Title
The Demand for Transportation: Models and Applications

Authors
Small, Kenneth A.
Winston, Clifford

Publication Date
1998-10-01

UCI-ITS-WP-98-8

The Demand for Transportation: Models and Applications

UCI-ITS-WP-98-8

Kenneth A. Small [1]
Clifford Winston [2]

[1] Department of Economics and Institute of Transportation Studies
University of California, Irvine; Irvine, CA 92697-5100, U.S.A
ksmall@uci.edu

[2] The Brookings Institution
1775 Massachusetts Avenue, N.W.; Washington, D.C. 20036-2188, U.S.A.
cwinston@brook.edu

October 1998

Institute of Transportation Studies
University of California, Irvine
Irvine, CA 92697-3600, U.S.A.
http://www.its.uci.edu

Draft Chapter Two in *Transportation Policy and Economics: A Handbook in Honor of John R. Myer*. J. Gomez-Iba nez, W. Tye and C. Winston, eds. Washington, D.C.: Brookings Institution, forthcoming.

Introduction

A distinguishing feature of transportation is that it is valued primarily as an input to other activities, which are many and varied. Firms ship products to distribution centers and retail outlets; businesses send their employees to meet with customers, suppliers, regulators, and co-workers; ordinary people travel to work and for leisure pursuits. Because of the variety of functions that transportation facilitates, researchers have developed a wide assortment of models to analyze transportation users' behavior.

These models must account for certain special features of transportation markets. First, transportation encompasses many interrelated decisions such as mode, destination, shipment characteristics, vehicle ownership, and residential and industrial location. The models must therefore also account for the mutual effects of these decisions upon each other and for their differing time horizons. Second, transportation consists of a large number of distinct services differentiated by location and time. Furthermore, knowing the spatial and temporal details of these transportation decisions is essential for facility planning and management.

A third feature is that travelers and shippers are sensitive to service quality. Thus demand models must incorporate quality indicators, some of which are readily measurable (like travel time, service frequency, and route coverage) while others are more amorphous (like comfort, crowding, and reliability). Since users differ in the values they place on these attributes, the models must also control for demographic or socioeconomic factors that influence these values. And because service quality often depends upon usage through congestion or crowding, the relationship between travel environment and transportation decisions is two-way; neither can be forecast without knowing the other, thus requiring iterative calculations between demand models and facility performance models.

This chapter describes how transportation demand is analyzed and what has been learned from doing so. We first present a selection of the most important transportation demand models,

We are grateful to David Brownstone, Charles Lave, Fred Mannering and Kenneth Train for helpful comments.

with an emphasis on disaggregate models because they have generally been the most successful in capturing essential features of travel behavior.[1] We then show how the models have enriched our substantive knowledge of the demand for transportation, and discuss how they have been used to address important transportation policy issues.

The traditional modeling structure for transportation demand distinguishes four decisions: how often to travel, where to travel to, what mode of transportation to use, and what route to take. These decisions, which apply to both passenger and freight transportation, are known as trip generation, trip distribution, mode choice, and route choice.[2] More recent work has taken up a number of collateral decisions such as vehicle ownership and time of day of travel. Land-use decisions, which interact with transportation decisions in a two-way causality, are dealt with in Chapter 12.

Trip generation and distributional have received relatively modest attention from economists, the models for them being closely related to land use.[3] For example, models from regional science project the trip-making potential from various types of land uses such as housing, shopping centers, or office buildings. Models of trip distribution typically use the travel distance or time between locations to convert these total trips into a set of origin-destination flows. The analysis of route choice relies heavily upon computerized networks and is often highly mathematical. Usually it makes relatively simple assumptions about the economic forces behind travel choices, while using a quite sophisticated framework of uncertainty, random influences, and dynamic considerations.[4]

Economists have primarily, though not exclusively, focussed on mode choice. Mode choice is often particularly sensitive to economic variables, and economic techniques are appropriate for illuminating its subtleties. For these reasons, we give mode choice the lion's share of attention in

---

[1] Other surveys of transportation demand models may be found in Oum, Waters, and Yong (1992), Small (1992), and Miller and Fan (1992), and Ortúzar and Willumsen (1994).

[2] For clear expositions see Meyer and Straszheim (1971, ch. 7) or Beesley and Kemp (1987).

[3] See Ortúzar and Willumsen (1994) for a good review.

[4] See Boyce and Ran (1996).

this chapter; but as we shall see, the techniques developed are quite broadly applicable.

Aggregate Demand Models

Aggregate models rely on data describing the behavior of large groups of travelers or shippers. The most satisfactory ones have been based on standard microeconomic demand theory, in which travelers are assumed to maximize utility (Oum and Gillen, 1983) or firms to minimize costs (Oum, 1979; Friedlaender and Spady, 1980). The best of these models impose the parametric restrictions implied by economic theory while using flexible functional forms.

For example, a neoclassical aggregate freight demand model can be derived by assuming that shippers are firms whose production techniques and transportation decisions are jointly chosen to minimize a cost function $C(Q,w,x,p)$, where Q is the firm's output, w is a set of factor prices relating to its production, x is a set of potential shipment characteristics, and p is a set of transportation prices. If it is assumed that the cost function is of a particular form known as translog,[5] then it is possible to derive an equation for the expenditure share on a given mode i which is linear in the logarithms of the variables in the cost function.[6] Furthermore, certain restrictions on the parameters of the cost function itself are imposed by the theoretical conditions for cost minimizing behavior. The parameters can be estimated from data on the expenditure shares alone, or on expenditure shares and costs, in either case using multiple-equations methods in standard regression packages.

