HOUSING CHOICE PROCESSES: STATED VERSUS REVEALED MODELLING APPROACHES

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1 Introduction

The topic of housing choice and housing preference continues to be heavily researched. It is an area of interest to scholars in numerous disciplines. Investigators have studied the topic from various angles. Each approach is based on a set of limiting assumptions and thus probably serves a particular goal. Several schemes could be used to classify these approaches to the study of housing choice and housing preference.

The present article focuses on cross-sectional models. Specifically, it gives an overview of revealed versus stated models of housing preference and housing choice. Revealed models are based on observational data of households' actual housing choices in real markets. In contrast, stated preference and choice models are based on people's reactions to hypothetical houses. It should be emphasized that the comments made here about revealed models only pertain to studies that attempt to derive utility functions from overt choice data. Many other studies of observed housing choice take a different approach. Their primary aim is to describe observed patterns of housing choice or to demonstrate how socio-economic variables, for example, covary with such patterns. Hence, these studies are best considered as descriptive research, having no explicit theoretical implications or underlying objectives.

The article is organized as follows. First we provide a general framework for positioning the various revealed and stated preference models. Then, we discuss some of the important modelling approaches, emphasizing the essentials of each one and pointing out some recent advances. We conclude with a discussion of some methodological issues pertinent to the study of housing choice and housing preference.

2 Framework

All the models that we discuss in this article have certain assumptions in common. First, they all assume that houses or residential environments can be described and qualified in terms of a set of attribute levels. Secondly, they all assume that individuals or households derive some part-worth utility from each of the attribute levels. Thirdly, all these models assume that individuals combine their part-worth utility according to some rule to arrive at an overall preference or choice. However, the models differ in the specification of these rules (that is, the assumptions made about the underlying decision-making process). Furthermore, the models differ in data collection procedures and, to some extent, also in regard to model estimation. Some models, for example, assume that individuals take a compensatory decision-making strategy. This assumption implies that a low part-worth utility for a particular attribute level can, at least partially, be compensated by higher part-worth utilities on one or more of the remaining attributes. In contrast, other models assume a non-compensatory decision strategy. That assumption implies that a low part-worth utility of a particular attribute level can never be compensated, regardless of the part-worth utility of the remaining attribute levels.

With regard to data collection, revealed models are based on observed housing choices in real markets. In the event that these models seek to derive a utility function from such observational choice data, they are based on the assumption that it is only in the act of choice that people can reveal their preferences. Hence, observational choice data are interpreted in terms of utility-maximizing behavior, and a utility function is derived from such data. In contrast, stated preference and choice models are based on the premise that observed choice will always reflect the joint influence of preferences, market conditions, and availability. Accordingly, it is difficult, if not impossible, to interpret choices in terms of utilities and preferences. Thus, stated preference and choice models are based on people's expressed preferences and choices. In some cases, this involves recording individuals' explicit and separate evaluations of housing attributes and/or importance weights (compositional models). Other models seek to derive the utility function by measuring overall preferences for real world houses or residential environments and by recording valuations of the constituting attributes (hybrid models). On that basis, the investigator can estimate the importance weights by performing a regression analysis using these measurements. The validity of this approach has proved to be relatively weak, however. The problem is that individuals have difficulty confining themselves to expressing their preferences for separate attributes. But they are not supposed to trade off the attributes. To accommodate this inclination, yet other models (conjoint models) are based on attribute profiles, which consist of attribute combinations. These profiles are constructed according to the design of statistical experiments. This allows the researcher to control the correlations between the attributes. Individuals are requested to express their preference for the resulting profiles. Alternatively, they are asked to choose a one of a set of profiles.

These three models are based on the assumption that some algebraic rule is adequate to describe housing preferences and utilities. A linear function can be used to describe compensatory decision strategies. Likewise, a multiplicative function may approximate non-compensatory structures. However, a particular set of models is based on the premise that decision strategies cannot be represented very well with the limited number of algebraic rules that one can apply. Decision plan nets, for instance, are based on the assumption that preference formation and decision-making are better described in terms of heuristic and qualitative statements. The purpose of the modelling approach is not to estimate algebraic models. Rather, decision plan nets and similar models are used to elicit the heuristics that are assumed to drive housing preference formation or housing choice.

