LINKING SPATIAL CHOICE MODELS

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ABSTRACT

Most models of spatial choice are single-activity, or sectoral, models dealing with only one field of spatial decision making. Models dealing with more than one decision field tend to be either too simplistic or very large. But even most advanced comprehensive multi-activity models suffer from incompatibility of their subsystem models and inconsistency of the linkages between them.

In this paper it is demonstrated that linking spatial choice models in a multi-activity modeling framework is a largely unresolved and widely neglected problem. It is argued that more attention should be paid to modeling the interdependencies between subsystems either by developing more compatible single-activity models or by developing unified models of multi-activity systems. In the final section of the paper, a concept of a unified multi-activity spatial choice model based on micro simulation is suggested.

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INTRODUCTION

The evolution of urban systems is not a self-governing, self-propelling process of nature, but altogether the result of human decisions, of thousands, millions of decisions, many small and some large, occurring over time as a broad stream of concurrent, unrelated or interrelated, individual or collective, decision acts.

In their search for understanding the overwhelming complexity of this stream of decisions, urban researchers have tried to identify groups of decision makers acting in similar ways, such as travelers, shoppers, workers, households, developers, and entrepreneurs. Next, they tried to separate decision fields or markets in which these actors operate to pursue certain activities such as travel, shopping, finding a job or a residence, or investing in housing or industry: the transport market, the retail market, the labor market, the housing market, the land and construction market. Finally, they constructed models dealing with each of these markets separately: transport models, retail models, employment models, residential location models, housing market models, or land use models.

In particular the most sophisticated of these models are usually restricted to one activity, market, or decision field. This forces them to make assumptions about interactions with other market sometimes so strong that the model results may be invalidated altogether. So other modeling approaches try to address the interconnectedness of the various urban activities or markets explicitly by modeling several of them together. This leads either to very simplistic models lacking much of the detail of single-activity models, or to very large models.

Large models have been critized in the past for being large, expensive, cumbersome to use, and deficient of theory (Lee 1973; Sayer 1976; 1979). This criticism will not be discussed here. Rather, the discussion will focus on more recent comprehensive models which, while still being large, do incorporate some of the most advanced, theoretically well defined subsystem models available.

In this paper, it will be demonstrated that even these most advanced comprehensive multi-activity models suffer from severe conceptual weaknesses with respect to the linkages between their subsystem models. In particular, it will be shown that most of these comprehensive models are eclectic in the choice of submodel types and often combine incompatible submodels in an ad-hoc, inconsistent, and sometimes misleading manner.

It will be concluded, therefore, that linking spatial choice models is a largely unresolved and widely negelected problem in urban modeling. It will be argued that more attention should be paid to model the interdependencies between subsystems either by developing more compatible single-activity models or by developing unified models of multi-activity systems. In the final section of the paper, a concept of a unified multi-activity spatial choice model based on micro simulation is suggested.

1. CHOICE MODELS

In this first section, a brief review of choice models, in particular spatial choice models, available to the urban modeler will be given.

1.1 Utility-based Choice Models

There has been a long way from the *homo oeconomicus* to contemporary behavioral choice theory. For a considerable time, economic theory did not even accept the notion of subjective utility, equating utility solely with monetary profit. But even after the introduction of the subjective expected utility (SEU) model (Savage 1954; Luce and Raiffa 1957), decision theory remained for a long time predominantly a prescriptive theory (cf. Keeney and Raiffa 1976).

Obviously, however, this theory did not say anything about how decisions were actually made. It was evident that the perfectly informed, perfectly rational utility maximizing decision maker was a fiction that had no counterpart in real life. Numerous psychological laboratory experiments demonstrated that lack of relevant information as well as information overload can lead to serious "pathologies" in the decision behavior of people, i.e. to gross deviations from the rational norm (Slovic 1972; Tversky and Kahnemann 1974). Consequently, there have been various attempts to revise the rational decision model, such as the concept of "bounded rationality" (Simon 1956), the "satisficing" concept (March and Simon 1958), or concepts based on heuristics like "elimination by aspects" (Tversky 1972).

An alternative way to account for the observed deviations of decision behavior from what seems to be the rational norm is to subsume all unexplained behavior into a random component of the utility function as it is done in the random utility model (Luce 1959):

$$u^*_{ij} = u_{ij} + \varepsilon_{ij} \qquad (1)$$

where u^*_{ij} is the perceived utility of a decision alternative j, j = 1,...,J, to a group of decision maker i, i = 1,...,I, and u_{ij} and ε_{ij} are its deterministic and stochastic components, respectively. The random term ε_{ij} is thought to represent all taste differences between individual decision makers in the group i as well as all inhomogeneity in j, plus all disturbances arising out of possible measurement errors in the preference function v_{ij}.

With this random extension of the utility function, the concept of utility maximizing behavior can be retained: Decision maker group i will choose alternative j over alternative j' if $u^*_{ij} > u^*_{ij'}$, or probabilistically,

$$p_{ij} = \text{Prob}(u_{ij} + \varepsilon_{ij} > u_{ij'} + \varepsilon_{ij'};\ j' = 1,\ldots,J) \qquad (2)$$

$$i = 1,\ldots,I$$
$$j = 1,\ldots,J$$

where p_{ij} is the probability of alternative j being chosen by decision maker group i, and

$$\sum_j p_{ij} = 1 \qquad (3)$$

In passing, it may be noted that lumping all variation of i and j into one random variable certainly is one of the crudest possible ways of dealing with reality. In particular, the random utility model completely ignores the impact of uncertainty or risk on decision behavior treated explicitly in the SEU model.