Many of the earlier aggregate models explained mode shares over a cross-section of city

---

[5] A translog function is a linear combination of all possible first- and second-order terms in the logarithms of independent variables; for example a first-order term might be $\beta_Q \ln Q$ while a second-order term might be $\beta_{QQ}(\ln Q)^2$ or $\beta_{Qx}(\ln Q)(\ln x)$ if x is just a single characteristic. This form can closely approximate an arbitrary function when the variables are close to a particular set of values chosen in advance, such as the average values in the sample.

[6] The derivation makes use of Shepherd's lemma, which states that a small increase in the price of an input increases cost by an amount equal to the use of that input. See Oum (1979) or Friedlaender and Spady (1980).

pairs or mileage blocks.[7] An alternative is the *direct demand* model, in which the total use of a given type of transportation is expressed as a function of its own characteristics and those of competing types, without worrying about where the function comes from. The advantage of this approach is that it automatically combines trip generation, distribution, and mode choice decisions. For example, Domencich and Kraft (1970) estimate equations to explain the total number of urban trips between a given origin and destination by a given mode for a given purpose. Explanatory variables include demographic and land-use characteristics of the origin and of the destination, and travel times and costs both for the mode in question and for competing modes. This type of approach is still in use as illustrated by Wardman's (1997) estimation of the demand for intercity rail travel in Great Britain.

Direct demand models are also used in a time series context. For example, Gaudry (1975) uses monthly data on ridership of Montreal's public transit system to explain how its ridership depends on average real income, weather, transit strikes, special tourist attractions, and other factors as well as on fares and service times for both transit and car. Voith (1997) uses a combined time-series and cross-sectional approach to estimate how commuter rail ridership in Philadelphia varies with the characteristics of the route, some of which change over the period covered by the data.

Disaggregate Demand Models

Another class of models uses data on individual decision makers, reaping several advantages (Domencich and McFadden, 1975). First, the number of observations is much larger, leading to more precise estimates of parameters. Second, it is feasible to use a richer empirical specification, thus better capturing the variation in decision-maker characteristics and accounting for a more complete set of service-quality attributes. Third, disaggregate models are well grounded in a microeconomic theory of individual or firm behavior that does not require the unrealistic

[7] For examples, see Perle (1964), Quandt and Baumol (1966), McLynn and Watkins (1967), and Kraft and Kraft (1974).

assumption of identical decision makers. Fourth, disaggregate models are explicit about the source of random disturbances, which has improved their statistical properties.

Disaggregate models also use the actual values of variables facing each decision maker, rather than average values which may obscure a significant amount of information. The advantage of this is illustrated by the importance of shipment size and trip distance in mode choice for surface freight. Small shipments and those going short distances tend overwhelmingly to use truck. Thus an aggregate model that uses average values for these variables may include many shipments where truck and rail do not seriously compete against each other. As a result the model may overstate the sensitivity of demand to price and service quality in some markets and understate it in others.

In this section and the next we present several of the most useful disaggregate demand models, each in the context of an important transportation application.[8] This section presents the underlying framework and three widely used disaggregate models. The next section describes more technically advanced models that enable researchers to analyze simultaneous choices, taste variation, and varied sources of unobserved influences.

The Random Utility Framework.

The common starting point for virtually all disaggregate models in current use[9] is that developed by McFadden (1973), based on a utility function with a random component. We describe it in the context of mode choice, but the same approach is used for the choice among any finite set of alternatives.

---

[8] Ben-Akiva and Lerman (1985) and Train (1986) provide excellent and thorough treatments of disaggregate models, with emphasis on transportation applications.

[9] An exception is the Poisson model for analyzing trip generation at a disaggregate level, as exemplified by Terza and Wilson (1990).

Suppose the decision maker chooses among J alternative modes such as auto, bus, and air for intercity passenger travel. The chosen mode is assumed to maximize the decision maker's utility, which for mode j is:

$$U_j = V(X_j, S; \beta) + \varepsilon_j \tag{1}$$

where X_j denotes a set of modal attributes, S denotes characteristics of the decision maker, β denotes unknown parameters, and ε_j is an unobserved ("random") utility component representing other influences on the decision maker including idiosyncratic preferences for mode j. The modal attributes X_j may contain an indicator (known as a "dummy variable") for mode j; in that case its coefficient (one of the parameters in vector β) represents an average preference for mode j, while ε_j represents a deviation from that average preference. The function V is called the "systematic" utility because the same functional form applies to all decision makers, unlike the random component which varies across decision makers.

