost of providing space conditioning services reduces the utility of a space conditioning system, all else equal. The capital cost variable, K_i, also has a negative coefficient, although at a low level of significance, indicating that an increase in system installed cost reduces utility. We suspect that the low significance level for the parameter of the capital cost variable is due to limited variation in capital costs of heating systems (which are primarily gas hot air systems) in the sample used to calibrate the model.

Two of the convenience variables -- $\sqrt{R_i} \cdot CDD$ in the air conditioning choice equation and $DNCH_i HDD$ in the heating system choice equation -- have the expected signs. The first of these, which is a measure of cooling system comfort, has a significant positive coefficient and the second, which is a measure of comfort of noncentral heating systems relative to hot air systems, has a significant negative coefficient. The remaining

Table 4-1

PARAMETER ESTIMATES FOR AIR CONDITIONER CHOICE

Variable	Coefficient	Asymptotic Standard Error	t-Statistic
OCC_i	-.0000265	.0000232	1.14
K_i	-.000814	.000745	1.09
$\sqrt{R_i} \cdot CDD$	.00222	.00073	3.04

Number of observations = 44

-2 log likelihood = -15.879

SOURCE: Estimated by Charles River Associates, 1979.

Table 4-2

PARAMETER ESTIMATES FOR HEATING SYSTEM CHOICE

Variable	Coefficient	Asymptotic Standard Error	t-Statistic[1]
Inclusive price from air conditioner choice	1.140	.750	1.52
$DRAD_i HDD$	-.000371	.000161	2.30
$DNCH_i HDD$	-.001488	.000659	2.26

Number of observations = 44

-2 log likelihood = -69.595

[1]The computer software used in this study does not adjust t-statistics to account for the fact that the values of the inclusive price variable are estimated.

SOURCE: Estimated by Charles River Associates, 1979.

Table 4-3

PARAMETER ESTIMATES FOR HEATING FUEL CHOICE

Variable	Coefficient	Asymptotic Standard Error	t-Statistic[1]
Inclusive price from heating system choice	.675	.591	1.14
OCH_i	-.0000363	.00000828	4.38

Number of observations = 44

-2 log likelihood = -52.333

[1]These t-statistics have not been adjusted to account for the fact that the values of the inclusive price variable are estimated.

SOURCE: Estimated by Charles River Associates, 1979.

convenience variable, $DRAD_i HDD$ in the heating system choice equation, has a significant negative coefficient which we did not expect. We thought that radiant systems would be preferred to hot air systems, all else equal, because of the greater evenness of the heat provided.

The coefficients on the inclusive price variables linking together the stages of the sequential logit model are interesting. Neither coefficient is significantly different from unity; this result suggests that *in the particular sample used to calibrate the sequential logit model* the assumptions of the basic multinomial logit model are satisfied.[1] This is an unexpected result. It will be interesting to see if it can be replicated when data sets on space conditioning system purchases containing households with and without access to natural gas become available.

The empirical model of choice of individual decision making units among alternative heating and cooling system combinations presented in this chapter can be used to project the acceptance of innovative systems by decision makers. To do this, the appropriate values of cost and other variables for the new system are entered into the above estimated equations in sequence and conditional choice probabilities are calculated for each of the three steps of the conceptualized decision making process.[2] The initial empirical specification of the model presented here is limited by the data set on which it is calibrated to applications in which all decision making units have access to natural gas. Nevertheless, as demonstrated in the following chapter for the case of gas heat pumps, the model can be used to analyze the market acceptance of important innovative energy-using technologies.

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[1]In this case, therefore, the order in which the decision-making process is factored does not matter.

[2]According to Equation (2-2).

Chapter 5
INCORPORATION OF THE DISCRETE CHOICE MODEL IN A MODEL OF MARKET PENETRATION

Given fuel prices, equipment costs, efficiencies of alternative systems, dwelling units size, climate characteristics, and income, the discrete choice model estimated in the preceding chapter can be used to forecast the fraction of equipment sales represented by the new technology at any point in time. The model cannot be used by itself to forecast the fraction of the equipment stock represented by the new technology, i.e., it cannot be used directly to forecast the market penetration of the new technology. Besides modeling the purchase choice, it is also necessary to model the physical depreciation and replacement of existing equipment, and the growth of the capital stock. Thus, while the discrete choice model provides information on the purchase decision, the other two factors determine when these purchases are made.

We demonstrate the interaction of these influences in this chapter by simulating the market penetration of gas heat pumps in the state of Kansas. Determination of each of

the three major factors is described in detail; their interaction is discussed and an empirical model is developed to demonstrate the forecast of gas heat pumps over a 30-year simulation interval in the sample state. We lack actual data on many of the exogenous variables, and several important influences including uncertainty are not included in this limited version of the model. Therefore, *this forecast should be viewed only as illustrative of the market penetration process.*

Before examining the determinants of market penetration, several issues are addressed. The aggregation problem encountered in applying a model estimated with household data to forecasting choices on an aggregate geographical basis is addressed. Difficulties in our analysis posed by excluding the impacts of uncertainty are also discussed. Finally, we define several scenarios used to illustrate the impacts of exogenous factors on market penetration.