Hence, as a general framework to organize the present article, we decided to make a distinction between revealed and stated models. The latter group of models is further differentiated into algebraic and non-algebraic modelling approaches. We distinguish between two types of algebraic models: compositional models and conjoint models. In the following discussion, we point out the most important elements of these approaches in turn.

3 Modelling approaches

3.1 Revealed models of housing choice

This class of models is based on observations of housing choices in real markets. Such housing choice data is assumed to reflect people's preferences. The modelers' task is to examine whether some assumed preference structure will adequately describe observed housing patterns. In some cases, housing attributes are correlated with observed choice patterns, typically using (log-linear) regression analysis. This approach provides interesting information about the attributes influencing housing choice, which often can be used for segmentation purposes. Nevertheless, this approach does not allow the researcher to examine or test preference functions.

A more theoretical approach involves making assumptions about some underlying preference or utility function. Furthermore, observed housing choice patterns are assumed to be the result of utility-maximizing behavior. If these assumptions appear to describe observed housing choice patterns well, the approach would seem to support the validity of the assumed preference structure. A common theoretical framework is random utility theory. It is based on the assumption that people's utility for choice alternatives is based on a deterministic component and a random component. The latter may reflect measurement error, inconsistent behavior, heterogeneity, etcetera, depending upon the specific model. If one then assumes utility-maximizing behavior, the choice probabilities can be derived. The specific model thus depends on the assumptions one is willing to make about the distributions of the error terms. The most frequently used model in studies of housing preference and housing choice is the multinomial logit (MNL) model. That model can be derived from the assumption that the error terms are independently and identically Weibull-distributed.

When this model is applied in housing studies, some problems arise. One reason is that many attributes influence housing choice decisions. Moreover, housing markets tend to be highly regulated. Consequently, the assumption that people choose between all alternatives, an idea that underlies the MNL model, is probably not valid. It is more likely that people choose from available alternatives in submarkets. The MNL model does not permit examination of such structures. The reason is its so-called independence from irrelevant alternatives property. According to that property, the introduction of a new alternative will detract market shares from all existing alternatives in one's choice set in direct proportion to the original utilities.

In a different vein, researchers have worked with a nested logit model. This model assumes a hierarchical or sequential decision structure. Housing alternatives are placed into nests, based on some attributes. Then the choice process is modeled according to this nested structure. When the parameters of the nested logit model lie within certain limits, the results reflect utility-maximizing behavior. The nested structure, of course, permits incorporation of elements of submarkets and differential competition in the modelling attempt. Examples of these discrete choice models in studies of housing preference and housing choice include McFadden (1978), Onaka and Clark (1983), Quigley (1985), Clark and Onaka (1985), Timmermans, Borgers and Veldhuisen (1986), Aufhauser, Fischer and Schonhofer (1986), Huff and Waldorf (1988), and Fischer and Aufhauser (1988).

The revealed choice approach has been successfully applied in many different housing preference and housing choice studies. Yet this approach has a fundamental methodological problem: the assumption that revealed choice reflects underlying preferences. In reality, overt choice is also influenced by the prevailing market conditions. Hence, it is very difficult, if not impossible, to disentangle preference from disequilibrium conditions in the marketplace. Moreover, in order to estimate (nested) logit models, it is necessary to make rather simplifying and rigorous assumptions about the independence of the alternatives. It is hard to see how these models could be developed beyond their present complexity. If they could be refined, they would allow one to examine context, substitution, and market structure effects; options that represent the cutting edge of other approaches.

3.2 Stated models of housing preference and housing choice

3.2.1 Algebraic models

Compositional models of housing preferences

Compositional models are probably the most commonly used in applied studies. Housing preference structures are estimated by recording separately and explicitly how people evaluate housing attributes and by measuring the relative importance of each attribute. This information is then combined, using some assumed algebraic rule, to arrive at an overall evaluation, satisfaction, or preference measure. The linear additive rule is the one used most frequently. It assumes that overall preference is a weighted additive function of attribute evaluations. Of course, various other model structures could be assumed, although we are not aware of any. Examples of this modelling approach in academic studies of housing preference include Lindberg, Gärling and Montgomery, (1988, 1989) and Rohrman and Borcherding (1988).