Because utility is partly random, we can predict choices only as probabilities. The probability that the decision maker will choose mode i is:

$$\begin{aligned} P_i &= \text{Prob } [\ U_i > U_j \quad \text{for all } j \neq i\ ] \\ &= \text{Prob } [\ V_j + \varepsilon_j < V_i + \varepsilon_i \quad \text{for all } j \neq i\ ] \\ &= \text{Prob } [\ \varepsilon_j - \varepsilon_i < V_i - V_j \quad \text{for all } j \neq i\ ] \end{aligned} \tag{2}$$

where V_j is shorthand for $V(X_j, S; \beta)$. Thus the choice probability depends not only on the systematic utility differences $V_i - V_j$, but also on how the random-utility differences $(\varepsilon_j - \varepsilon_i)$ are distributed across the population. Most of the models in subsequent sections differ only in their assumptions about this latter distribution.

The model is estimated by finding the values for unknown parameters that yield predicted choice probabilities matching actual choices as closely as possible. A common algorithm is the following: choose a trial set of parameters, calculate the logarithms of the probabilities of the observed choice for all members of the sample, add them, then repeat using new parameter values until this sum is made as large as possible. This method is called *maximum likelihood.*

The process is usually simplified by assuming the utility function $V(X_j,S;\beta)$ is linear in parameters β. This is not at all necessary; Gaudry and Wills (1978) argue, for example, that more flexible functions known as Box-Cox transformations often provide a better fit to the data.[10] Even if utility is constrained to be linear in parameters, it can be a quite flexible function of the variables X_j, containing ratios, quadratic terms, logarithms, or other transformations and combinations.

Once the model is estimated, we still have to describe the decision makers who are relevant for any particular scenario under study. The most common way to accomplish this is *sample enumeration.* Based on information about the actual population of interest, the analyst chooses a representative sample of individual decision makers, possibly but not necessarily the same as the sample on which the disaggregate model is estimated. Each member of the enumeration sample is assumed to represent a population segment of real decision makers, all with the same observed characteristics as that sample member. The predicted probability of each choice is then used to estimate the fraction of that population segment making that choice.

Binary Probit and The Value of Travel Time.

The simplest choice model involves just two alternatives. Consider the mode choice for an urban work trip. Let's call auto "alternative 1" and bus "alternative 2". Then there is only one utility difference, namely ε_2-ε_1, in equation (2). A reasonable assumption is that this utility difference follows a bell curve, i.e. it is normally distributed across the population. This assumption leads to the *probit* choice probability:

[10] One of several studies using Box-Cox transformations is that of Mandel, Gaudry, and Rothengatter (1994), who analyze rail travel in Germany.

$$P_1 = \Phi(V_1 - V_2) \tag{3}$$

where P_1 is the probability of choosing auto and Φ is the cumulative standard normal distribution function.[11] This choice model is simple to estimate and was used early on by Lisco (1967) and Lave (1969) to measure the value of time in urban commuting.

Lave analyzed a sample, taken in the mid-1960s, of 280 urban commuters in the Chicago area choosing between automobile and transit. The estimated systematic utility function is:

$$V = -2.08D^{T} \quad -0.00759w \cdot t \quad -0.0186c \quad -0.0254(Inc \cdot Dist \cdot D^{T}) \quad +0.0255(Age \cdot D^{T}) \\ -0.057(Female \cdot D^{T})$$

where D^{T} is an "alternative-specific dummy variable" equal to one for transit and zero for auto. It enters the model independently (in the first term) and also interacted with the traveler's income (*Inc*), trip distance (*Dist*), age, and a dummy variable indicating whether the traveler is female. The traveler's wage rate is denoted by w, travel time by t, and travel cost by c. Note that D^{T}, t, and c all vary from one mode to the other, whereas w, *Inc*, *Dist*, *Age*, and *Female* do not. Lave's more detailed results show that all estimated parameters are statistically significant except the last. The model indicates that travelers are less likely to take transit if their income or trip distance increases, but more likely to take transit as they become older.

This utility function is linear in travel time and cost. The value of travel time (*VOT*), defined as the marginal rate of substitution between time and cost, is just the ratio of the time and

---

[11] That is,

$$\Phi(x) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{x} (t^2/2)dt .$$

This function is tabulated in mathematical handbooks and is readily generated by most any mathematical or statistical computer program.

cost coefficients of that linear relation:[12]

$$VOT = \frac{-0.00759w}{-0.0186} = 0.41w \quad .$$

Lave's finding, which is representative of other estimates in the literature, is that time is valued at 41 percent of the average wage rate. Note that the variables in this model were specified so that VOT is proportional to the wage rate. This is consistent with models of time allocation, such as by Becker (1965) and Bruzelius (1979), which suggest that a person's tradeoff between travel time and money is strongly related to his or her possibilities for earning money in the labor market.[13]

What if there are more than two alternatives? Although the probit model can be extended for this situation, it becomes much more difficult to estimate. The reason is that the right-hand side of equation (3) becomes a multidimensional cumulative normal function, which can be computed only using difficult numerical approximations. Thus when Lave wanted to consider other modes, such as rapid rail and commuter rail, he had to examine each pair separately, although recognizing that this approach could lead to inconsistencies. Fortunately, researchers have subsequently developed other models that can estimate many alternatives simultaneously, as we now describe.

Multinomial Logit and Urban Mode Choice.

When there are more than two alternatives, the key to obtaining a computationally convenient choice model is to have an easily calculated expression for the choice probability. McFadden (1973) derives such a model by assuming that each of the random utilities follows the extreme value distribution, which is almost indistinguishable from the normal distribution in

---

[12] More generally, the value of time is defined as $VOT = (\partial V/\partial t)/(\partial V/\partial c)$, where ∂ denotes a partial derivative.