With certain assumptions about the distributions of the disturbance terms ε_{ij} (cf. Domencich and McFadden 1975), it is possible to calculate the odds that alternative j is preferred over alternative j' as a loglinear function of the difference between the mean, or deterministic, utilities u_{ij}, i.e. ignoring the disturbance terms ε_{ij}:

$$\ln(p_{ij}/p_{ij'}) = \beta_i(u_{ij} - u_{ij'}) \tag{4}$$

This equation is based on the *choice axiom* by Luce (1959) stating that the choice ratio of two alternatives depends only on their utility and is independent of other alternatives of the choice set. From (3) and (4), the multinomial logit choice model can be derived:

$$p_{ij} = \frac{\exp(\beta_i u_{ij})}{\sum_{j'} \exp(\beta_i u_{ij'})} \tag{5}$$

where p_{ij} is the probability that of all alternatives j', j' = 1,...,J, alternative j will be selected. The parameter β_i in (4) and (5) is inversely related to the standard deviation of ε_{ij} (cf. Anas 1981) and can thus be interpreted as a measure of homogeneity of the preferences hidden behind the mean utility. Another useful way to look at β_i is to interpret it as a kind of elasticity indicating (by determining the gradient of the exponential function) how much the p_{ij} should be affected by a small difference in the u_{ij}. Both interpretations mean the same. Small values of β_i indicate a high degree of diversity in preferences and/or alternatives, accordingly, the choice pattern will be dispersed; large values of β_i indicate homogeneity of preferences and alternatives, accordingly, the choice pattern will tend to maximize utility u_{ij}; if $\beta_i = \infty$, strict optimization occurs (cf. Brotchie et al. 1980).

In most cases, the deterministic part of utility, u_{ij}, will be multiattribute, i.e. will be composed of several attributes contributing in various degrees to overall utility. The most commonly used model for aggregating component utilities is the additive multiattribute (MAU) model based on the theory of conjoint measurement (Luce and Tukey 1964), which can be written:

$$u_{ij} = \sum_k w_{ik} v_{ik} [f_{jk}(\underline{x}_j)] \tag{6}$$

where $f_{jk}(.)$ is a *generating function* specifying how to construct a composite attribute k from one or more elements of a vector $\underline{x}_j$ of raw attributes of alternative j; $v_{ik}(.)$ is a *value function* mapping composite attribute k onto a standardized utility scale such that, say, $0 \leq v_{ik}(.) \leq 1$; and the w_{ik}, $k = 1,\ldots,K$, are *importance weights* standardized such that

$$\sum_k w_{ik} = 1 \tag{7}$$

Different w_{ik} and $v_{ik}(.)$ are specified for different groups of decision makers i to account for different perceptions of utility. Note that by standardizing the w_{ik} and $v_{ik}(.)$, it is guaranteed that all u_{ik} are standardized such that $0 \leq u_{ik} \leq 1$; and this implies that also the β_i in (5) are comparable across applications. Figure 1 illustrates the transformation of utility into odds by standardized exponential functions with various values of β_i and the resulting market shares in the binomial case.

In most applications, the β_i, w_{ik}, $v_{ik}(.)$, and $f_{jk}(.)$ are usually lumped together into one vector of coefficients that can be estimated by maximum likelihood (see, for instance, Anas 1981b). While this is dictated by the estimation technique, it must still be considered as very unfortunate, as it obscures the sequence of transformations the data have to undergo rendering the estimated coefficients virtually uninterpretable. This, however, makes the model totally dependent on survey data and seriously restricts its transferability from one application to another.

Despite these problems, the multinomial logit model is widely used because of its convenient properties. As all additive utility models, it requires that additivity constraints in the attributes be satisfied (cf. Keeney and Raiffa 1976), besides, the choice axiom, on which it rests, may produce unplausible results for nearly identical alternatives (cf. Domencich and McFadden 1975). However, these pitfalls can be avoided by careful design of the model. One particularly

