Location, Housing, Automobile Ownership, and Mode to Work: A Joint Choice Model

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Household location decisions are closely related to other choices of housing, automobile ownership, and mode to work. This paper describes a model that considers these long-run decisions, termed the mobility bundle, as jointly determined, thus eliminating the need for an arbitrary set of assumptions about a sequence of choices. The model developed is based on disaggregate choice theory. Each potential location-housing-automobile ownership-mode to work combination is a distinct alternative, of which only one is selected by each household. The basic methodology used is the multinomial logit model. A sample of skilled, single worker households working and residing in the Washington, D.C., metropolitan area in 1968 was used to estimate the model. The variables used to describe each alternative included locational attributes, housing attributes, transportation level of service to work, spatial opportunities for shopping trips, automobile ownership attributes, and the socioeconomic characteristics of the household. Even with the relatively small sample used, a wide range of behavioral effects were measured. It is concluded that models such as the one described here could replace existing model systems used to forecast residential location patterns. The increase in behavioral content such models permit would allow credible work-trip forecasts to be made as a part of land use forecasting.

Transportation planners have long recognized that the facilities they implement today will have a great influence on the future location patterns of the activities those facilities will serve. These long-term interactions between transportation and location, termed activity shifts, have been the focal point of much of the debate about the desirability of various fixed transportation investments such as highways or rail rapid transit systems. The locational impacts of such facilities are not only important in and of themselves; they also have an enormous influence on the future transportation demand in that the size and characteristics of the served population may be greatly altered over the useful life of the facility.

These locational effects may be most significant in urban transportation planning. For example, a new transit system in a city will in the short run attract current highway users; this mode choice effect has been the principal focus of the vast bulk of travel demand modeling efforts and is probably the best understood aspect of travel behavior. However, in the longer run, the same system may have profound effects on residential and employment location patterns. Sites near transit stations will be more desirable (1), and those farther away may experience reduced levels of activity. Furthermore, as a consequence of the new location and work trip patterns, households may alter their automobile ownership and housing decisions. Thus, over its useful life, a major transportation facility may have the potential to completely alter the spatial structure of a city. Until the nature of the interactions among transportation services, location decisions, and travel demand is understood, there is little hope that existing forecasting models will provide reliable tools for long-run policy analysis (2).

This paper describes a model that applies disaggregate choice models to represent household location and the related choices of housing type, automobile ownership level, and mode to work. The particular choice theory methodology used is the multinomial logit model (3), which is analytically tractable and widely used (4, 5, 6).

The first section of the paper describes the set of available alternatives, i.e., the various location-housing-automobile ownership-mode to work combination or mobility bundles, that are feasible choices for representation in the model. The next section is a brief description of the way in which the various factors that affect the choice of mobility bundle are combined to form the variables entering into the household utility function. [This description is somewhat cursory; further descriptions of the model structure, the motivation for the variables used, and the final functional form can be found in Lerman (7)]. This is followed by a presentation of the parameter estimation results and, finally, by a revised forecasting framework that uses the model structure developed and is consistent with a behavioral theory of how household decisions are reached.

DEFINITION OF MOBILITY BUNDLES

Location, housing, automobile ownership, and mode of travel to work can be almost infinitely subdivided. Locations can be taken to be cities, towns, census tracts, blocks, zones, or any other geographical unit. Alternatively, location can be defined simply in terms of distance from the CBD or in terms of whether a site is in the central city, urban ring, suburbia, or rural fringe. Housing can be defined along a broad spectrum of dimensions, including age of the structure, lot size, architectural style, number of rooms of various types, garage space, quality and condition of unit, and type of tenure. Automobile ownership can consist of the number of automobiles as well as their make, age, gas mileage, horsepower, or operating cost. Mode to work can be classified as transit or car, or further described as bus, trolley, rail rapid transit, taxi, shared ride, paid car pool, or drive alone.

Clearly, at some level of detail the number of possible alternative mobility bundles is enormous. Even if suitable data were available, a model developed with such detailed alternatives would be almost impossible to estimate and apply. Some level of abstraction in defining alternatives is required.

Reducing the number of alternatives of the location dimension of the mobility choice presents some basic methodological difficulties. Ultimately, each household selects a particular dwelling unit, of which there are thousands or millions in any one metropolitan area. Any method of grouping alternatives is by its very nature somewhat arbitrary. Fortunately, it is possible under a set of fairly rigorous approximations to use the multinomial logit model in a way that allows one to rely on data about arbitrarily defined groups of dwelling units, but still obtain consistent estimates of parameters describing how households perceive the dwelling units themselves (7). This approximation makes it possible to consider census tracts as the basic locational alternative and permits the use of a large, relatively reliable data base.