[13] See Small (1992, pp. 36-45) for further discussion and for a review of empirical findings on the value of time.

practice.[14] The resulting choice probability is:

$$P_i = \frac{e^{V_i}}{\sum_{j=1}^{J} e^{V_j}} . \tag{4}$$

This model is known as *multinomial logit*, or just "logit".[15]

The computational complexity of multinomial logit is not affected by whether J, the number of alternatives, is 3 or 300. But this simple structure does not come without a cost. Multinomial logit has a property called *independence from irrelevant alternatives* (*IIA*): the ratio of the probabilities of any two alternatives i and j depends on the corresponding systematic utilities V_i and V_j, but not on the systematic utilities for any other alternatives. This property implies, for example, that adding a new alternative mode k will not affect the relative proportions of people using existing modes; thus its patronage will be drawn proportionally from all these modes rather than preferentially from one or two close substitutes. The *IIA* assumption can be tested statistically,[16] and if it is rejected one can use alternative models as discussed below.

McFadden, Talvitie, and Associates (1977, pp. 121-123) present a multinomial logit model of mode choice for urban work trips. This model is estimated from data generated by San Francisco Bay Area commuters choosing among four modes: (1) auto driving alone, (2) bus with walk access, (3) bus with auto access, and (4) carpool (two or more occupants). (The survey was undertaken shortly before BART, the rapid rail system, was opened.) Mode choice is explained

---

[14] The extreme value distribution is defined by $\text{Prob}[\varepsilon_i < x] = \exp(-e^{-\mu x})$, where $\exp(\cdot)$ and $e^{\bullet}$ both denote the exponential function, and μ is a scale parameter conventionally normalized to one.

[15] A few authors still reserve the term "multinomial logit" for a version of the model in which the coefficients, rather than the variables, depend on the alternative being considered — that is, the strict utility in (1) is written as $V(X,S;\beta_j)$ instead of $V(X_j,S;\beta)$. These authors use the term "conditional logit" for the model as we have defined it. As noted by Maddala (1983, p. 42), these are just two ways of writing the same model, so the distinction matters only for the terminology used to describe results and data structure.

[16] For example Hausman and McFadden (1984), Small and Hsaio (1985), McFadden (1987), and Small (1994).

by three observed attributes: round-trip variable cost c (in cents, including parking, tolls, gasoline, and maintenance); in-vehicle travel time t (in minutes); and out-of-vehicle travel time t^0 (in minutes, including walk, wait, and transfer times). Unobserved attributes for mode j are captured by the "mode-specific dummy" D^j, which, like D^T in the previous section, is defined as one for mode j and zero for the other modes. (Because only utility differences affect mode choice, one of these mode-specific dummies — D^2 in this case — is omitted, thus defining a "base mode" to which the others are compared.) One socioeconomic characteristic, the traveler's after-tax wage rate w (in cents per minute), is also included in the model. The estimated utility function is:

$$\begin{array}{llllllll} V = & -0.0412c/w & -0.0201t & -0.0531t^0 & -0.89D^1 & -1.78D^3 & -2.15D^4 \\ & (0.0054) & (0.0072) & (0.0070) & (0.26) & (0.24) & (0.25) \end{array}$$

with the standard errors of the parameter estimates shown in parentheses.

As expected, higher travel cost or greater in-vehicle or out-of-vehicle time for a given mode decreases the probability that commuters will select that mode. The negative mode-specific constants (the coefficients of D^1, D^3, and D^4) show that a traveler facing equal times and costs on all four modes would prefer bus with walk access (mode 2, the base mode). The especially large negative constants for bus with auto access (mode 3) and carpool (mode 4) may reflect unmeasured inconvenience associated with getting from the car to the bus stop and with arranging carpools. These are examples of service-quality attributes that would be difficult to measure directly.

Once again, the model is specified so that the ratio of each of the time coefficients to the cost coefficient is proportional to the after-tax wage rate. The estimated parameters indicate that travelers value their in-vehicle and out-of-vehicle travel time at 49 percent and 129 percent, respectively, of their wage rate.[17] This much higher value of out-of-vehicle relative to in-vehicle time indicates that travelers dislike the time they must spend accessing, transferring to, or waiting for a mode. An important consequence of this finding, which has been verified by other studies,

[17] Since $(-0.0201)/(-0.0412/w) = 0.49w$, and $(-0.0531)/(-0.0412/w) = 1.29w$.

is that auto's low out-of-vehicle time gives it a significant competitive advantage over other modes.

Nested Logit and Vacation Travel Choice.

In most transportation settings, mode choices are made jointly with other travel-related decisions. For example, a commuter may simultaneously choose what mode to use and how many cars to own. A freight shipper may simultaneously select a shipping mode and shipment size. If the two choices depend on each other in important ways, we err by pretending one is exogenous while analyzing the other. For example, the number of automobiles owned by a household has a powerful influence on urban mode choice when it is included as an explanatory variable; but including it without accounting for the reverse causation (mode choice affecting auto ownership) will cause the influence of auto ownership to be overstated, and the influence of other factors to be understated. This is why auto ownership is omitted as a variable in both of the studies just reviewed.