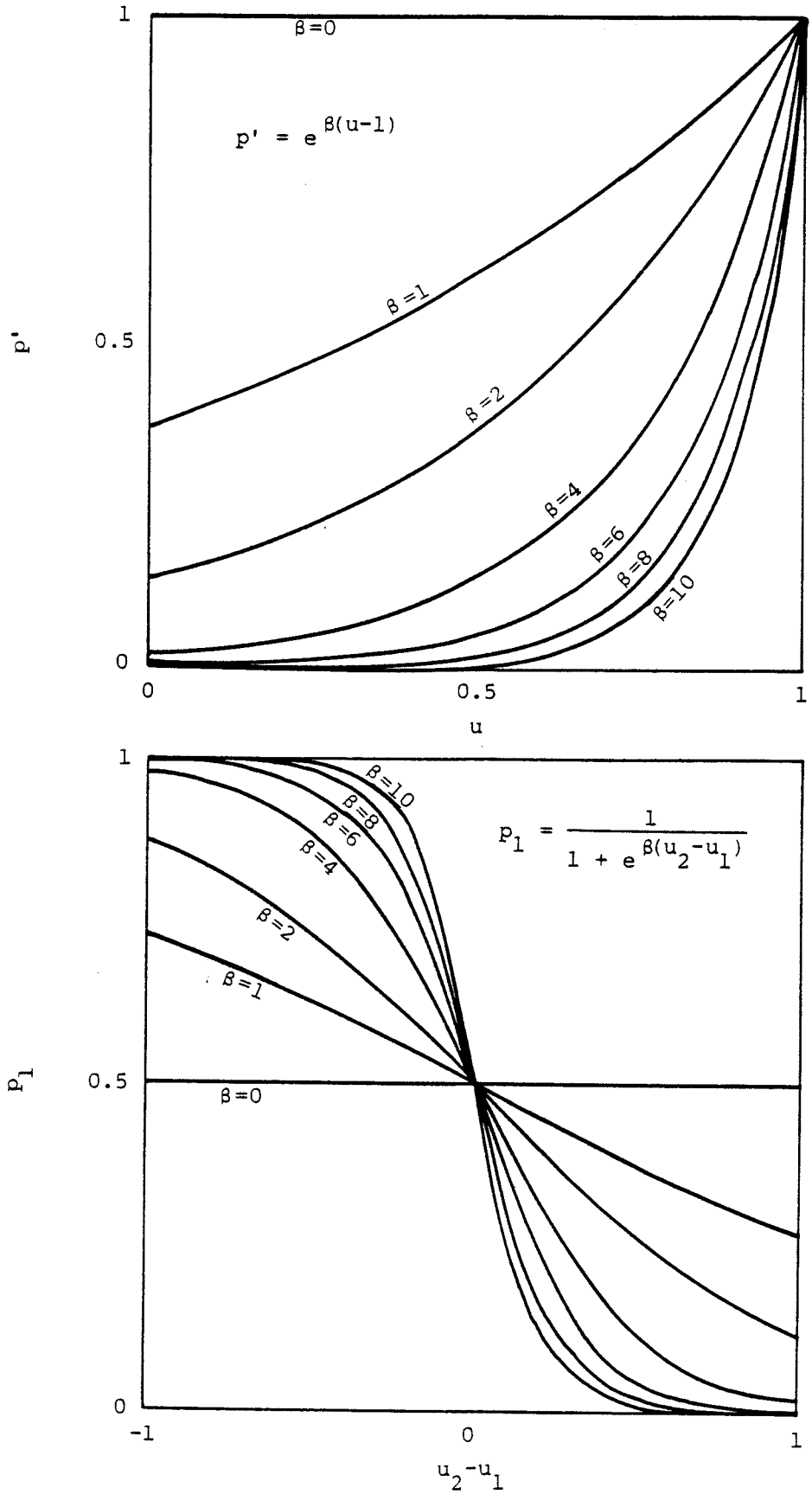

Figure 1. Standard exponential functions (top) and corresponding market shares in the binomial case (bottom).

appealing way of doing this is to hierarchically structure the choice process into choice sequences or levels, thus arriving at the sequential or multilevel logit model. Other random utility models, like the probit model, in which the assumptions about the distribution of the error terms ε_{ij} are relaxed, may become of value for practical applications in the future. For a description of these and other choice models see van Lierop and Nijkamp (1981).

1.2 Spatial Choice Models

If the alternatives are distributed over space, a spatial choice model arises. Spatial choices occur in most urban activity fields or markets. Travelers choose among destinations, transport modes, or routes; workers decide to take on a job at a particular location; individuals or households decide to shop at a particular retail location, to settle down in a certain residential neighborhood, or to use a public facility at a particular location; developers or entrepreneurs select a particular parcel of land for residential development or industrial location or relocation.

No different kind of choice models is needed for modeling such choices, as all relevant determinants of spatial choice can be easily incorporated into the general utility-based models presented above. In particular, it can be shown that the family of spatial interaction models based on the principle of entropy maximization (Wilson 1970) can be reinterpreted within the framework of random utility theory. For instance in the production-constrained trip distribution model, the proportion of trips originating in zone i and ending in zone j can be expressed as

$$p_{ij} = \frac{T_{ij}}{O_i} = \frac{W_j \exp(\beta\, u_{ij})}{\sum_{j'} W_{j'} \exp(\beta\, u_{ij'})} \tag{8}$$

where T_{ij} are trips from i to j, O_i are trips originating in i, and W_j are attractor variables indicating potential trip destinations in j, and the u_{ij} are utilities of a trip from i to j.

This expression is identical to (5) except for the attractor variables W_j. The W_j are weights accounting for the fact that the alternatives are aggregates of equal or similar subalternatives having the same mean utility u_{ij}. In this case, the aggregates are zones of different size, and the subalternatives are potential destinations in the zones. If each zone contained only one potential destination, the choice set would be disaggregate, and equation (8) would collapse to (5).

While the form of equation (8) differs for the disaggregate and the aggregate choice set, it does not depend on the level of aggregation on the side of the decision maker or actor. The choice function looks the same in the strictly disaggregate case (single actors), in the semi-disaggregate case (groups of actors), and in the strictly aggregate case (all actors). However, with increasing aggregation, the aggregation error in the β and the u_{ij} increases.

Anas (1981b) has shown that all kinds of spatial interaction models from the unconstrained to the doubly-constrained model can be derived from the entropy-maximizing as well as from the utility-maximizing approach at all levels of aggregation, and that both types of models give identical results at the same level of aggregation.

As entropy-based and utility-based models are formally identical, the only difference between them rests on their interpretation. If only the macro behavior of the system is of interest, the entropy interpretation is appropriate. If, however, one is interested in modeling spatial choice on a micro scale, clearly the utility-based interpretation is more preferable. This becomes obvious if one looks at the utilities u_{ij} in (8). A utility-based approach would suggest to think of them as aggregates of component utilities, say, of travel time d_{ij} and travel cost c_{ij} additively aggregated in the manner of equation (6):

$$u_{ij} = w_d \, v_d(d_{ij}) + w_c \, v_c(c_{ij}) \qquad (9)$$

where w_d and w_c are weights summing up to unity, and $v_d(.)$ and $v_c(.)$ are value functions mapping travel time or travel cost,

respectively, onto a utility scale. For $v_d(d_{ij})$, for instance, a logistic function of the difference between d_{ij} and a standard travel time $d°$ may be appropriate:

$$v_d(d_{ij}) = \frac{1}{1 + \exp\,[\gamma(d_{ij} - d°)]} \tag{10}$$

Such a formulation would guarantee that all possible values of $v_d(.)$, $v_c(.)$, and u_{ij} lie between zero and one, and that the parameter β in (8) would have the same magnitude and interpretation as the β_i in (5).

Within the limits of the multinomial logit model, equation (8) may be considered as the basic model of spatial choice from which most spatial choice models presently used in practical modeling applications can be derived. This will be demonstrated in the following section.

2. MULTI-ACTIVITY SPATIAL CHOICE MODELS

Although the main emphasis of urban modeling research has in the past been on sectoral, single-activity models, there have been some attempts to link two or more urban activity fields in a common model framework. Figure 2 contains a list of some more recent multi-activity models together with a few historical ones. For each model it is indicated which subsystems or processes are generated *endogenously* in the model. That is, only two-way interactions between subsystems are taken into account. For instance, a residential location model using a fixed impedance matrix as exogenous input for constructing its work trip table, is not considered as having a transport model and therefore would not be included in the list of multi-activity models. However, the list contains residential location models in which travel costs change due to congestion or in which the modal split is determined endogenously. In these cases, transport is counted as a separate activity.