Aggregation Problems

The first obstacle encountered in using the sequential logit model to forecast gas heat pump sales in Kansas concerns the aggregation problem. The empirical model was estimated using individual household data and therefore is strictly applicable to forecasting choice probabilities for individual households within the population. Since individual household data for the population do not exist and since the market penetration analysis requires the fraction of the purchasing population choosing the new technology, other methods of forecasting population purchase decisions must be used. One method is to use average values of the independent variables in the state and to forecast equipment choice for this "average" household. Since the purchase estimate is a nonlinear

function of independent variables, this approach is likely to introduce large aggregation errors because a nonlinear function of average independent variables is not generally the average of the individual nonlinear functions evaluated for each individual household. A preferred approach that will minimize these aggregation errors and still not represent unmanageable data requirements is to divide the state population into cells that are defined so that cell inhabitants are relatively homogeneous, thereby minimizing the aggregation bias for each individual cell. Purchase fractions are then weighted by cell population and aggregated across cells to derive the population purchase forecasts. Cells were defined for this exercise using data from the Annual Housing Survey two-way frequency tables of household income and dwelling unit size for the North Central Region. These cells are defined in Table 5-1. In the simulations that follow we assume that the cell frequencies remain constant over the simulation period.

Implications of Excluding Uncertainty

Uncertainty concerning operating characteristics of new technologies and future fuel prices contribute to the attractiveness of a new technology relative to existing technologies. The impact of uncertainty in these variables decreases both the probability of choice of the new technology and the rate of existing equipment replacement. The state of the art in empirically representing uncertainty and the unavailability of data needed to represent these influences clearly make the explicit consideration of uncertainty infeasible in this study.

Table 5-1

TWO WAY FREQUENCY TABLE:
HOUSING SIZE BY 1976 HOUSEHOLD INCOME
(Information from Occupied[1] Housing Units in the North Central Census Region)

1976 Income (Dollars)	Housing Size by Number of Rooms					
	3 or Less	4	5	6	7 or More	Total[2]
Less than 3,000	.0257	.0212	.0168	.0111	.0093	.0841
3,000 - 5,000	.0208	.0274	.0265	.0161	.0105	.1013
5,000 - 7,000	.0148	.0219	.0238	.0148	.0107	.0860
7,000 - 10,000	.0147	.0309	.0325	.0220	.0174	.1175
10,000 - 15,000	.0191	.0374	.0591	.0476	.0395	.2027
15,000 - 20,000	.0078	.0224	.0475	.0432	.0389	.1598
20,000 - 25,000	.0023	.0094	.0271	.0315	.0351	.1054
25,000 - 35,000	.0015	.0061	.0197	.0255	.0379	.0907
35,000 or Greater	.0014	.0016	.0072	.0127	.0307	.0526
TOTAL	.1071	.1783	.2602	.2244	.2300	1.0000

[1] Sum of owner and renter occupied dwelling units.

[2] Totals may not equal sums of columns and rows due to independent rounding.

SOURCE: U.S. Bureau of Census, *Annual Housing Survey: 1975, Financial Characteristics of the Housing Inventory* (Washington, D.C.: U.S. Government Printing Office, 1976), Table C-1, pp. 177, 179.

It is evident, however, from our discussion of the equipment choice model in the last chapter and the discussion of the replacement decision later in this chapter, that an increase in uncertainty over operating characteristics and fuel prices and an increase in new technology equipment costs are both inversely related to the probability of equipment choice and the rate of replacement. That is, changes in equipment cost and uncertainty both exhibit the same qualitative influence on market penetration. For example, the qualitative impact of a reduction of uncertainty concerning operating characteristics over the first decade that a new technology is on the market is identical to the impacts of a reduction in equipment cost over the same period of time.

Therefore, if our simulation results indicate that the equipment cost influence is likely to significantly influence market penetration, a case has been made to include both influences explicitly in a full-scale disaggregate representation of the market penetration model. In any case, the correspondence of the two influences allows us to ignore one of them in pursuing the primary objective of this study, which is to demonstrate the feasibility of a disaggregate modeling of market penetration developed directly from investment theory.

Scenario Descriptions

The baseline scenario incorporates fuel price forecasts based on trends in DOE price forecasts for 1975 through 1995 and a 0.6 percent rate of growth of the housing stock. The stock growth rate is identical to the historic growth rate

in Kansas between 1960 and 1970. Since each dwelling unit has one heating ventilation and air conditioning (HVAC) system, the housing stock is identical to the HVAC stock. These series are presented in Table 5-2. Heating and cooling degree days are identical across scenarios and represent normal climatic conditions in Kansas. We assume that the initial cost of the various systems as presented in Table A-3 of the Appendix do not change over time. We also assume that efficiencies, dwelling unit size, and real income do not vary over the 30-year simulation period. We assume that the gas heat pump is introduced in the initial period; this immediate introduction allows a greater interval for the evaluation of the market penetration function.