This modelling approach has the advantage of simplicity. There is no estimation involved; one can apply different structures, and the survey questions are straightforward. Housing attribute evaluations are usually measured on a rating scale. The importance assigned to an attribute is measured by using the same scales; in some cases, constant sum scales are used. Research has consistently questioned the reliability and validity of the separate scales, however. We feel this is largely because respondents are requested to evaluate the housing attributes separately. Hence, they do not know what to assume about the remaining attributes influencing their choice behavior. Moreover, because they are not asked to trade off attributes, the measurement task does not reflect the mechanisms underlying actual decision-making and choice processes.

Conjoint models of housing preference and housing choice

Conjoint preference models are based on the measurement of people's evaluations of housing profiles. These profiles are compiled according to the principles underlying the design of statistical experiments. The model is built in several steps. First, the attributes assumed to influence housing preference are elicited. Next, levels or categories are identified for each attribute. For example, let us assume, for the sake of simplicity, that tenure, costs, and number of rooms have an influence on housing choice. Tenure can be operationalized as owner-occupied and rental. We could identify four categories for costs (say *f* 500, 700, 900, 1100 per month). Similarly, we could differentiate between two, three, four and five rooms. The next step is to create housing profiles by combining these attribute levels according to some experimental design. One combination would be rental, two rooms, and *f* 500. The total number of combinations in this example would be $2 \cdot 4^2 = 32$ combinations. Obviously, the number of possible profiles increases rapidly as the amount of attributes and/or attribute levels rises. A full factorial design covers all possible combinations. All contributions that (combinations of) attribute levels make to housing preference can be estimated with this design. However, in many cases, it is unfeasible or too demanding to present all combinations of attribute levels. In that event, a fractional factorial design, covering only a subset of all combinations, is presented to the respondents. For example, one could present only 16 profiles (1/2 fraction). A fractional factorial design increases the feasibility and reliability of the task. But this comes at a cost. The user cannot estimate all higher-order interaction effects. Different designs have different properties and thus allow the user to estimate different models. One frequently applied design allows the user to estimate a main-effect model only. More sophisticated designs can be used to estimate some interactions between housing attributes. Of course, such interactions would be indicative of a more complicated preference function. Orthogonal designs have a particular advantage. They permit unbiased estimates of the contributions of the attributes to overall preference. Thereby, the user circumvents the main problem of revealed housing choice models.

Once the profiles are constructed, individuals are requested to express their overall preference for each profile in a ranking or rating task. The preference function may be estimated using regression analysis, for example (Timmermans, 1984). This approach involves a focus on housing preferences. If one wishes to simulate housing choice, additional assumptions have to be made regarding the relationship between housing preference and housing choice. The simplest solution would be to assume that the alternative with the highest preference score will always be chosen. However, a deterministic choice rule like this one ignores the fact that preferences are stochastic. Therefore, probabilistic choice rules are based on assumptions regarding the error term. Once these rules are formulated, various model structures may be formulated. The multinomial logit model is one of these. Examples of conjoint preference models can be found in Knight and Menchik (1976), Louviere (1979), Boag and Sarkar (1984), Phipps and Carter (1984, 1985), Veldhuisen and Timmermans (1984), Joseph, Smit and McIlravey (1989), and Phipps (1989).

Nevertheless, these choice rules necessarily remain ad hoc. Louviere and Woodworth (1983) have therefore advocated the use of *conjoint choice models*. Conjoint choice models differ from conjoint preference models in that the dependent variable represents choices rather than preference ratings or rankings. This has at least two important ramifications. First, because the user is interested in choices, the choice alternatives cannot be presented singly in sequence. To estimate choice models, attribute profiles or choice alternatives have to be worked into choice sets. Diverse design strategies may be adopted. One strategy is to use pairwise designs; that is, the choice sets have a size of two. This strategy is selected when the attributes are generic. Alternatively, one might create choice sets of a larger but fixed size. This strategy is often used if one has for alternative-specific attributes. In that event, the choice sets contain the same named alternatives but they differ across sets in terms of attribute levels. Furthermore, varying choice sets of different size and composition can be created. This entails using 2^N designs, where N is the total number of choice alternatives. In all these cases, it is advisable to add a base alternative (e.g., none of these) to each choice set to fix the unit of the utility scale and retain the orthogonality properties of the design.