Before discussing the problems of linking subsystems in multi-activity models, in this section a brief review based on the

	employment		population			housing		land use		transport		
	nonservice employment	retail/service employment	unemployment/labor force	population/households	aging/household formation	housing supply	housing price	land use	land price	car ownership	modal split	capacity restraint
Lowry (Lowry 1964, Garin 1966)		x		x								
Empiric (Hill 1965)	x	x		x								
ARC (Geraldes, Echenique et al. 1979)	x	x		x		x	x	x	x		x	x
ITLUP (Putman 1980)	x	x		x								x
TOPAZ (Brotchie et al. 1980)	x	x		x				x			x	
NBER (Kain et al. 1976)		x		x	x	x	x		x			
Berechman (1976)		x		x								x
Boyce (1977)				x								x
Leeds (Mackett 1980)	x	x	x	x	x	x		x			x	
TRANSLOC (Lundqvist 1978)	x	x		x							x	(x)
Los (1978)				x			x					x
Toronto (Said, Hutchinson 1980)	x	x	x	x	x	x		x				x
Dortmund (Wegener 1980)	x	x	x	x	x	x	x	x	x	x	x	x
MRRM (Oguri 1980)				x	x		x		x			
SILUS (Mehta, Dajani 1981)				x		x	x		x			x
Brussels (Allen et al. 1981)	x	x		x								
Choukroun, Harris (1981)	x	x		x								
Anas (1981a)				x							x	
Beaumont, Clarke, Wilson (1981)		x		x		x						

Figure 2. Selected multi-activity models and their submodels.

analysis of the 19 models listed in Figure 2 will given. For each of the model subsystems indicated in Figure 2 (employment, population, housing, land use, and transport) the alternative modeling approaches represented in the sample of models will be compared. In each case it will be asked whether the model can be interpreted or reinterpreted as a spatial choice model and which behavioral assumptions would be implied by such interpretation.

This part of the paper is still in the process of being written.

3. LINKING SPATIAL CHOICE MODELS

In this section, the urban models reviewed in the preceding section will be evaluated as multi-activity models, i.e., with respect to their subsystem linkages. The discussion will identify problems arising from these linkages as a consequence of submodel incompatibility or because of the nature of the linking mechanisms themselves.

3.1 Missing Submodels

As it can be seen from Figure 2, all models include a residential location submodel; indeed, this is the only submodel present in all models. The next most frequent activity modeled is retail and/or household-serving employment. That is somewhat surprising, as these sectors comprise only a relatively small fraction of total employment, but may be explained by the fact that a number of well-known models exist for modeling household-serving employment. Models for locating nonservice employment are much less frequent in the sample of models, and this may be considered a serious omission as virtually all residential location submodels in the sample rely in some way on the work-to-home spatial relationship, which means that in all models the location of employment has to be provided either endogenously or exogenously.

Perhaps the most startling result of the review of the 19 models is that only a minority of them take the aging of the population and the formation of households into account. It can be shown that natural increase or decrease of the population and changes of the status of households in terms of income and size during their life cycle largely determine the volume and composition of the demand for housing in a region. This omission has far-reaching consequences for the residential location submodel and its linkage with the transport submodel, as it will be demonstrated below.

Another blind spot of many models of the sample is the lack of a housing supply submodel. This omission means either to assume that housing supply is perfectly elastic to demand or to completely specify the housing supply exogenously. If the num-

ber of vacancies in the housing stock is low, the latter may eliminate the need for a residential location model altogether. The problem of linking demand and supply in spatial choice models will be discussed below.

If a housing supply submodel is included in the model, a kind of land use accounting framework seems to be necessary, as scarcity of vacant buildable land is one of the major forces behind urban spatial deconcentration. Yet there are several models in the sample which have a housing supply submodel, but no land use submodel. A similar critique may be applicable to models containing an employment location submodel without taking supply of industrial land into account.

Most of the transport submodels in the sample have an endogenous modal split and/or capacity restraint (network congestion) part. There is nothing wrong with that, but if this is the only other submodel linked to a residential location submodel, more meaningful input requiring much less computing could be imagined. Still another observation also pointing to a certain bias of urban modelers towards paying too much attention to interaction aspects, is that virtually all models include the costs of interaction, but only very few explicitly deal with housing prices or land prices, which may be equally or even more important.

3.2 Linking Activities and Transport

One of the most misleading concepts of urban modeling is the use of the singly-constrained spatial interaction model for locating activities. The idea, for instance, that if the work-to-home trips can be adequately predicted, the residential locations of workers are automatically known, may be formally true, but has no practical value.

Consider the static case. Even if the parameters of the model are well calibrated using all available information including the observed trip ends, the production-constrained model will usually give only poor predictions, unless zonal constraints are introduced. In most practical applications zonal constraints had to be imposed in order to get reasonable

results. The situation gets worse when the model is used for forecasting purposes. Even if the forecasted totals compared with the observed totals look acceptable, the forecasting errors with respect to the rates of change will not. But only the rates of change are of interest, because the totals are already known, and the rates of change are usually very small compared with the totals.

Many modelers have responded to this difficulty by applying the spatial interaction type allocation model only to the increments of activities. However, this approach makes a separate model for updating the existing stock necessary: the aging and household formation submodel in the case of population, and a housing vintage model in the case of the housing stock. Where no such submodels exist, only the residential model allocating total demand can be used. Of the models in the sample, two use the incremental version of the production-constrained interaction model (Leeds, Toronto), while others have departed from the spatial interaction residential location model altogether (Empiric, NBER, Dortmund, MRRM, and Brussels).

Introducing zonal constraints into the spatial interaction residential location model creates new problems of subsystem linkage. Because nothing can prevent the model from allocating more activity to a zone than the constraints allow, the excess allocation has to be redistributed in a second or third iteration. In addition, in Lowry-type models in which the demand for retail or service employment is calculated via a population-service rate, the residential location submodel and the service employment location submodels have to be iteratively applied until they are in equilibrium. Berechman (1980) has shown that iterative solutions to this problem become inconsistent, when two-way interactions between the location submodels and the transportation submodel are assumed, i.e., when congestion-sensitive travel costs are fed back to the location submodels. In this case, in each iteration the location submodel is faced with a different set of travel costs and the allocation cumulated over all iterations will not represent a general equilibrium of both, the activity and transport subsystems.

3.3 Linking Supply and Demand

A second group of linking problems can be summarized as problems of linking supply and demand. One case of mismatch between supply and demand has been discussed already in the context of the singly-constrained interaction location model, where excess allocations are redistributed in subsequent iterations. A more interesting way to deal with these excess allocations is to interpret them as unsatisfied demand and use them to stimulate the generation of more supply, as this is done in the two dynamic models of the sample (Brussels; Beaumont, Clarke and Wilson). Similar adjustment processes, without the time dimension, are employed in the model by Choukroun and Harris.