The dimensions of housing alternatives used in this study are structure type and tenure. Four feasible choices, owner-occupied single family house, rented single family house, rented walk-up or garden apartment, and high rise dwelling, were used. This choice was determined primarily by the data available from the home interview survey. For the purposes of transportation planning, where the primary focus is on the spatial aspect of mobility rather than on the housing itself, this choice set should be adequate. However, the use of structure type and tenure only does restrict the applicability of this study to the analysis of housing policies, where issues of structure size and quality are very significant.

Automobile ownership choices have the dimensions of number owned, make, type, horsepower, and options. However, since the transportation planner is mainly interested in the ways in which people will alter their travel behavior in response to various policies, a consideration of the number of automobiles should be sufficient.

The final choice, mode of travel, is restricted to two modes of vehicular travel, car and transit. These two together constitute 93 percent of all work trips in the study city, Washington, D.C. (This figure does not include some very short work trips.) In order to further limit the scope of the empirical study, all forms of ride sharing were eliminated.

Not all possible residential location-housing-automobile ownership-mode to work combinations are feasible alternatives. For example, some locations are not served by transit, some tracts have a limited range of housing options due to zoning ordinances, certain households may not have some mobility bundles open to them (households without drivers do not own automobiles, and low-income households can only afford a limited subset of all feasible mobility bundles). In addition to restrictions such as these, the tracts available to any particular household are limited to the set of tracts actually selected by all workers (in the sample used) in the employment zone. This method of defining choice availability (5, 8) provides an operational way to avoid including infeasible alternatives in household choice sets: The fact that some feasible alternatives may be eliminated does not affect the properties of the parameter estimates in the multinomial logit model.

SPECIFICATION OF THE JOINT UTILITY FUNCTION

The variables that affect the choice of mobility bundle can be divided into six general categories. They are as follows:

1. Transportation level of service to work—travel time (in-vehicle and excess time) and cost for the work trip;
2. Automobile ownership attributes—taxes, depreciation, registration costs, maintenance, and title costs;
3. Locational attributes—neighborhood quality, demographic composition, taxes, urban services, parking availability, and local insurance rates;
4. Housing attributes—age of the structure, quality, size of the unit, garages, driveways, and structure type;
5. Spatial opportunities—measures of accessibility to shopping and other nonwork destinations; and
6. Socioeconomic characteristics—income, race, household size, number of drivers, number of workers, education, and marital status.

Each of the above six categories might be represented with a wide range of variables and each of the variables can, in theory, be combined with the others to produce a virtually limitless number of possible independent variables for each utility function. The final set of variables selected draws heavily on previous empirical work and on a set of more fully developed model estimations (7).

In a joint model of mobility choice there are an extremely large number of possible location-housing-automobile ownership-mode to work combinations. Thus, the number of utility functions is correspondingly great. Rather than consider each utility function individually, every variable will be defined as pertaining to all alternatives but as taking zero value for those utilities where it is not included.

The first group of variables are constant terms in the utility function. These constants measure the pure alternative effect, i.e., the net effect of all attributes of an alternative that are not measured by the other variables. In theory, a constant could be introduced into all but one utility function that would act as a base against which the effects of the other variables are measured. This choice of the base utility function would be arbitrary and have no influence on the parameter estimates of the choice probabilities. In practice, however, alternatives such as locations that are unranked and very numerous do not have constants associated with them unless they have particular attributes that make them distinguishable, such as the CBD in models of destination choice.

Even when the location choice group is ignored, the number of possible options is quite large. A household has a maximum of two modes: car and transit; three automobile ownership levels: zero, one, and two or more; and four housing types: to own a single family house, to rent a single family house, to rent a garden or walk-up apartment, and to rent a high-rise apartment. After the logically inconsistent alternative of zero automobile ownership and car to work is eliminated, there are 20 possible options for any one household. To reduce the number of dummy variables to less than 19 (the number of possible options minus one for a base), a way to approximate each independent effect by a linear combination of a smaller number must be found. The approach adopted here is to give each choice group a constant term for all its members but one, and assign constants to those of the interactions among choice groups that an exploratory data analysis had indicated to be significant. The resulting set of eight constant terms are as follows:

$$\text{DRENT1} = \begin{cases} 1 \text{ in the rent single family dwelling alternative} \\ 0 \text{ otherwise} \end{cases}$$

$$\text{DRENTG} = \begin{cases} 1 \text{ in the rent garden or walk-up apartment alternative} \\ 0 \text{ otherwise} \end{cases}$$

$$\text{DRENTH} = \begin{cases} 1 \text{ in the rent high rise apartment alternative} \\ 0 \text{ otherwise} \end{cases}$$

$$\text{DA01} = \begin{cases} 1 \text{ in the one automobile alternative} \\ 0 \text{ otherwise} \end{cases}$$

$$\text{DA02} = \begin{cases} 1 \text{ in the two or more automobiles alternative} \\ 0 \text{ otherwise} \end{cases}$$

$$\text{DCAR} = \begin{cases} 1 \text{ in the car to work alternative} \\ 0 \text{ otherwise} \end{cases}$$

$$\text{DAPTSTYL} = \begin{cases} 1 \text{ in the rent garden, walk-up, or high rise apartment and own less than two automobiles alternatives} \\ 0 \text{ otherwise} \end{cases}$$

$$\text{DSUBSTYL} = \begin{cases} 1 \text{ in the own single family dwelling and own two or more automobiles alternatives} \\ 0 \text{ otherwise} \end{cases}$$

The next two variables represent the travel time aspects of level of service to work. These variables have been expressed as the in-vehicle and out-of-vehicle time in most mode choice studies. More recent work (9, 10) has indicated that the disutility of out-of-vehicle time may be perceived as a function of the total trip length, which can be measured by travel distance. After experimentation with a number of alternative functional forms, the following specification (9) was chosen:

TOTIME = total two-way travel time (min) and

OVTT/DIST = two-way out-of-vehicle time (min) ÷ two-way travel distance (km)

In addition to these variables, a dummy variable was defined to reflect the added disutility associated with the use of a car in the downtown area as follows:

$$\text{DCITY} = \begin{cases} 1 \text{ for households with downtown workplaces in the car to work alternatives} \\ 0 \text{ otherwise} \end{cases}$$

The next variable arises from the fact that there are a large number of monetary measures such as household income; federal, state, and local taxes; housing costs; automobile ownership costs; and out-of-pocket travel costs for the work trip in the model. To avoid introducing a separate variable for each of these cost factors, they were combined into a single one termed for reference the Z variable, representing the money that would be available to the household if it selected each alternative. The value of Z (in dollars per year) is thus an estimate of the amount of money a household has after the following expenses: (a) federal taxes, (b) state taxes, (c) property taxes (if applicable), (d) housing cost, (e) direct automobile ownership costs, (f) automobile insurance, tags, and taxes, and (g) commuting cost to work. The coefficient of the Z variable in the utility function should always be positive, reflecting the fact that all else being equal households would rather have more money than less left for other things. The Z variable should not enter the utility functions linearly; the utility a poor family derives from extra money is much greater than that derived by a wealthy family. Thus, the marginal utility of money should decrease as the value of Z increases. This hypothesis can be reflected by using the natural log of Z rather than simply the value of Z as the independent variable.

The next variable used commonly appears in simple mode choice models in which automobile ownership is assumed fixed. It is defined as

$$\text{AALD} = \begin{cases} \text{number of automobiles in alternative} \div \text{number of licensed drivers in the household in the car to work alternatives} \\ 0 \text{ otherwise} \end{cases}$$

and represents the level of automobile availability that would be obtained if the household chose a given alternative. Alternatives with high automobile availability should be associated with high car to work utilities relative to those for transit to work alternatives; hence, the expected sign of its coefficient is positive.

The next variable was designed to reflect another effect of the number of licensed drivers within a household. While the number of licensed drivers impacts on choice of mode to work through the AALD variable, it also affects the level of automobile ownership directly: the more licensed drivers in a household, the more likely it will select a high automobile ownership level, independent of the mode to work selected. This effect was measured by introducing into each utility function a variable that reflects the number of licensed drivers with a different coefficient for each automobile ownership level, except one selected arbitrarily as a base. These variables are defined as follows:

$$\text{ILD1} = \begin{cases} 1/\text{number of licensed drivers in the household for one automobile alternative} \\ 0 \text{ otherwise} \end{cases}$$

$$\text{ILD2} = \begin{cases} 1/\text{number of licensed drivers in the household for two automobiles alternative} \\ 0 \text{ otherwise} \end{cases}$$