The second scenario assumes that initial cost of the gas heat pump is 50 percent greater than the estimated cost in the initial simulation period and that the cost declines over 15 years to correspond to costs in the baseline scenario. This scenario is consistent with a high initial and a declining cost of production of new technologies from learning by doing, economies of scale, and other factors that reduce production costs of a new product over time.

High fuel price and low fuel price scenarios are also specified, using the high initial-declining cost assumption of the second scenario. Gas price in the final year of the simulation is 25 percent higher in the high scenario and 25 percent lower in the low price scenario, relative to the baseline price assumptions at the end of the forecast period.

The final scenario incorporates an accelerated growth of housing stock assumption. The high initial-declining cost of the second scenario is used along with a housing stock growth rate of 1 percent per year instead of the baseline rate of 0.6 percent.

Table 5-2

BASELINE FUEL PRICE AND EQUIPMENT STOCK ASSUMPTIONS

Simulation Period (Annual)	Fuel Prices (1972 Dollars per Million Btu)			HVAC Stock[1] (Thousand Units)
	Gas	Oil	Electric	
1	1.29	2.05	7.46	700.7
5	1.50	2.08	7.50	722.0
10	1.77	2.51	7.62	743.9
15	2.15	2.85	7.52	760.5
20	2.61	3.34	7.57	789.8
25	2.88	3.68	7.57	813.7
30	3.18	3.95	7.57	838.4

[1] HVAC stands for heating ventilation and air conditioning equipment.

SOURCE: Data developed by Charles River Associates, July 1979.

While further scenarios can be defined to include assumptions on future incomes, dwelling unit size, and equipment efficiencies, an evaluation of the five scenarios defined above is sufficient to demonstrate the feasibility and advantages of the disaggregate structural approach in modeling market penetration.

Equipment Purchase Choice

The sequential choice logit model estimated in the preceding chapter is used to forecast choice of the new technology using the aggregation scheme outlined above. The model must be used to forecast purchase choices in both new dwelling units and existing dwelling units. These two situations must be distinguished because the relative costs of alternative heating and cooling systems differ depending on whether the systems are installed in new dwelling units or are used to replace existing systems. For instance, installation costs of gas hot water and gas hot air systems are nearly identical in new dwelling units. However, replacement of a gas hot water system with a gas hot air system is considerably more expensive than replacing a gas hot water system with a new gas hot water system because of the need to install ducting when switching from hot water to hot air systems. Assumed replacement system costs are presented in the Appendix, Table A-6.

Equipment choice for new dwelling units for the baseline scenario is presented in Table 5-3. These new equipment choices can be compared with the initial 1970 Kansas equipment shares of 52, 1, 1, and 46 percent for gas hot air, oil hot air, electric hot air, and other systems.

Table 5-3

SYSTEM CHOICES AS PERCENTAGE OF TOTAL PURCHASES, BASELINE SCENARIO FOR NEW DWELLING UNITS

Simulation Period	Gas Hot Air	Oil Hot Air	Electric Hot Air	Other [1]	Gas Heat Pump
1	42.16	13.77	.35	4.96	38.76
5	38.74	16.05	.39	4.88	39.94
10	37.58	12.56	.47	4.48	44.91
15	33.99	11.94	.69	4.12	49.26
20	30.06	10.16	.99	3.66	55.13
25	27.64	9.70	1.23	3.44	57.99
30	25.42	8.19	1.60	3.14	61.65

[1]Other includes gas and oil non-central electric resistance and gas and oil hot water systems.

SOURCE: Data developed by Charles River Associates, September 1979.

The purchase model indicates a minimal future choice of electric hot air and other systems (gas and oil hot water, gas and oil noncentral, electric resistance) and a relatively small choice of oil hot air systems. A comparison with the stock fractions above indicates that stock fractions can be expected to shift away from gas, electric and other systems to oil and gas heat pumps. The introduction of gas heat pumps in the first simulation period results in a gas heat pump purchase share of 39 percent. Gas hot air systems sales are affected most by the introduction of new technology. The sales fraction of gas heat pumps increases from 39 percent to 62 percent at the end of the 30-year simulation period. Gas hot air, oil hot air, and other systems sales fractions decline by roughly 40 percent over the simulation interval. Electric hot air, on the other hand, increases its sales performance as the price of fossil fuels rises at a greater rate than electricity prices; however, at the end of the simulation, electric hot air still accounts for only 2 percent of sales.

The relatively large increase in market sales of gas heat pumps is a result of the fact that relative to its two primary competitors, gas hot air and oil hot air, the smaller operating cost component of the gas heat pump system, along with significant fuel price increases, makes gas heat pumps more attractive options for each year of the simulation.