The respondents' task is to evaluate each choice set and then select the alternative they are most likely to choose in the real world. On the other hand, respondents may be asked to allocate some fixed budget, dividing it among the alternatives in each choice set. Because we are dealing with choices rather than preference ratings, multiple regression analysis is not an appropriate estimation technique. Choice data can be analyzed by three steps: (i) aggregating the choices across respondents to generate relative choice frequencies; (ii) assuming some choice model that underlies the behavior of interest; and (iii) estimating the parameters by a method that is appropriate for the assumed model. The properties of the design discussed above are consistent with the multinomial logit model. Therefore, choice experiments are generally analyzed using this model specification. Its parameters can be estimated using weighted regression analysis, iteratively reweighted least squares analysis, or maximum likelihood estimation techniques.

The above steps briefly describe the construction of conjoint models. Given the segmented nature of many housing markets, it is important to derive utility functions for the segments. Various approaches can be taken. Of these, two are the most important: ad hoc grouping on the basis of estimated individual-level preference functions; and inclusion of socio-demographic variables in the specification of the choice model. One could argue that conjoint models closely resemble the revealed models of housing choice. The main difference lies in the method of data collection. Corresponding to the method used, some differences exist in the statistical properties associated with the approaches. Recently, some advances have been made in regard to conjoint choice experiments. However, these experiments seem rather difficult to replicate with revealed choice data. Conventional conjoint choice models have recently been extended in four ways: (i) to include many influential attributes, where revealed choice models would be likely to break down as a result of their variance-covariance structures; (ii) to include context effects; (iii) to examine substitution effects; and (iv) to examine group choice rather than individual choice behavior.

Many influential attributes can be included in the choice model under certain conditions. The modeler must be willing to assume that individuals follow a hierarchical decision-making process. In that process, they first group the attributes into higher-order decision constructs and form preferences for such constructs. Then they trade off their preferences or evaluations for the higher-order decision constructs to arrive at an overall preference or choice (Timmermans, 1989; Louviere and Timmermans, 1990). For example, house, residential environments, and relative location can be used as higher-order constructs. Based on this assumption of a hierarchical decision-making process, the modeler can construct experimental designs for each of these constructs separately. The next step is to construct a bridging or overall design to scale the higher-order constructs. In the experimental task of this bridging design, individuals express their overall preference for housing profiles. These are described in terms of ratings for the higher-order decision constructs. This approach has some potential disadvantages. Respondents are not exposed to all attributes, as this would be too demanding. Furthermore, they may adopt patterned, simple response patterns in the bridging experiment. Oppewal, Louviere and Timmermans (1994) have therefore developed an alternative. It includes the higher remaining order constructs in the design of the subexperiments for a particular higher-order construct. This approach has an additional advantage: one can actually perform statistical tests on the assumed hierarchical decision-making structure.

All of these models assume that the **context/background** of the choice situation does not affect the evaluations of the housing alternatives. However, people's evaluations of housing attributes might be conditional upon their mortgage rates, tax levels, etcetera. Context effects and background effects can be incorporated in the MNL framework by extending the specification of the utility function, as suggested by Oppewal and Timmermans (1991). The utility function can be extended with terms that represent the effects of background variables on utility. Background variables that affect the utilities of alternatives can be treated as additional factors in the factorial design to create treatments that vary the hypothetical background. Such an approach employs the same design principles that underlie standard conjoint choice experiments, though with one exception. In standard experiments, the main focus is often on the main effects of the attributes. In stated background experiments, all effects have to be specified. They must be specified as interactions with alternative specific constants and/or as interactions with alternative specific variables. This is because if some background variable would be specified as a generic effect, the effects of this variable on each of the alternatives would be equal and hence cancel out.