When these variables were originally introduced into the model, it was hypothesized that the effect for the two car alternative (as measured by the coefficient value) would be twice as great as the effect for the one car alternative. Statistical tests by Lerman and Ben-Akiva have indicated that this is indeed the case and that ILD1 and ILD2 can be combined into a single variable defined as follows:

$$\text{ILD} = \begin{cases} 0 \text{ for the zero automobile alternatives} \\ \text{ILD1 for the one automobile alternatives} \\ 2\text{ILD1 for the two automobiles alternatives} \end{cases}$$

The use of the inverse of the number of drivers rather than the number itself reflects the hypothesis that, as the number of drivers increases, the marginal effect of an additional driver on the need for automobiles decreases. Clearly, the coefficient of ILD should be less than zero.

Spatial opportunities influence the mobility decision in at least two ways. First, the absolute level of accessibility to shopping by either car or transit is probably important in a household choice of location. Second, the level of shopping accessibility by car relative to that of transit affects the mode with which the household will travel to shop, which in turn influences their desired level of automobile ownership.

The first of these effects was represented by

GPTINV = 1/expected generalized shopping price by transit

The generalized shopping price by transit is a weighted sum of estimates of the average in-vehicle time, out-of-vehicle time, and out-of-pocket cost of a shopping trip by transit that is derived from a disaggregate shopping trip choice model (10). The variable GPTINV is zero when transit is completely unavailable since the transit generalized price in such areas is, for practical purposes, infinite. The coefficient of this variable should be positive, since decreased travel costs resulting from improved transit service should increase the household utility.

Attempts to use a corresponding variable for the absolute level of car accessibility produced statistically insignificant coefficient estimates having an unexpected sign. This problem (15) may be the result of the high levels of externalities (such as noise and traffic congestion) often associated with locations with good highway accessibility (12). Thus, the car accessibility coefficient may also be measuring the effects of some omitted variables. For this reason, it was not included in the final specification.

The effect of the relative accessibility was measured by a variable defined as follows:

R = expected generalized car costs for shopping ÷ expected generalized transit cost for shopping

This variable does not change value for different automobile ownership alternatives, and therefore must be introduced into the utility function as alternative specific. Thus, the following two variables appear in the model:

$$\mathrm{R1} = \begin{cases} \text{R in one automobile alternatives} \\ 0 \text{ otherwise} \end{cases}$$

and

$$\mathrm{R2} = \begin{cases} \text{R in two automobiles alternatives} \\ 0 \text{ otherwise} \end{cases}$$

As the generalized shopping cost by car increases, the value of R increases. This increase in car cost should result in greater use of transit for shopping trips and, consequently, the likelihood of high automobile ownership should decrease. The coefficients of both R1 and R2 should therefore be negative, since they both measure the effect of shopping accessibility relative to the zero automobile-transit to work alternatives. Furthermore, the effect should be greater for the two automobiles alternatives than for the one automobile options, and the magnitude of the coefficient of R2 should be greater that that of R1.

In order to reflect the effect of household size on the desire for living in a single family dwelling, the following variable was defined:

$$\mathrm{HHSIZE1} = \begin{cases} \text{household size in single family dwelling} \\ \quad \text{alternative (own or rent)} \\ 0 \text{ otherwise} \end{cases}$$

The coefficient estimate of this variable should be greater than zero, since, other things being equal, larger households probably have a stronger perference for single family dwellings than do smaller households.

The next group of variables are all locational attributes and are defined as follows:

$$\mathrm{INCDIFF} = \begin{cases} (Y - \overline{Y})^2 \text{ for } Y \geq \overline{Y}, \text{ where Y and } \overline{Y} \text{ are the} \\ \quad \text{household and average annual tract in-} \\ \quad \text{come, in thousands of dollars} \\ 0 \text{ otherwise} \end{cases}$$

$$\mathrm{FBFORW} = \begin{cases} \text{fraction of nonwhite households in tract} \\ \quad \text{for white households} \\ 0 \text{ for non-whites} \end{cases}$$

$$\mathrm{FBFORB} = \begin{cases} \text{fraction of nonwhite households in tract} \\ \quad \text{for nonwhites} \\ 0 \text{ for whites} \end{cases}$$

$$\mathrm{DENSITY} = \begin{cases} \text{net residential density in households per} \\ \quad \text{acre} \end{cases}$$

$$\mathrm{SCHOOL} = \begin{cases} \text{per pupil school expenditures (in dollars} \\ \quad \text{per year) except in District of Columbia} \\ 0 \text{ in District of Columbia} \end{cases}$$

$$\mathrm{DOC} = \begin{cases} 1 \text{ in District of Columbia} \\ 0 \text{ otherwise} \end{cases}$$

The first variable is a measure of the neighborhood quality in a tract. The income differential is squared, reflecting the hypothesis that large differences are proportionately much more important than small ones. This variable should have a negative coefficient. The opposite variable, which is defined as non-zero when the household income is less than the average, consistently gave very small, statistically insignificant estimates having the wrong sign, and was omitted in the final specifications.