The high initial-declining cost scenario (Table 5-4), as expected, reduces the purchase fractions of gas heat pumps until the fifteenth year, at which time gas heat pump costs are identical to the base case scenario. The

Table 5-4

SYSTEM CHOICES AS PERCENTAGE OF TOTAL SALES, DECLINING COST SCENARIO FOR NEW DWELLING UNITS

Simulation Period	Gas Hot Air	Oil Hot Air	Electric Hot Air	Other[1]	Gas Heat Pump
1	55.35	17.42	.40	6.44	20.39
5	47.08	19.06	.43	5.87	27.56
10	41.99	13.80	.49	4.99	38.73
15	33.99	11.94	.69	4.12	49.26
20	30.06	10.16	.99	3.66	55.13
25	27.64	9.70	1.23	3.44	57.99
30	25.42	8.19	1.60	3.14	61.65

[1]Other includes gas and oil non-central electric resistance and gas and oil hot water systems.

Source: Data developed by Charles River Associates, September 1979.

declining initial cost scenario forecasts a sales increase from 20 to 62 percent of the market, more than tripling in the thirty-year simulation.

Purchase fractions for the replacement systems start at roughly half of the fractions for the new systems and are about three quarters of the new systems fractions by the end of the simulation. This trend in the replacement reflects the fact that it is not economical to install hot air systems given an existing non-hot air system, and the fact that the initial stock of dwelling units, with a preponderance of non-hot air systems, is being depreciated and removed from the stock at the rate of 1 percent per year in the simulation model.

Depreciation and Replacement of Existing Equipment

Comparison of new stock additions to the existing stock indicates that the most important determinant of the market penetration in the years shortly after introduction of the new technology is the replacement of existing stock by the new technology. For instance, given our stock growth assumption of 0.6 percent per year along with a 1 percent removal rate of dwelling units and a fifteen year lifetime for heating and cooling sytems, the sales of systems for new dwelling units amounts to 1.6 percent of total stock, while sales for replacement of systems is 6.6 percent. On the other hand, if an average system's lifetime is ten years, replacement systems represent 9.9 percent of the total stock.

To model replacement decisions, we assume a one-horse-shay replacement rule. That is, all equipment is replaced after it reaches the optimal replacement age. We also assume that households make replacement decisions such that discounted future operating and initial costs are minimized. These assumptions allow us to derive the condition under which present equipment will be replaced by a new purchase. In general terms the optimal replacement condition is given as:[1]

$$c_i(t_i^*) = r\left[F_{i+1} + \int_0^{t_{i+1}^*} c_{i+1}(t)e^{-rt}dt\right], \quad i=1,\ldots,n-1 \quad , \qquad (5\text{-}1)$$

where:

F_i = capital (or fixed) cost of the *ith* durable good inclusive of the cost of installation, where i denotes temporal ordering;

$c_i(t)$ = operating and maintenance (or variable) cost of production using the *ith* durable good, which is assumed to increase monotonically with elapsed time since installation;

t_i^* = optimal age to replacement of the *ith* durable good;

r = continuous rate of discount.

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[1]See Jackson and Kaserman, *op. cit.*

That is, the optimal replacement period is defined as that time at which the operating cost of existing equipment equals total discounted operating cost and initial cost of the new system times the household discount rate. Since r is the value of a dollar per unit time to the household, r times the discounted life cycle cost of the new system is the opportunity cost of delaying the purchase of the new system. This cost will exactly equal the cost of operating the present equipment one time period at the moment at which replacement becomes optimal.

This relationship is used to help determine a depreciation rate that is consistent with initial cost estimates, operating cost estimates and average lifetimes of the alternative systems. The relationship is also used to determine changes in optimal replacement times given changes in fuel prices and initial costs. It is obvious from Equation (5-1) that price increases increase both the operating cost of the existing system and the operating cost of the new system. Generally the changes occur in ways that are not offsetting, so that the optimal age to replace existing equipment will change over the simulation period in response to the variations in fuel price. A change in the initial cost of the new equipment will change the replacement time in the same direction. Thus a reduction in the cost of a new technology will result in earlier replacement of existing equipment. The high initial-declining gas heat pump cost scenario will alter optimal replacement time by initially delaying replacement of existing equipment with the gas heat pump. These observations underscore the necessity of considering both replacement and purchase decisions in market penetration analysis.

To implement this relationship in the simulation model we represent the general relationship by:

$$P_{j,t} \cdot E_j \cdot (1+d_j)^{t-to} = r\left[F_{K,t} + \sum_{i=0}^{A} P_{K,t+i} \cdot E_K \cdot (1+d_K)^i / (1+r)^i\right] \qquad (5\text{-}2)$$

where

$P_{j,t}$ = price of fuel for the jth system at time t;

E_j = energy use requirement of the jth system;

d_j = depreciation rate of the jth system;

t_o = existing equipment purchase time;

$t-t_o$ = replacement age;

F_j = initial cost of the jth system;

r = household discount rate; and

A = expected lifetime of new equipment.

Assuming a value for the discount rate, Equation (5-2) allows us to derive depreciation rates consistent with estimated lifetimes, fuel prices, and average energy use requirements.[1]

Given the estimated depreciation rate we can solve (5-2) analytically for the optimal replacement age, $t-t_o$, which is a function of fuel prices, initial equipment costs, depreciation rate, discount rates, and expected lifetime of the new equipment. Optimal replacement time for the baseline and the high initial-declining gas heat pump initial cost scenario are presented in Table 5-5, for replacement of the two most important conventional systems with the gas heat pump.