Joint choice models are designed to account for such simultaneity of decisions. Here we treat joint choices where both choices are discrete in nature. The earliest such models identified and combined all possible combinations of two or more discrete choices, and used logit to estimate the choice among the combined alternatives.[18] But if a decision maker has idiosyncratic preferences for an entire class of outcomes — for example, all those involving not owning a car — then the random utilities for all those outcomes would be correlated with each other and the probabilities would violate the IIA assumption.

McFadden (1978) developed a widely used generalization of multinomial logit, called *nested logit*, that allows for such idiosyncratic preferences. This model explicitly structures the joint choice process in terms of groups of possible outcomes. Random utilities are allowed to be correlated within groups, but are assumed to be independent across groups. The model therefore

---

[18] For example, Ben-Akiva and Lerman (1974) estimate logit models of the joint choice of automobile ownership and work-trip mode. Lerman (1981) adds to those two choices two more: residential location and housing type, both treated as discrete.

allows for more flexible substitution patterns than logit, and does not have to obey the *IIA* restriction.

Morrison and Winston (1985) estimate a nested logit model of intercity vacation travel. The authors assume that vacation travelers simultaneously make three choices: where to travel, how to get there, and whether to rent a car at the destination. The structure of these choices is indicated by figure 1, in which each of the dashed lines indicates an additional branch of the tree analogous to the one shown for the same level node. (A node is a decision point, represented by a dot.) This diagram is not intended to indicate a sequential decision process, but rather the pattern of similarities within a simultaneous decision process. The diagram indicates that all the various ways of getting to New York, for example, are viewed by the traveler as more similar to each other than, say, all the places one can go by air. The two possible choices for air travel to New York — with or without renting a car — are even more similar to each other, hence appear as branches attached at the lowest level of the tree.

The random error components are assumed to follow an extreme value distribution, as in logit; but those components representing branches connecting to a common node are positively correlated with each other while others are independent. This assumption produces the pattern of similarity suggested by the tree diagram and results in a convenient form for the choice probabilities: conditional on choosing any particular node, the choice probability for the next lower decision on the diagram is given by a logit probability! For example, conditional on New York as a destination, the choice among travel modes has the multinomial logit form of equation (4). In that case the utility V_j of each travel mode j (e.g., air) is a combination of traits of that mode (e.g. airline prices to New York) and a summary index of the ease of getting around New York. That index, known as an "inclusive value," is constructed from the systematic utilities of the lower-level decision of whether to rent a car, which in turn reflect factors like rental-car prices at airports in the New York area.

The model was estimated on a sample of 1,893 households making vacation trips in 1977. Here we describe just one part of the results, namely the estimated utility function for the top decision level, destination choice. Choice of destination is explained by round-trip distance to the

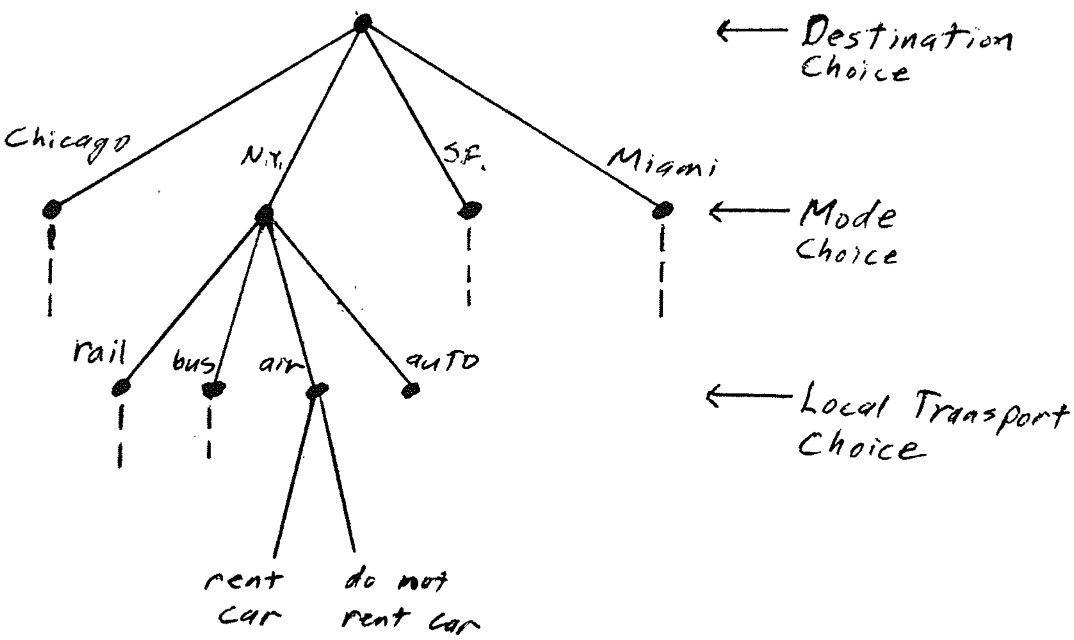

Figure 1. Preference Tree for Intercity Vacation Travel

destination (*dist* — measured in thousands of miles); a dummy variable (D^{plan}) equal to one if the traveler planned the trip more than a month in advance and zero otherwise; two characteristics of the destination — mean temperature at the destination during the month of travel (*temp*) and a dummy variable for whether public transit is available there (D^{pt}); and the "inclusive value" index (I_{d}) for mode choices at that destination.[19] The estimated destination utility is:

$$\begin{array}{lllllll} V_d = & -0.364(1-D^{plan})\cdot dist_d & +0.270D^{plan}\cdot dist_d & +0.019temp_d & +0.309D_d^{pt} & +0.519I_d \\ & (0.088) & (0.075) & (0.003) & (0.058) & (0.069) \end{array}$$

where again standard errors of the parameter estimates are shown in parentheses. The first two estimated parameters indicate that travelers prefer closer destinations if they do not plan their travel far in advance, and farther destinations if they do plan far in advance. Travelers on average prefer destinations that are warm and that have public transit.

The coefficient of inclusive value is positive, indicating that travelers' choice of where to spend their vacation is interconnected with their choice of mode to get there. For example, if air fares to San Francisco fall and those to other destinations do not, San Francisco is more likely to be selected as a destination— in addition to air becoming a more likely mode of travel. The coefficient of inclusive value is also less than one by a statistically significant amount, which tells us that the nested logit structure is consistent with utility maximizing behavior and fits better than a pure joint logit (McFadden, 1978).

Nested logit need not be used only for joint choices; it is suitable for any set of discrete choices where alternatives are grouped by decision makers. In fact, nested logit is just one of a

---

[19] The inclusive value for the mode choices available to destination d is defined as:

$$I_d = \ln \sum_i \exp(V_{i|d} + \theta J_{i|d})$$

where $V_{\text{i}|\text{d}}$ is the systematic utility pertaining to using mode I to travel to destination d; $J_{\text{i}|\text{d}} = \ln \Sigma_\delta \exp(V_{\delta|\text{i,d}})$ is the inclusive value of the two alternative forms of local transportation (denoted $\delta=1$ or 2) when mode I is used to travel to destination d; $V_{\delta|\text{i,d}}$ is the systematic utility of either of these two forms of local transportation; and θ is a parameter related to the correlation between the random utilities of the two forms of local transportation.

class of models, known as *generalized extreme value* (GEV) models, having logit as a special case (McFadden, 1981). The random utility components in all GEV models have the extreme-value distribution, just like in logit, but they have a correlation pattern that varies from model to model. For example, the alternatives may have a natural ordering, as in the choice among several departure-time intervals for a work trip, with nearby intervals viewed as more similar to each other (Small, 1987). Nesting structures can be developed in which the groups overlap (Chu, 1981); for example in choosing among car types, all sports cars might form one group and all foreign cars another. And ordered structures can be embedded within nesting structures, thus providing additional flexibility (Small, 1994; Bhat, 1998).

Advanced Disaggregate Models

As computational capabilities increase, researchers are turning more often to advanced techniques that can handle more sophisticated model structures. We describe three such techniques in this section, again with applications. Non-technical readers can omit this section.

Joint Discrete and Continuous Choices

Earlier we introduced a nested logit model in which two discrete choices are made simultaneously. Another kind of joint choice occurs when a continuous choice, such as how many miles per year a household chooses to drive an automobile, is made simultaneously with a discrete choice, such as the type of vehicle to own. This kind of structure has proven extremely useful in transportation demand studies. However, it requires some additional theoretical and econometric modeling to account for the interrelationship between the two decisions (Mannering and Hensher, 1987).

The basic theoretical framework for discrete/continuous models was pioneered by Dubin and McFadden (1984). They specify a random utility function that forms the basis for the discrete choice and use Roy's Identity to derive the continuous choice;[20] thus both choices are consistent with utility maximizing behavior. Mannering and Winston (1985) use this framework to estimate a model of vehicle type choice and utilization.[21] Other researchers have estimated combined discrete and continuous choice models of freight mode and shipment size.[22]

The primary wrinkle for analyzing this type of model is that the continuous part, which may look like an ordinary regression equation, contains a type of selection bias because that equation is conditional on a particular outcome of the discrete choice, which is interrelated. Take the example of a household choosing whether to own a car and, if so, how much to use it. The equation to explain utilization contains, of course, a random error term. But it will be estimated only on a portion the full sample, namely those who choose to own a car, who are more likely to have idiosyncratic reasons to use their car a lot. Thus, the sample on which the utilization equation is estimated is self-selected to contain people likely to have relatively high utilization. Suppose the utilization equation were estimated on that sample without correcting for this bias, then used to analyze road-building policies that encourage more people to buy cars. It would overpredict the usage by the new car owners. Simple corrections are available for this type of bias.[23]

Multinomial Probit and Freight Mode Choice.

A probit framework developed by Hausman and Wise (1978) offers another way, besides

---

[20] Roy's Identity expresses an ordinary demand function in terms of the partial derivatives of an indirect utility function with respect to price and income.

[21] Another study of automobile ownership and utilization is that of Train (1986, ch. 8), who uses simple approximations to functional form rather than relying on strict utility-maximizing behavior.

[22] Chiang, Roberts, and Ben-Akiva (1981); McFadden, Winston, and Boersch-Supan (1985).