Therefore, the minimal main effects designs that are often used in standard experiments are not sufficient. It is necessary to use larger designs that permit the independent estimation of these types of interactions. An easy way to construct larger designs is by nesting a standard design, which varies the attributes of alternatives, under a design that specifies the levels of the background variables. This amounts to the completion of a series of standard choice experiments, one for each condition of the background design. The advantage of employing a background design is that the separate experiments can be integrated into one choice model. That model includes parameters for the utility effects of the background variables.

Conventional models also assume that the utility of a house is dependent on its own attributes, and not on the attributes of other alternatives in the choice set. This implies that in choice studies, similarity has no impact on choice probabilities. It could be argued, however, that this is a rather rigorous assumption. One would assume that housing alternatives that are very similar compete more for the same market segment than houses that are very dissimilar.

One way of modelling this effect has recently been suggested by Timmermans and van Noortwijk (1994). Substitution effects can be modeled as part of a conjoint choice experiment. This is possible under experimental designs that allow the modeler to produce unbiased estimates of the effects of any other alternative on the utility of a given choice alternative. The additional effects incorporated in the model, sometimes called cross-effects, represent corrections on the utilities as predicted by the standard MNL model. Significant cross-effects may be interpreted in terms of substitution.

Design strategies that allow the estimation of substitution effects are only slightly more complicated than those required to estimate conventional conjoint choice models. One of two strategies is commonly selected: (i) construct choice sets of fixed size in which all attributes of all choice alternatives are orthogonal; or (ii) construct choice sets of varying size and composition using a 2^N design. In both cases, a base alternative is added to each choice set. Respondents are asked to perform one of the following tasks: to choose one alternative from each choice set; or to allocate some fixed resources among the alternatives in each choice set. Their choices are then aggregated. Any of the conventional estimation methods can be used to estimate the parameters of the assumed choice model.

There is one more assumption underlying all choice models: that of individual choice behavior. In some situations, the choice process may best be considered as a group choice process. This is probably true for housing choice. In that event, the choices made by the individual respondent are assumed to provide a valid and reliable reflection of the whole group. As this assumption is doubtful, Timmermans, Borgers, van Dijk and Oppewal (1992) extended the hierarchical approach in a study of residential choice behavior of dual-earner households. Their approach includes an experimental task which structures the overall evaluation process of each partner into separate tasks. One of these is for the assumed higher-order decision constructs. The other task concerns an overall integration of joint decision-making. The model of joint decision-making thus involves several steps. First, the attributes that are assumed to influence the choice process are identified. Next, these causal variables are clustered into sets that are assumed to represent higher-order decision constructs. Then, an experimental design is constructed to produce multiattribute descriptions of the assumed higher-order decision constructs. Each member of the household is requested to evaluate each combination of attribute levels for the constructs separately and individually. In addition, they are requested to evaluate the combined profiles. The response data for each set and each partner are analyzed separately to develop statistical models that describe how the partworth utilities associated with the decision constructs are integrated to arrive at the overall preference for the higher-order constructs. Statistical models are developed to describe the contribution of the selected attributes to the evaluation of the overall profile. The overall preference scores of the members of the household for the decision-construct profiles are treated as factors in a subsequent choice design. The levels of these factors are numerical scores from the rating scales that the household members used to evaluate the two higher-order constructs. When choice sets are created, household members are asked to imagine that they gave the ratings for the decision constructs. They are then instructed to choose jointly among the descriptions included in the choice set. These choice data are statistically analyzed using an assumed choice model. More recently, Molin, Oppewal, and Timmermans (1994) tested different measurement approaches and models. They found that the group model significantly outperformed the conventional conjoint model in terms of its ability to predict the evaluation of a set of holdout housing profiles.

3.2.2 Non-algebraic models

All of the above models assume that simple algebraic rules can be used to represent people's utility functions for housing. The simple algebraic rules have specific behavioral implications. For example, they imply compensatory decision-making for the linear additive rule. There is some evidence, though, that these rules may not be able to represent actual decision-making processes. For instance, noncompensatory behavior can only be approximated at best. People may screen housing alternatives on an attribute-by-attribute basis. They no longer consider a housing alternative if it does not meet specific conditions regardless of all other attributes. Moreover, algebraic models by definition cannot represent more complicated if-then structures.