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[1]A discount rate of .18 was chosen for this simulation exercise.

Table 5-5
OPTIMAL REPLACEMENT AGE FOR GAS HEAT PUMP REPLACEMENT
OF GAS AND OIL HOT AIR SYSTEMS
(years)

Simulation Period	Baseline Scenario		High Initial-Declining Cost Scenario	
	Gas Hot Air	Oil Hot Air	Gas Hot Air	Oil Hot Air
1	14	12	20	22
5	13	13	17	19
10	12	11	13	13
15	10	10	10	10
20	9	8	9	8
25	8	8	8	8
30	8	7	8	7

SOURCE: Data developed by Charles River Associates, July 1979.

As Table 5-5 indicates, the increased initial cost of the gas heat pump in the second scenario delays replacement of gas hot air and oil hot air by gas heat pumps over the first fifteen years. Thus the introduction of more expensive new technologies will tend to delay purchase of the new technology more than if the technology were less expensive.

Growth of the Housing Stock

Two different assumptions are made with respect to growth of equipment stock. The assumption used for all scenarios but one is that the HVAC stock increases at the rate of .6 percent per year as was the case over the 1960-1970 period. A high stock growth rate of 1 percent is assumed for the high growth scenario. These two assumptions result in a total stock at the end of the thirty year simulation period that is 20 percent and 35 percent greater than the initial stock for the baseline and high stock scenario respectively. At the end of the simulation period however, HVAC systems installed in new dwelling units since the initial time period represent 39 percent and 45 percent of the total stock. The difference between the housing stock growth and new HVAC system growth results from the fact that many of the initial dwelling units have been removed from the stock and replaced by new dwelling units with new HVAC systems.

Market Penetration of Gas Heat Pumps

The market penetration of gas heat pumps in Kansas for the different scenarios described above can now be forecast by combining our representations of equipment depreciation and replacement, growth of the equipment stock, and the econometrically estimated discrete choice model.

This process is carried out with a computer simulation program developed for this application. The simulation model represents the equipment stock by age and equipment type. Equipment stock figures are consistent with the Kansas census of housing (1970). Age distribution of the equipment stock was developed from data on additions to the housing stock from 1955 to 1977[1] and an even distribution across ages for the pre-1955 stock. The resulting age distribution corresponds closely to a uniform distribution. The simulation model determines additions of new equipment in new dwelling units required by depreciation (1 percent per year) and growth of the housing stock. Existing equipment stock is reduced by 1 percent to represent depreciation of the housing stock; the stock is aged appropriately over the thirty year simulation interval.

Information on fuel prices, income dwelling unit sizes, weather, and equipment efficiencies and costs are used in each simulation period to estimate equipment choice for new and existing dwelling units. The purchase fractions are applied directly to the stock of equipment required by new dwelling units to determine the number and type of new equipment required in new dwelling units.

Optimal age for replacement of conventional systems with gas heat pumps is calculated for each simulation period using the appropriate fuel price and equipment cost variables. Equipment that is older than the optimal replacement age in each simulation period is replaced with conventional systems or the gas heat pump. This equipment choice is determined with the sequential logit model forecasts where input exogenous variables are the same as the new dwelling unit case except that equipment costs represent the cost of replacing an existing system with the gas heat pump. These replacement costs are documented in Table A-6 of the Appendix.

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[1]U.S. Department of Commerce, *Construction Review*, numerous volumes.