The two racial composition variables reflect the hypothesis that whites and nonwhites perceive the racial composition quite differently. The coefficients of FBFORW and FBFORB should be negative and positive respectively.

The density variable is self-explanatory; a negative coefficient should be expected. The DOC dummy variable was defined to correct for the setting of the annual per pupil school expenditure variable to zero in the SCHOOL variable, the coefficient of which should have a positive sign. The SCHOOL variable is defined to be zero for households without children even though the DOC variable is not. This was done to explore the possibility that the District has certain attributes that make it distinct from other locations regardless of whether or not a household has children.

The final variable in the model is the measure of tract size required to correct for the fact that a census tract is actually a group of housing units. Other conditions being equal, a very large tract (i.e., one with a large number of housing units) would have a higher probability of being selected than a very small one, since the number of disaggregate opportunities is greater in the former than the latter. If all units of a particular type in a given zone are relatively homogeneous and the logit model applies to each individual unit, then the appropriate term to correct for tract size is the natural logarithm of the number of units (7). This variable, denoted as lnN, should, under the previously cited assumptions, have a coefficient of one. However, if the assumptions of the logit model are violated, the coefficient may differ from one; for this reason, parameter estimates both with and without the coefficient of lnN constrained to unity are reported.

In order to derive the structure of the utility function for any particular location-housing-automobile ownership-mode to work combination, the variables that are set to zero for that alternative can be omitted.

ESTIMATION RESULTS

The variables in the model described above were estimated using the maximum likelihood method (13) with data from a 1968 Washington, D.C., home interview sur-

Table 1. Parameter estimates for the model.

No.	Variable	Unconstrained Estimates	Constrained Estimates
1	DRENT1	-0.361	0.393
		(-1.03)	(1.18)
2	DRENTG	2.31	2.93
		(2.87)	(3.58)
3	DRENTH	0.828	0.809
		(1.02)	(0.973)
4	DAO1	7.86	7.98
		(2.57)	(2.60)
5	DAO2	12.0	12.1
		(2.71)	(2.78)
6	DCAR	0.433	0.483
		(0.500)	(0.501)
7	DAPTSTYL	0.542	0.524
		(0.966)	(0.927)
8	DSUBSTYL	0.336	0.261
		(0.764)	(0.591)
9	TOTIME	-0.008 31	-0.008 18
		(-2.13)	(-2.05)
10	OVTT/DIST	-0.057 0	-0.052 6
		(-0.787)	(-0.708)
11	DCITY	-0.437	-0.415
		(-0.932)	(-0.879)
12	ln Z	1.07	1.20
		(2.64)	(2.81)
13	AALD	0.964	0.975
		(1.01)	(1.02)
14	ILD	-6.57	-6.56
		(-2.17)	(-2.16)
15	GPTINV	2.92	3.14
		(1.38)	(1.47)
16	R1	-1.35	-1.54
		(-1.08)	(-1.21)
17	R2	-4.05	-4.11
		(-3.01)	(-3.03)
18	HHSIZE1	0.850	0.875
		(5.21)	(5.16)
19	INCDIFF	-0.012 3	-0.012 1
		(-2.89)	(-2.80)
20	FBFORW	-2.18	-2.21
		(-3.79)	(-3.78)
21	FBFORB	1.95	1.85
		(2.23)	(2.12)
22	DENSITY	-0.005 57	-0.008 10
		(-1.25)	(-1.75)
23	SCHOOL	0.000 442	0.000 342
		(0.685)	(0.523)
24	DOC	-0.009 93	-0.100
		(-2.06)	(-0.204)
25	ln N	0.492	1
		(5.25)	—[a]
	$L^*(0)$	-824.4	-824.4
	$L^*(\hat{\beta})$	-645.9	-658.4
	NOBS	177	177
	NCASES	25 601	25 601
	Percent right	8.5	10.2

[a]Constraint imposed, hence t statistic not relevant

vey for a small sample of single worker households in which the worker was at least minimally skilled. This data set was augmented by 1970 census housing data (appropriately deflated) and transportation level of service from highway and transit networks. Two different estimations were made. The first allowed the coefficient of the tract size variable, lnN, to attain its highest probable value: These estimates are shown in column 3 of Table 1. The second set of estimates are based on the constraint that the coefficient of the tract size variable is unity: These estimates are shown in column 4 of Table 1. For each model, the asymptotic t-statistics are given in parentheses below their corresponding parameter estimates. In addition, five summary statistics are given.