In the NBER and TOPAZ models, the optimization technique applied requires that demand and supply are equal. This is achieved in the NBER model by simply removing excess households or excess dwellings out of the market until the next simulation period. In the TOPAZ model, a dummy activity, vacant land, is introduced to make supply and demand equal. In the other optimzing models of the sample (Boyce, TRANSLOC, Los), no such problems seem to exist. No mismatch between supply and demand can arise in the models using micro simulation (Dortmund, MRRM, SILUS).

A special problem of supply-demand linkage exists only for models in which households are allocated to the housing stock through the simulation of the housing market (NBER, Dortmund, MRRM, SILUS). This problem arises from the fact that housing markets are largely "second-hand" markets, in which new dwellings constitute only a very small segment of the total housing stock, while the bulk of the housing supply offered on the market consists of dwellings which, at the beginning of the housing market simulation, are occupied by households who will represent the housing demand during the market period.

This makes it difficult to derive the housing demand and the housing supply in two separate models. The standard approach to this problem is to link the demand and supply submodels by household-housing occupancy information and jointly es-

timate mover households and vacant dwellings, and temporarily storing the mover households in a "mover pool". This approach has been followed by the NBER, MRRM, and SILUS models.

A drawback of this approach is that it separates the decision to move from the choice of a dwelling and a residential location. But clearly these are not independent from each other, beacuse a household who cannot find a more attractive dwelling than its present one will certainly not move and will not vacate its dwelling. In the Dortmund model, therefore, the decision to move and the search for a new dwelling are jointly modeled in a common micro simulation model.

3.4 Linking Choice and Non-Choice Models

In the models sampled, the only submodel which is not a model of human decisions, is the aging and household formation submodel. Its purpose is to age the model population by one simulation period, including births and deaths, and to estimate the evolution of households in terms of age, size, and income, including new and dissolving households.

Only five of the 19 models contain an aging and household formation submodel. They all use a kind of semi-Markov approach applying exogenously or endogenously specified transition rates to the population and/or household distributions. While this kind of model is straightforward conceptionally, it is not easy to link it with the other, decision-based submodels. The reason for this lies in the conflicting time structures of both kinds of models. In reality, both, choice and non-choice processes occur in a continuous stream of events. However, this cannot be replicated in the model, as different modeling techniques are used for the two types of models. For instance, the NBER model uses a micro simulation approach for the household formation model, but a more aggregated multinomial logit choice plus an optimization model for the housing demand and market clearing submodels. In the Dortmund model, however, the household formation model is solved by matrix multiplication, whereas the housing market model uses micro simulation.

As a concequence, in all five models the choice and non-choice submodels are not processed simultaneously, but sequen-

tially. This creates problems of consistency (e.g., when migrants entering the region at mid-period are to be merged with the existing population), but also of plausibility. For instance, in the Dortmund model the household formation submodel is executed first followed by the housing market simulation, just as if the total housing market process were compressed to the very last day of the simulation period.

3.5 Problems of Sequence

The last example illustrates that most of the problems of linking spatial choice models in multi-activity models are problems of sequence resulting from the fake block-recursive structure of these models.

Typically, the multiactivity models consist of submodels, which may contain systems of simultaneous equations, e.g., optimization procedures, within their boundaries, but which are designed to be executed only once during a simulation period. However, each of these submodels is connected with at least one other submodel, mostly by a two-way link. This is particularly true for the transport submodel, which is bidirectionally connected with most other submodels.

Moreover, several submodels operate on the same model variables. One example was the household formation model which changes the household distributions of the zones as does the residential location or housing market model. The same applies to the housing market model and the housing supply model. Land use is another example as all other activities need land and in fact compete for it where it is scarce.

So the decision of the model builder in which sequence the submodels of a multi-activity model are to be processed may be crucial. To decide that submodel A is to precede submodel B means that A has priority access to scarce resources, e.g., land, but will know what is going on in B only in the next simulation period. Conversely, B may get less from the scarce resources, but can utilize the results of A immediately. By his decision on submodel sequence, the model builder in fact decides on the implicit lag structure of his model.

Some of these problems can be eliminated by iteratively processing blocks of submodels several times, and indeed that is the common practice. However, especially in the larger models serious problems of sequence remain. Unfortunately, in the model descriptions these questions are almost never discussed.

4. A UNIFIED CHOICE MODEL OF URBAN CHANGE

In the final section of this paper, a concept for a unified multi-activity spatial choice model will be suggested. It is necessary to remark at the beginning that for practical and economic reasons a model of the kind suggested here will not be feasible in the near future. Therefore, this presentation should be taken as a conceptual exercise intended to stimulate discussion and criticism.

Consider a model consisting *only* of a controlled sequence of individual *choice processes* formally similar, but different in substance. The basic building block of this model, called the *choice module*, is described below.

4.1 The Choice Module

The choice module is a procedure simulating a probabilistic choice process in a given context. For this purpose, the procedure first generates a probabilistic choice situation and then makes a choice based on random utility maximization.

The simulation of a choice process in the choice module has four phases: a sampling phase, a search phase, a choice phase, and an aggregation phase:

- In the *sampling phase*, a decision maker or choice actor is sampled from all possible choice actors depending on the given context.
- In the *search phase*, the choice set is searched for a suitable choice alternative, and one alternative is selected.
- In the *choice phase*, a decision is made to accept or not to accept the selected alternative.

- In the *aggregation* phase, the consequences of the choice made are aggregated and executed in the system.

The following illustrative description of a choice process is taken from the context of the housing market as modeled in the Dortmund model and draws on Wegener (1981a):

In the *sampling phase*, a household looking for a dwelling or a landlord looking for a tenant for his vacant dwelling is sampled. In general, households and landlords are sampled *pro rata*, but if the household is occupying a dwelling, i.e., if a move is to be generated, it is assumed that the propensity to move depends on the satisfaction (or dissatisfaction) with the present dwelling. Households occupying a dwelling are stored in a three-dimensional matrix $\underset{\sim}{R}$ of dimensions m, m = 1,...,M for household type, k, k = 1,...,K for dwelling type, and i, i = 1,...,I for zone. The satisfaction of a household with its dwelling, u_{mki}, is a weighted average of housing attributes with the dimensions housing size and quality, neighborhood quality, location, and housing cost. Then

$$p(k|mi) = \frac{R_{mki} \exp(-\alpha\, u_{mki})}{\sum_k R_{mki} \exp(-\alpha\, u_{mki})} \tag{11}$$

is the probability that of all households of type m living in zone i, one occupying a dwelling of type k will be sampled.