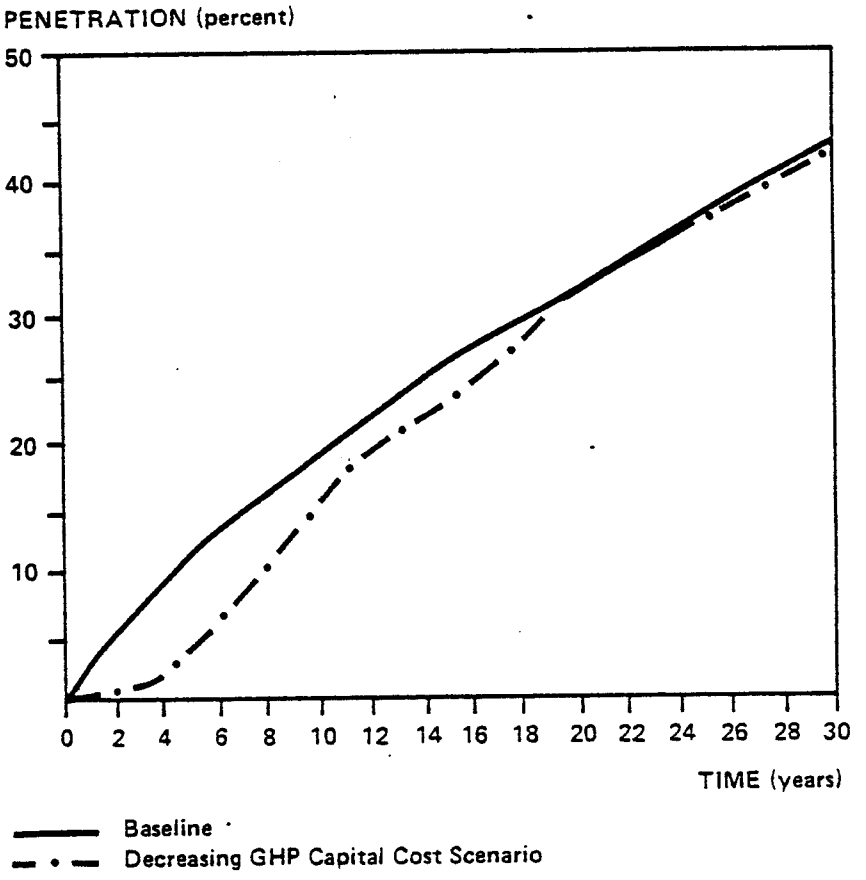
Figure 5-1 represents market penetration curves for the baseline and the high initial-declining cost scenario. The baseline penetration function resembles the commonly observed exponential penetration function and the declining cost scenario is similar to the more usual s-shaped penetration function. The higher initial cost of the gas heat pump in the second scenario causes replacement purchases to be postponed and reduces the fraction of new purchases represented by the gas heat pump. When existing systems begin to turn over, the declining cost of the heat pump causes the replacement to accelerate and the purchase fraction to increase so that the initial portion of the penetration curve has a slope that increases slowly, then at an increasing rate, and finally at a decreasing rate as the market becomes saturated.

Two additional scenarios are presented in Figure 5-2. As expected, the accelerated growth of the housing stock increases the penetration of gas heat pumps. This result is expected since the new dwelling unit market is penetrated to a greater extent than the replacement market. It is interesting to note, however, that even though the total stock is 5 percent greater at the end of the simulation under the accelerated growth, gas heat pump penetration is only about 2 percent greater, indicating the strong influence of the replacement market.

The low gas price scenario (gas prices at the end of the simulation that are 25 percent less than the baseline) results in a decrease in market penetration of gas heat pumps. The reason for this result is that conventional gas systems with higher operating but lower initial costs are more attractive relative to the baseline case. The impacts of a high gas price are nearly symmetrical and are not represented in Figure 5-2.

Figure 5—1

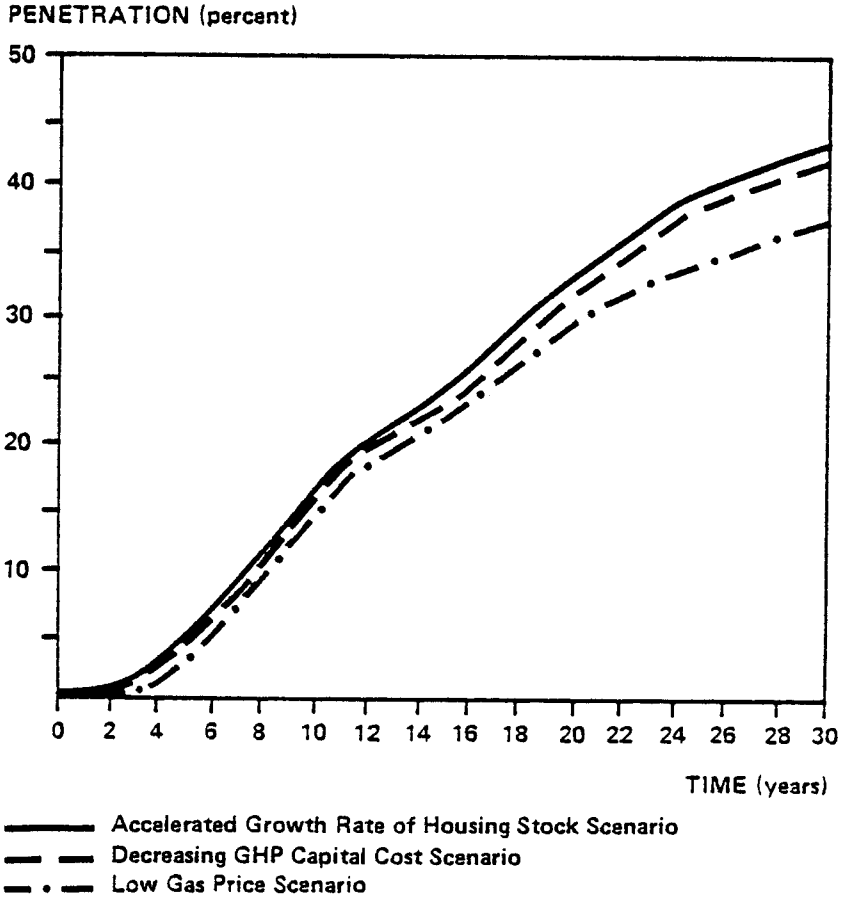
PENETRATION OF THE GAS FIRED HEAT PUMP



SOURCE: Charles River Associates Incorporated, 1979.