[23] Two classic treatments are Heckman (1978) and Lee (1979). Train (1986, ch. 5) provides a readable textbook presentation.

nested logit, to incorporate complex correlation patterns among alternatives. At the same time it can capture taste variation across a population of transportation users. It does this by means of random coefficients: each variable enters the systematic utility not through a single coefficient, but through one that varies across the population. (For example, some travelers may greatly prefer warmer vacations destinations as in the Morrison-Winston model discussed earlier, while others may care less or not at all.) Thus the Hausman-Wise model complicates equation (1) in two ways. First, the random terms are distributed in accordance with a multivariate normal distribution with an arbitrary correlation pattern. Second, the unknown parameters vary randomly across the population, also following a normal distribution.

One application of multinomial probit with random coefficients has been to understand mode choice for freight shipments. Typically the decision is made by a physical distribution manager, who may have a particular attitude toward the uncertainties associated with long transit times and with variability in delivery time.[24] Since the manager's attitude may depend on his job security and personal characteristics, which are not easily observable, it is natural to model it as a random coefficient. Indeed, surveys of American and French freight managers provides evidence for substantial variability in their concern for shipment time.[25]

Winston (1981a) specifies the distribution manager's utility function to include not only transit time but uncertainty in transit time, both with random coefficients. For some products, the results indicate clear variation across managers; for others, they do not. An example of the first situation is (formerly) regulated agriculture, which tends to be low value per weight. Shippers have the choice of rail, common-carrier truck, or private truck. The estimated utility function depends on three modal attributes: freight charges (*cost*) in thousands of dollars, mean transit time (*time*) in days, and the standard deviation of transit time (σ). The utility of certain modes relative to others also depends on characteristics of the shipment itself: more precisely, shipment size (*size*, in thousands of pounds), value-to-weight ratio (*value*, in dollars per thousand pounds), and distance

[24] See, for example, Daughety and Inaba (1978) and Daughety (1979).

[25] Gellman Research Associates (1977); Wynter (1995).

from the nearest rail siding (*dist*, in miles) are all hypothesized to affect choice of rail relative to the others, whereas total annual sales by the shipper (*sales*, in billions of dollars per year) is hypothesized to affect the feasibility of private trucking. The estimated utility function for the average shipper is:

$$V = -3.09cost -2.44time -12.7\sigma +11.5(\sigma/time) +0.536D^{r}\cdot size +0.035D^{r}\cdot value -35.4D^{r}\cdot dist -0.17D^{p}\cdot sales$$

where D^r and D^p are dummy variables for rail and for private trucking, respectively. The values shown here are only averages since the actual coefficients are assumed to vary randomly across the population of shippers, with standard deviations that are estimated along with these average values.

The parameter estimates indicate that these agricultural shippers are responsive to freight charges, transit time, and uncertainty in transit time (they are averse to such uncertainty, but less so for shorter shipments). They are more likely to use rail for larger shipments and if they are located close to a rail siding. The coefficients for these variables are statistically significant and the coefficients for *value* and *sales* are statistically insignificant.

This model suggests that transit time and its uncertainty are important considerations to shippers. For the mean sample member, the elasticity of demand for common-carrier trucking is -0.32 with respect to cost, -0.59 with respect to transit time, and -0.18 with respect to the standard deviation of transit time. The demand for rail is somewhat less sensitive to transit time but more sensitive to its uncertainty.

Finally, the fact that these agricultural shippers are revealed to vary in their evaluations of these factors means there are some relatively "captive" markets, consisting of shippers who will not readily change their preferred mode, and others in which shippers are quite sensitive to price and service quality. Other commodities showing similar variation in shipper evaluation of price and service quality are chemicals, metals, machinery, and stone, clay, and glass products. Each of these industries contains some products that are quite standardized and heavy and others that are specialized, suggesting it may be rational considerations rather than personality quirks that account for the variation among shippers.

Mixed Logit and the Demand for Electric Vehicles.

The Hausman-Wise model is not the only way to account for taste variations. Boyd and Mellman (1980) and Cardell and Dunbar (1980) estimate logit models of automobile purchase with random coefficients in order to analyze how vehicle fuel economy is affected by regulation and market forces. Similarly Ben-Akiva, Bolduc, and Bradley (1992) allow the value of time for intercity travel to vary randomly across the population, even for people with the same wage or income.

Recent breakthroughs in computational methods have made it possible to consider even more general models of taste variation within the extended logit family. The approach is nicely illustrated by a study of the potential market for passenger vehicles powered by fuels other than gasoline (Brownstone and Train, forthcoming). It combines random coefficients with a very flexible error structure for the random-utility components. Their approach is to add another random term η_j to the random utility function, equation (1), and allow its distribution to depend quite generally on characteristics z_j of choice j. These characteristics could be the same as those in the systematic utility function, in which case this new random term captures the effect of random variation in coefficients across consumers. Or they could just be indicators of where alternative j fits into a tree structure, in which case the model is nested logit or some other type of generalized extreme value model. More generally, z_j could include both types of variables. The other random term, ε_j, is distributed the same way as in multinomial logit. This type of model is called *mixed logit*.

Mixed logit has become a viable force in travel demand because of the development of Monte Carlo methods for calculating the choice probabilities.[26] The basic idea is simple. If the

[26] Such methods are known as "simulation"; see Stern (1997) for a general review, and Hajivassiliou and Ruud (1994) for applications to discrete choice.