In the *search phase*, the sampled household looks for a suitable dwelling, or the sampled landlord looks for a tenant for his dwelling. It is assumed that the household first chooses a zone in which to look for a dwelling. This is not independent from its present residence *and* its present work zone. The probability that the household tries zone i' is:

$$p(i'|mki) = \frac{\sum_{k'} D_{k'i'} \exp(\beta\, s_{ii'})}{\sum_{i'} \sum_{k'} D_{k'i'} \exp(\beta\, s_{ii'})} \tag{12}$$

where $\underset{\sim}{D}$ is the matrix of vacant dwellings with dimensions $K \times I$, and $s_{ii'}$ is an expression indicating the locational attractiveness of zone i' as a new residential location for a household now living in zone i and working in a zone j near i (see Wegener 1981b).

The household then looks for a vacant dwelling in zone i'. The probability that it inspects a dwelling of type k' is

$$p(k'|mkii') = \frac{D_{k'i'} \exp(\gamma\, u_{mk'i'})}{\sum_{k'} D_{k'i'}\, ex'(\gamma\, u_{mk'i'})} \qquad (13)$$

Figure 3 shows all possible sequences of sampling and search steps for households and landlords as implemented in the Dortmund model. Here the choice modules are called market transactions.

In the *choice phase*, in all cases the household decides whether to accept the inspected dwelling or not. It is assumed that it does if it can improve its housing satisfaction by a certain margin, i.e., it acts as a satisficer. If it declines, it enters another search phase, but with each try it accepts a lesser improvement. After a number of unsuccessful attempts it abandons the idea of a move.

In the *aggregation phase*, all changes of the relevant household and housing distributions, multiplied by the sampling factor are performed. Then the next market transaction is started.

4.2 Linking Choice Modules

Similar choice modules can be constructed for about every aspect of urban life. The right-hand column of Figure 4 shows a selection of conceivable choice modules corresponding to the activities and submodels of Figure 2.

start of transaction						
dwelling wanted				dwelling for rent / sale		
outmigration	inmigration	new household forced move	move	inmigration	new household forced move	move
household of type m	*household of type m*	*household of type m*	*household of type m*	*dwelling of type k'*	*dwelling of type k'*	*dwelling of type k'*
living in zone i		*living in zone i*	*living in zone i*	*in zone i' offered to*	*in zone i' offered to*	*in zone i' offered to*
in dwelling of type k			*in dwelling of type k*	*household of type m*	*household of type m*	*household of type m*
	working in zone j	*working in zone j*	*working in zone j*	*working in zone j*	*working in zone j*	*working in zone j*
	looks in zone i'	*looks in zone i'*	*looks in zone i'*		*living in zone i*	*living in zone i*
	for dwelling of type k'	*for dwelling of type k'*	*for dwelling of type k'*			*in dwelling of type k*
	decision	*decision*	*decision*	*decision*	*decision*	*decision*
releases old dwelling			*releases old dwelling*			*releases old dwelling*
transaction completed						

Figure 3. Two choice modules in the housing market part of the Dortmund model.