Figure 5—2

PENETRATION OF THE GAS FIRED HEAT PUMP
ALTERNATIVE SCENARIOS



SOURCE: Charles River Associates Incorporated, 1979.

Several conclusions can be drawn from the four scenarios presented in Figures 5-1 and 5-2. Reasonable assumptions on the exogenous variables that determine these three factors produced, in Figure 5-1, the two most widely observed market penetration functions reported in the literature. Growth of the equipment stock and the initial cost of the new technology relative to existing systems are the most important determinants of the shape of the penetration function in the years immediately following the new technology introduction. The impact of these and other variables tends to result in a simple shifting of the curve in the later years of the simulation.

It is interesting to note the conclusions that might be drawn if the result of only the discrete choice model were used to evaluate the near term energy savings impacts of new technologies. For instance, the scenarios in Figure 5-1 represent penetrations of 11.4 percent and 3.8 percent after five years. Utilizing the results of the discrete choice model to reflect penetration misstates the difference in the energy impacts of the two scenarios because purchase choices are much closer in relative terms: 40 percent and 28 percent.

The simulations also point out the importance of accurately modeling replacement investment decisions. Modeling of replacement investment is presently an underdeveloped topic in the economics literature; considerable headway must be made in this area.

The similarity of impacts resulting from changes in equipment cost and uncertainty and the results of the declining cost scenario point out the potentially significant

influence of uncertainty on market penetration. It is likely that costs decline and uncertainty of operating characteristics increases over the early years of equipment availability. Therefore, the initial s-shape can be expected to be even more pronounced than indicated in the figures. In any case, uncertainty will affect both the rate of increase and the level of market penetration of the new technology.

Finally, the simulations indicate that it is possible to empirically model the complex interaction between equipment stock growth in a manner consistent with economic theory and engineering characteristics of the competing systems.

Implementation of the Market Penetration Framework in the ORNL Models of Residential and Commercial Energy Demand

The implementation of this market penetration modeling approach in the ORNL models of residential and commercial energy demand will provide the first opportunity to study market penetration of detailed end-use systems using an approach based on something other than ad hoc relationships. The first task required in such an implementation is the modification of the ORNL models to incorporate the required detail on age characteristics of existing equipment. The second task relates to the development of comprehensive models of equipment choice for both households and commercial firms. The model estimated in this study is based on too small a sample to be used to represent national HVAC equipment choices. Unfortunately, we used the most detailed data

set available consistent with data needs of the sequential logit model. We hope data presently being collected by the Department of Energy as part of their national surveys will provide sufficient information to estimate equipment choice relationships for the most important end uses. Finally, considerably more information must be developed for items such as age distribution of existing equipment, depreciation characteristics of both structures and equipment, and information that is required to forecast equipment choice (e.g., income and dwelling unit size distributions).

A detailed comprehensive incorporation of this market penetration approach will require staff and budget commitments similar to those required in the early development of the ORNL end-use demand models. Considering the policy importance of questions that hinge on the ability to forecast market penetration of new technologies, such an investment appears to be a prudent undertaking.

Appendix

Table A-1

COMPETITIVE DELIVERED FUEL PRICES FOR HOME HEATING, DECEMBER 31, 1975
(Dollars per million British thermal units)

City	Natural Gas	Electricity	Number 2 Fuel Oil
Boston	$2.990	$11.723	$2.972
Denver	1.003	9.437	2.535
Des Moines	1.045	5.510	2.535
Lubbock, TX	1.150	6.477	2.676[a]
Miami[b]	2.200	16.640	2.958
Minneapolis	1.360[c]	4.396[c]	2.746[a]
New Orleans	1.370	9.378	2.676
Owensboro, KY	1.140	10.550	2.042
Philadelphia	2.080	7.561	2.634
Portland, ME	2.500	14.946[d]	2.676
St. Louis	1.570	4.308	2.753
San Diego	1.558	12.485	2.817[e]
Spokane[f]	2.360	4.396	3.669
Topeka	1.030	5.979	2.608
Trenton[g]	2.305	8.498	2.803
Tucson	1.450[h]	13.188[h]	2.614[i]

[a]Price in Houston.

[b]Prices in Fort Lauderdale.

[c]Price in Lafayette.

[d]Price in Portsmouth.

[e]Price in Los Angeles.

[f]Prices in Yakima.

[g]Prices in Elizabeth.

[h]Price in Flagstaff.

[i]Mean of prices in Houston, Los Angeles, Denver and Salt Lake City.

SOURCE: American Gas Association, *Gas Househeating Survey, Present and Prospective Customers 1975-1978*, pp. 39-47.

Table A-2

SELECTED NORMAL WEATHER DATA

City	Annual Heating Degree Days	Annual Cooling Degree Days
Boston	5621	661
Denver	6016	625
Des Moines	6710	928
Lubbock, TX	3545	1647
Miami	206	4038
Minneapolis	8159	585
New Orleans	1465	2706
Owensboro, KY[a]	4629	1364
Philadelphia	4865	1104
Portland, ME	7498	252
St. Louis	4750	1475
San Diego	1507	722
Spokane	6835	388
Topeka	5243	1361
Trenton	4952	968
Tucson	1752	2814

[a]Data for Evansville used.