Hence, as an alternative to the algebraic models, many different qualitative modelling approaches have been suggested. These range from production systems to neural networks, decision tables, and decision nets. Here, we briefly discuss only the last approach, decision nets. The following discussion is intended to place the article by Goetgeluk and Zwetselaar (1994), which is published elsewhere in this special issue, in a wider context.

Basically, decision nets represent a structured interview. Its aim is to disentangle people's decision-making processes. Individuals are requested to identify the attributes that influence their decisions of interest. Then, for each of these attributes, they are asked to determine the levels at which they would no longer consider that choice alternative (rejection-inducing attribute). The participants can also indicate whether or not they would still consider the alternative if it were to meet their criteria on all other attributes. Similarly, they can indicate whether or not this attribute would be compensated by better scores on one or more of the other attributes (trade-off attribute). Timmermans and van der Heijden (1987) applied this modelling approach to the study of recreational behavior. Decision nets have also found increasing application in housing studies in the Netherlands (Op 't Veld, Timmermans, and Starmans, 1987).

Many of these studies only attempted to identify the attributes of interest and their role in the decision-making process. Accordingly, those studies reveal a decision net describing the nature of the decision-making process under investigation. These results assist in identifying constraints, trade-off dimensions, etc. Yet in order to use decision nets for prediction, the implied logical conditions must be represented. Expert systems and Prolog or Lisp constitute natural environments for this kind of analysis. By using the qualitative conditions as rules in such systems, actual housing choice behavior can be simulated in principle. This basically involves testing whether a particular house meets the conditions posed by the system. In some cases, additional ad hoc rules may be required to perform a complete simulation that will result in a single choice.

The main advantage of this approach over the algebraic rules is its flexibility. Many different kinds of assumptions can be made, and the simulation can be as creative as one can imagine. However, this may also be the main disadvantage of this approach. It lacks the theoretical and analytical rigor of the conjoint choice models. Moreover, it does not have an error theory. Accordingly, one either relies on the measurements or makes ad hoc non-testable assumptions. The question remains whether or not subjects are able to reproduce their decision-making process. This seems to be an avenue for empirical research.

4 Conclusion and discussion

The aim of the present paper is to provide a brief overview of cross-sectional modelling approaches of housing preference and housing choice. In addition, this paper discussed some recent advances and methodological issues. A distinction is made between revealed and stated preference models. The latter class of models in turn is differentiated in algebraic and non-algebraic models.

In general, it is difficult to say which of these approaches is best. That question remains open to empirical investigation. But in light of our experience with these models, both in housing studies and in many other contexts, we can make some recommendations. We have found that revealed choice models are not well-suited for identifying underlying preference structures, as too may factors driving housing choice are confounded. However, they often outperform other models in terms of their predictive ability, at least in the short run. Compositional models are easy to administer. They do not require much expertise to estimate and apply. However, our research consistently indicates that their reliability, validity, and predictive ability is substantially lower than that of the conjoint type of models. Conjoint models compare well in terms of rigor, theoretical foundations, advanced error theory, and flexibility for developing more sophisticated and advanced models. Yet conjoint models have a potential disadvantage, which relates to their derivation from experimental design data. Consequently, when using these models, one always has to demonstrate that individual preferences and choices under experimental conditions are systematically related to real-world housing choices. Finally, the main advantage of decision plan nets and related modelling approaches is their flexibility. They allow the construction of simulation models that can incorporate many aspects, constraints, and conditions affecting housing choice. These factors are very difficult or impossible to incorporate into algebraic models. Over and above these disadvantages, these models have a potentially serious drawback. The problem is that their reliability is in question. They depend upon a person's ability to reconstruct decision-making processes. Furthermore, they do not have an error theory to compensate for such potential limitations.

Unfortunately, as in many other choice contexts, very little research has been done to systematically compare different modelling approaches regarding these and other methodological aspects. We hope that the present brief overview, which focuses on the essential features of these approaches, may stimulate such comparative research.

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