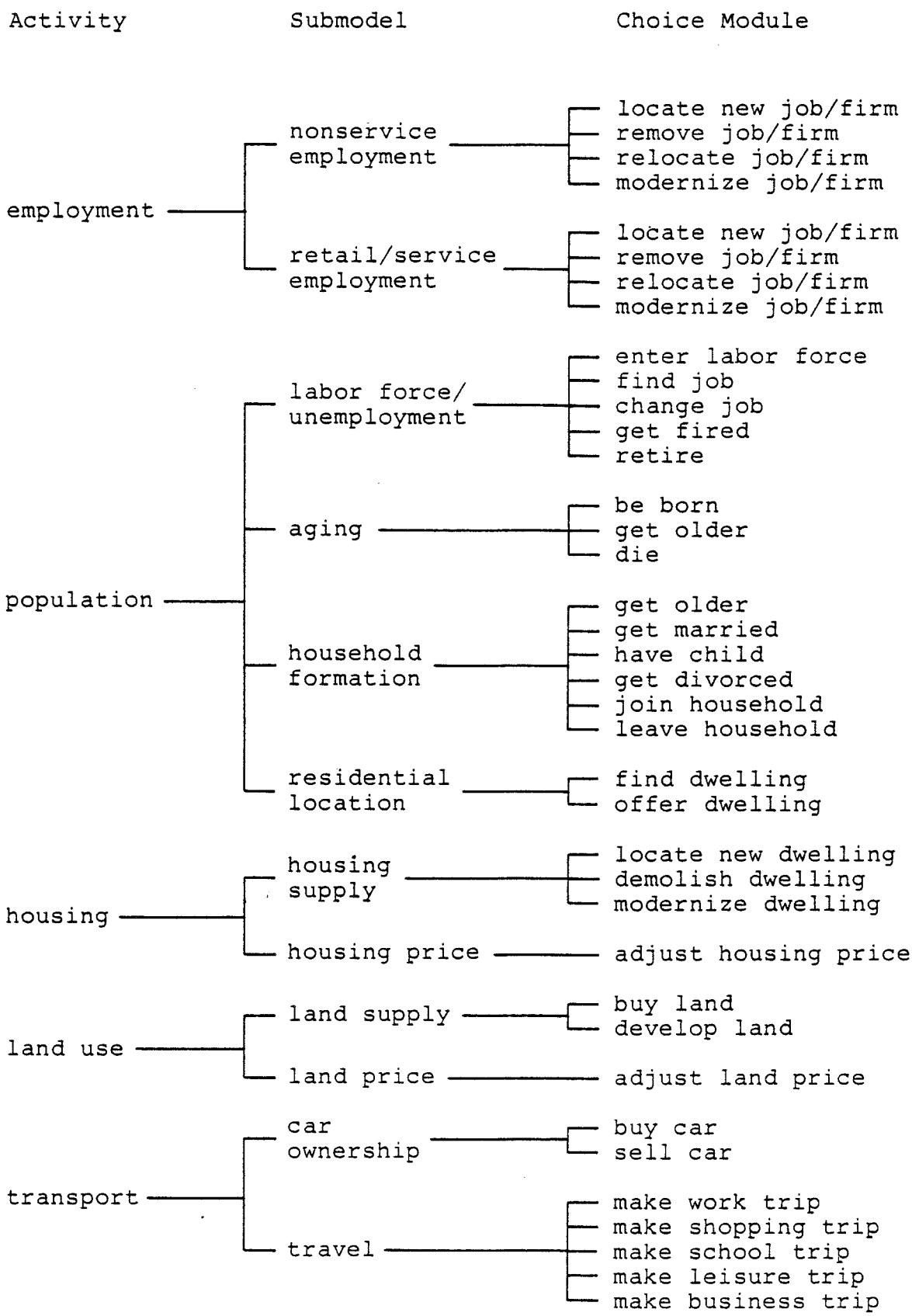

Figure 4. Activities, submodels, and choice modules.

The choice models are linked and driven by micro simulation, more specifically, Monte Carlo simulation. The principle of Monte Carlo simulation consists in drawing sequences of random numbers and mapping them onto cumulated probability distributions of the kind of (11)-(13). This method has been first used in social science applications by Orcutt et al. (1961, 1978), and in urban simulation by Chapin and Weiss (1968), and has recently received new interest for its flexibility and ease of application (Kreibich 1979; Clarke et al. 1979, 1980).

The difference in the application of Monte Carlo simulation suggested here is that it is used with probabilities derived from random utility choice models like the ones in (11)-(13), whereas the earlier applications used observed choice probabilities (with the exception of Chapin and Weiss who employed some notion of locational attractiveness).

The macro structure of the model now becomes extremely simple and can be described by a five-line algorithm:

```
for n = 1,N do
  select activity
  select submodel
  select choice module
end
```

where n is a counter counting the choice modules executed, until some limit N is reached.

Note that after each choice module, a new activity and a new submodel are selected. That is to say that submodels are no longer treated as solid blocks executed one after the other, but are split into innumerable small segments which are processed in a randomly interspersed fashion.

The sequence in which activities, submodels, and choice modules are selected, is not completely random, but is controlled by probability distributions reflecting the macro state of the

system including information from its outer environment such as the international, national, or state levels.

The great advantages of this modeling approach are its simplicity and modularity. It is immediately obvious that the interlinked parallel processing of all submodels completely eliminates all problems of sequence and consistency discussed above. Because of its modularity, the model can easily be changed and adapted to new problem fields or be tested with different hypotheses about search and choice behavior.

Unfortunately, even with very large and fast computers running this model will presently be still quite expensive. This, however, need not to be a restriction for a long time. If memory and computing costs continue to go down at the present rate for only a number of years, there will be no longer the need to build more complicated smaller models.

4.3 Calibration

The united spatial choice model can be calibrated like any other multinomial logit model, although it may be difficult to get all necessary data.

However, the model is also suited for non-survey calibration if the transofmrations of attributes into utilities described earlier in this paper are employed. As the model contains only one-to-one replications of actual choice situations it is possible to derive the weights and value functions needed for computing utilities from interviews or even from secondary sources by very simple direct scaling techniques. This approach has been followed successfully with the housing market part of the Dortmund model (see Wegener 1981b).

The rationale underlying this approach is that human choice behavior, irrespective of its sometimes erratic appearance, rests on a few very stable patterns which, like the "deep structures" of a language (Chomsky 1957) are hidden behind the observable surface phenomena. These patterns are determined by, among

others, very simple constraints of time and space and biological and technical conditions which will not change very much in a short time. If that is correct, choice in spatial choice models may be not as free, as choice modelers like to believe, and it may be sufficient to model the constraints well to have a good model.

CONCLUSION

In this paper it has been shown that linking spatial choice models in a multi-activity modeling framework is a largely unresolved and widely neglected problem.

Two conclusions may be drawn from this result: One possible approach is to develop more compatible single-activity models which can be linked more easily and consistently. The problem with this approach is that there will always remain conflicts of submodel sequence, which will introduce implicit lags into the model. The other possible approach is to develop unified models of multi-activity systems. The hypothetical model presented in the paper demonstrates that this may be possible without losing the desirable property of model modularity, but presently such models seem not to be feasible for practical and economic reasons.

REFERENCES

Allen, P.M., M. Sanglier, and F. Boon (1981) Intra-Urban Evolution. Part II in Models of Urban Settlements and Structure as Dynamic Self-Organizing Systems, edited by D. Kahn. Washington, DC: Department of Transportation.

Anas, A. (1981a) The Estimation of Multinomial Logit Models of Joint Location and Mode Choice from Aggregated Data. Journal of Regional Science 21:223-242.

Anas, A. (1981b) Discrete Choice Theory, Information Theory and the Multinomial Logit and Gravity Models. Paper presented at the North American Meeting of the Regional Science Association, Montreal.

Beaumont, J.R., M. Clarke, A.G. Wilson (1981) The Dynamics of Urban Spatial Structure: Some Exploratory Results Using Difference Equations and Bifurcation Theory. Environment and Planning A 13:1473-1483.

Berechman, J. (1976) Interfacing the Urban Land-Use Activity System and the Transportation System. Journal of Regional Science 16:183-194.

Berechman, J. (1980) Analytical Problems in Linking an Activity Model with a Transportation Network Model. Working Paper, Institute of Transportation Studies, University of California at Irvine.

Boyce, D.E. (1977) Equilibrium Solutions to Combined Urban Residential Location, Modal Choice, and Trip Assignment Models. R.S.R.I. Discussion Paper 98. Philadelphia: Regional Science Research Institute.

Brotchie, J.F., J.W. Tickey, and R. Sharpe (1980) TOPAZ - General Planning Technique and its Applications at the Regional, Urban, and Facility Planning Levels. Berlin-Heidelberg-New York: Springer Verlag.

Chapin, F.S., and S.F. Weiss (1968) A Probabilistic Model for Residential Growth. Transportation Research 2:375-390.

Chomsky, N. (1957) Syntactic Structures. The Hague: Mouton and Co.