1. $L^*(0)$ is the value of the log probability function when all of the parameters are zero (i.e., when every alternative has the same probability);
2. $L^*(\hat{\beta})$ is the value of the log probability function at the maximum probability coefficient values;
3. NOBS is the number of households in the sample;
4. NCASES is the number of available alternatives (in excess of one per household) used in the estimation; and
5. Percent right is the percentage of households for which the alternative with the highest systematic component of utility was actually selected. This value is maximized when the maximum score estimation technique is used (6).

All of the coefficient estimates in both the unconstrained and constrained models for variables about which hypotheses were formulated have the expected sign. However, the statistical significance of some coefficients such as the estimate for OVTT/DIST is marginal. This probably results from the very small sample used, since mode choice models with larger samples of the Washington data result in estimates significantly different from zero at fairly high levels of confidence.

The constrained estimates are similar to the unconstrained ones, with the exception of the coefficient of DRENT1. This suggests the possibility of some measurement error in the value of N, the number of units of rented single family dwellings.

As might be expected with an average of over 145 alternatives available for each household, the percent right result is low in absolute terms. A useful way of viewing this is in terms of the probability of a model classifying a given percent correctly if all the alternatives were actually equally likely. Suppose that all households have exactly 145 available alternatives, and that each is equally likely. In this case, the probability of a model classifying none of the 177 observations correctly is

$$(144/145)^{177} = 0.2938$$

and the probability of classifying k of 177 correctly is distributed as binomial, i.e.,

$$\Pr(k \text{ correct}) = \binom{177}{k} (1/145)^k (144/145)^{177-k}$$

According to this formula, the probability of classifying nine or more households correctly (about 5 percent right) is less than 0.0001, but the percent right found for the unconstrained and constrained estimates are 8.5 percent and 10.2 percent respectively.

IMPLICATIONS OF THE RESEARCH FOR REVISED ANALYSIS FRAMEWORK

Forecasts of urban land use have traditionally played an important role in the transportation planning process. However, the models used to forecast residential location patterns have usually been logically separable from those used to forecast both automobile ownership and trip-making patterns. Land use models have provided forecasts of zonal population and employment before a separate automobile ownership model is applied. These forecasts are then used as inputs to the four-step process, consisting of trip generation, distribution, mode split, and assignment.

A critical implication of the theory upon which this study is based is that such a forecasting approach fails to behaviorally represent the true process it seeks to model. In reality, it is more reasonable to assume that both automobile ownership and work-trip travel patterns arise as a logical consequence of a long-term choice process and should therefore be forecast within what has traditionally been termed urban land use forecasting. For work trips, trip generation actually represents labor force participation in a decision process that probably depends more on the household structure and life-style and the state of the regional economy than on the transportation system. Work-trip distribution is simply the outcome of urban location patterns rather than a distinct behavioral phenomenon that can be modeled separately.

Nonwork trips can then be modeled as conditional on the outcome of the work-trip pattern. Feedback between the longer run land use component and the nonwork trip patterns can readily be incorporated by extending the shopping generalized price variables to include other relevant trip purposes.

The choice models developed in this paper are prototypes for one part of such a system of models. Many of the other required model system components are the object of a great deal of research (8, 13). New models of the land use supply sector are being studied by the National Bureau of Economic Research. Thus, the proposed forecasting process represents a synthesis of the results of research in a variety of areas, and could possibly be implemented in a fairly short time.

This study represents one step in the process of improving land use forecasts by introducing joint behavioral choice models into the representation of the household mobility choice. Obviously, if the models described here are to be used effectively, they must be a portion of a much larger research effort to restructure the entire travel forecasting process to better reflect a behavioral understanding of the true causal mechanisms that determine supply and demand. Only by developing more behaviorally structured models can transportation analysts and urban planners hope to provide reliable forecasts of the impact of alternative policies on which an informed decision-making process can act.

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