SOURCE: National Oceanic and Atmospheric Administration, *Local Climatological Data, 1976*.

Table A-3

ESTIMATED INITIAL COSTS OF VARIOUS HEATING AND COOLING SYSTEMS, JANUARY 1976[a]

System	Estimated Cost (Dollars)
Gas hot water	$ 2950
Oil hot water	2575
Gas hot air	2675
Oil hot air	2475
Electric hot air	1650
Central air conditioner, with hot air system	650
Central air conditioner, separate	1975
Electric heat pump	2575
Electric resistance	1475
Evaporative cooler, with gas hot air system	325
Evaporative cooler, separate	1650
Room air conditioner, per unit	290
Gas heat pump[b]	3100

[a]Installed costs in a typical six-room ranch style house in the Boston area. All costs converted to a January 1976 basis using U.S. wholesale price index, household appliances.

[b]The gas heat pump is considered in our application of the model to forecasting the market penetration of new technologies.

SOURCE: Charles River Associates, *Analysis of Household Appliance Choice* (Cambridge, Mass.: CRA, January 1979), p. 6-12. Based on discussions with equipment installers and manufacturers. Gas heat pump cost is taken from "Comparison of the Assumptions, Methodologies, and Conclusions of Three Residential Space Conditioning Systems Studies," Booz, Allen and Hamilton, Inc., May 1978.

Table A-4

ELECTRIC HEAT PUMP EFFICIENCIES AND MEAN NUMBER OF ROOM AIR CONDITIONERS FOR HOUSEHOLDS WITH ROOM AIR CONDITIONERS

City	Heat Pump Heating Efficiency[a]	Mean Number of Room Air Conditioners[b]
Boston	2.22	1.63
Denver	2.20	1.11
Des Moines	2.15	1.29
Lubbock, TX	2.30	1.11
Miami	2.62	1.80
Minneapolis	2.05	1.29
New Orleans	2.50	1.54
Owensboro, KY	2.21	1.28
Philadelphia	2.24	1.28
Portland, ME	2.14	1.00
St. Louis	2.20	1.52
San Diego	2.50	1.09
Spokane	2.19	1.10
Topeka	2.21	1.30
Trenton	2.23	1.35
Tucson	2.41	1.10

[a]Based on average high and low temperature efficiencies for 52 heat pumps of approximately 35,000 Btuh capacity, from *1975 Directory of Unitary Air Conditioners, Unitary Heat Pumps*, Air Conditioning and Refrigeration Institute. Efficiencies at temperatures other than the test temperatures were calculated by interpolation, and mean monthly temperatures for each city were used to calculate average monthly efficiencies. The seasonal efficiency for each city then was approximated by the mean of the monthly efficiencies for those months in which the mean temperature was less than 65°F.

[b]From tabulations provided by Midwest Research Institute with the dataset they collected, mean number of room air conditioners for households with room air conditioners.

SOURCE: Charles River Associates, *Analysis of Household Appliance Choice*, (Cambridge, Mass.: CRA, January 1979), p. 6-12.

Table A-5

EFFICIENCIES FOR HEATING AND COOLING SYSTEMS
OTHER THAN ELECTRIC HEAT PUMP
(Constant across cities)

System	Efficiency
Electric resistance heating[a]	1.00
Gas heating[b]	0.730
Oil heating[b]	0.707
Room air conditioner[c]	2.17
Central air conditioner[d]	1.98
Evaporative cooler[e]	7.92
Heat pump cooling[f]	1.89

[a]By definition.

[b]From D. W. DeWerth and J. F. D. Caprio, American Gas Association, Performance Tests of Residential Hot Water Boilers, Gas Vs. Oil," 1966, p. 8.

[c]Based on average efficiency of 72 room air conditioners of approximately 10,000 Btuh capacity from *1979 AHAM Directory of Certified Room Air Conditioners*.

[d]Based on average efficiency for 42 central conditioner models of approximately 35,000 Btuh capacity, from *1975 Directory of Unitary Air Conditioners, Unitary Heat Pumps*, Air Conditioning and Refrigeration Institute.

[e]Based on conversations with manufacturers.

[f]Based on average efficiency for heat pumps described in footnote a of Table 4A-4.

SOURCE: Charles River Associates, *Analysis of Household Appliance Choice*, (Cambridge, Mass.: CRA, January 1979), p. 6-13

Table A-6

ESTIMATED REPLACEMENT COSTS OF VARIOUS
HOT AIR HEATING AND COOLING SYSTEMS

System	Estimated Cost (Dollars)
Gas hot air	$350
Oil hot air	560
Electric hot air	290
Gas heat pump	1,525
Central air conditioner, with hot air system	650
Room air conditioner, per unit	290

SOURCE: Costs based on conversation with David Storkey, Heat, Inc.