Chonkroun, J.-M., and B. Harris (1981) Modeling Complex Urban Locational Systems. Pages E12-1 - E12-43, in Essays in Societal System Dynamics and Transportation, edited by D. Kahn. Washington, DC: Department of Transportation.

Clarke, M., P. Keys, and H.C.W.L. Williams (1979) Household Dynamics and Socio-Economic Forecasting: A Micro Simulation Approach. Working Paper 257. Leeds: School of Geography, University of Leeds.

Clarke, M., P. Keys, and H.C.W.L. Williams (1980) Micro-Analysis and Simulation of Socio-Economic Systems: Progress and Prospects. Working Paper 269. Leeds: School of Geography, University of Leeds.

Domencich, F.A., and D. McFadden (1975) Urban Travel Demand. Amsterdam: North-Holland.

Garin, R.A. (1966) A Matrix Formulation of the Lowry Model for Intra-Metropolitan Activity Location. Journal of the American Institute of Planners 32:361-364.

Geraldes, P., M.H. Echenique, and I.N. Williams (1979) A Spatial Economic Model for Bilbao. PTRC Summer Annual Meeting 1979, Warwick.

Hill, D.M. (1965) A Growth Allocation Model for the Boston Region. Journal of the American Institute of Planners 31:111-120.

Kain, J.F., W.C. Apgar, Jr., and J.R. Ginn (1976) Simulation of Market Effects of Housing Allowances Vol. I: Descrip- of the NBER Urban Simulation Model. Research Report R77-2. Cambridge, Mass.: Department of City and Regional Planning, Harvard University.

Keeney, R.L., and H. Raiffa (1976) Decision Analysis with Multiple Conflicting Objectives. New York: Wiley.

Kreibich, V. (1979) Modelling Car Availability, Modal Split and Trip Distribution by Monte Carlo Simulation: A Short Way to Integrated Models. Transportation 8:153-166.

Lee, D.B., Jr. (1973) Requiem for Large-Scale Models. Journal of the American Institute of Planners.

Lierop, W. van, and P. Nijkamp (1981) Disaggregate Models of Choice in a Spatial Context. Research memorandum 1981-4. Amsterdam: Vrije Universiteit.

Los, M. (1978) Simultaneous Optimization of Land Use and Transportation. Regional Science and Urban Economics 8:21-42.

Lowry, I.S. (1964) A Model of Metropolis. RM-4035-RC. Santa Monica, California: Rand Corporation.

Luce, R.D. (1959) Individual Choice Behavior. New York: Wiley.

Luce, R.D., and H. Raiffa (1957) Games and Decisions. New York: Wiley.

Luce, R.D., and J.W. Tukey (1964) Simultaneous Conjoint Measurement: A New Type of Fundamental Measurement. Journal of Mathematical Psychology 1:1-27.

Lundqvist, L. (1978) Urban Planning of Locational Structures with Due Regard to User Behaviour. Environment and Planning A 10:1413-1429.

Mackett, R.L. (1980) The Mathematical Representation of a Model of the Relationships between Transport and Land Use. Working Paper 123. Leeds: Institute for Transport Studies, The University of Leeds.

March, J.G., and H.A. Simon (1958) Organizations. New York: Wiley.

Mehta, S., and J.S. Dajani (1981) SILUS: The Stanford Infrastructure and Land Use System. Report IPM-12. Stanford: Department of Civil Engineering, Stanford University.

Oguri, Y. (1980) A Metropolitan Residential Relocation Model for the Evaluation of Housing Policies of the Tokyo Region. Paper presented at the 27th North American Meetings of the Regional Science Association, Milwaukee.

Orcutt, G., M. Greenberger, A Rivlin, and J. Korbel (1961) Microanalysis of Socioeconomic Systems: a Simulation Study. New York: Harper and Row.

Orcutt, G., S. Caldwell, and R. Wertheimer (1978) Policy Exploration through Micro-analytic Simulation. Washington, DC: The Urban Institute.

Putman, S.H. (1980) Integrated Policy Analysis of Metropolitan Transportation and Location. Washington, DC: Department of Transportation.

Said, G.M., and B.G. Hutchinson (1980) An Urban Systems Model for the Toronto Region: 1. Model Structure. Working Paper. Waterloo, Ontario: University of Waterloo.

Savage, L.J. (1954) The Foundations of Statistics. New York: Wiley.

Sayer, R.A. (1976) A Critique of Urban Modelling: From Regional Science to Urban and Regional Political Economy. Progress in Planning 6:187-254.

Sayer, R.A. (1979) Understanding Urban Models Versus Understanding Cities. Environment and Planning A 11:853-862.

Simon, H.A. (1956) A Behavioral Model of Rational Choice. Pages 241-260 in Models of Man - Social and Rational, edited by H.A. Simon. 3rd Edition, 1964. New York: Wiley.

Slovic, P. (1972) From Shakespeare to Simon: Speculations - and some Evidence about Man's Ability to Process Information. ORI Research Bulletin 12(2). Eugene, Oregon: Oregon Research Institute.

Tversky, A. (1972) Elimination by Aspects: A Theory of Choice. Psychological Review 79:281-299.

Tversky, A., and D. Kahnemann (1974) Judgment under Uncertainty: Heuristics and Biases. Pages 141-162 in Utility, Probability, and Human Decision Making, edited by D. Wendt and C.A.J. Vlek. Dordrecht: Reidel.

Wegener, M. (1980) A Multilevel Economic-Demographic Model for the Dortmund Region. Paper prepared for the IIASA-ISS Workshop on Urban Systems Modeling, Moscow. (Forthcoming in Sistemi Urbani.)

Wegener, M. (1981a) The Housing Market in the Dortmund Region: A Micro Simulation. Pages 127-138 in Strategic Planning in a Dynamic Society, edited by H. Voogd. Delft: Delftsche Uitgevers Maatschappij.

Wegener, M. (1981b) A Simulation Study of Movement in the Dortmund Housing Market. Paper prepared for the International Seminar on Migration and Small Area Population Forecasting, Rotterdam. (Forthcoming in Tijdschrift voor Economische en Sociale Geografie.)

Wilson, A.G. (1970) Entropy in Urban and Regional Modelling. London: Pion.