"new" utility terms, η_j, were known, the choice probability would just be multinomial logit, which is easy to calculate. We don't know the values of η_j, but the model does postulate a distribution for them. So we use a random number generator to choose a possible value for each η_j, and calculate all the choice probabilities P_i. Then we draw another set of random numbers and recalculate P_i. By repeating this procedure many times and averaging the results, we obtain a good approximation to P_i.

The Brownstone-Train study also illustrates the use of *stated preference* data in travel demand, which reflect individuals' preferences in hypothetical situations. (We discuss this type of data in the next section.) In this application, stated preferences are used to forecast consumers' willingness to purchase cars not now available on the market. The model postulates vehicle choice among four fuel types — gasoline, natural gas, methanol, and electricity — as well as among several different body types and sizes. Respondents were asked to choose among hypothetical vehicles with specified characteristics; by varying these characteristics systematically (one of the luxuries of a stated-preference survey), the researcher can find out how much weight people place on each.

A partial listing of estimation results is as follows:

$$V = -0.264[\mathit{price}/\ln(\mathit{income})] + 0.517\mathit{range} + (1.43+7.45\phi_1)\mathit{size} + (1.70+5.99\phi_2)\mathit{luggage} + 2.46\phi_3\mathit{nonelectric} + 1.07\phi_4\mathit{noncompressed} + (\mathit{other\ terms})$$

where *income* and vehicle *price* are in thousands of dollars; the *range* between refueling (or recharging) is in hundreds of miles; *luggage* is luggage space (as a fraction of that typical of a comparably sized gasoline vehicle); *nonelectric* is a dummy variable for cars not running on electricity; and *noncompressed* is a dummy for cars not using natural gas. Among the "other terms" are additional vehicle performance measures, indicators for vehicle classification (station wagon, sports car, etc.), and several indicators of pure preference for or against any of the three non-conventional fuels. All parameters shown above are estimated with enough precision to easily pass tests of statistical significance.

The terms involving ϕ_1 and ϕ_2 represent the random coefficients. The first indicates that the coefficient of *size* varies according to a bell curve with mean 1.43 and standard deviation 7.45. The second indicates that the coefficient of *luggage* has mean 1.70 and standard deviation 5.99. These estimates indicate a very wide variation in people's evaluation of these characteristics.[27]

The terms involving ϕ_3 and ϕ_4 represent correlation in random preferences across the four fuel types. They are specified in such a way as to produce an overlapping nested structure: the three non-electric vehicle types are viewed as somewhat similar (for example, all rely on fossil fuels), and so do the three using fuels that are not compressed (for example, the fuel distribution system could perhaps be serviced by a home mechanic). Different people may evaluate these facets of the various fuels quite differently; accordingly, these terms measure the degree of similarity, not the average direction, of preferences among fuels. Thus the coefficient $2.46\phi_3$ on *nonelectric* indicates neither a positive nor negative preference on average (such a preference is contained in some of the "*other terms*"), but rather a random positive or negative preference that tends to affect all three non-electric vehicles similarly. A comparable statement can be made about the coefficient involving ϕ_4. Note that methanol and gasoline share both sets of idiosyncratic preferences, so are especially close substitutes; whereas electric and natural-gas vehicles share neither set and so are especially distant substitutes.

The practical value of using random coefficients is illustrated by policy simulations conducted by the authors. Suppose we start with the current population of mostly gasoline-powered vehicles and introduce a small electric car into the market. Because people have idiosyncratic preferences for size (the term involving ϕ_1), such a car will draw buyers disproportionately from owners of other small vehicles, rather than uniformly from all owners as the logit model would predict. Because smaller gasoline vehicles emit less pollution than some

[27] For example, the average person in the sample, with *luggage* coefficient 1.70, would sacrifice $(0.517/1.70)=30$ percent of typical luggage space for a 100-mile increase in range; but someone whose *size* coefficient is one standard deviation above the mean, or $1.70+5.99=7.69$, would sacrifice only $(0.517/7.69)=6.7$ percent of luggage space for the same range increase. Many people (those for whom $1.70+5.99\phi_2<0$) actually prefer *less* luggage space, presumably because it would allow more interior room for the same size of vehicle.

larger vehicles such as trucks and vans, the predicted impact of electric vehicles on air quality will be smaller using this model than using a standard logit model. Now suppose that sometime later a large methanol car is also introduced into the market. The mixed logit model predicts more switching from large than from small cars, for the same reason just stated; it also predicts more switching from gasoline than from electric cars, because gasoline and methanol are closer substitutes than electric and methanol according to the correlation structure just described. Then the methanol car in this instance will have a *greater* impact on air quality than the logit model would predict. These substitution patterns are intuitive and important in developing strategies to introduce new fuel types, yet would be missed by many conventional demand models.

Concluding Observations About Disaggregate Models.

One cannot help but be impressed by the steady technical progress in disaggregate transportation demand modeling, which has enabled researchers to address questions involving complex substitution patterns, taste variation, and inter-related travel decisions. These more complex demand structures are becoming easier to estimate. Most econometric software packages now have standard routines to estimate multinomial and nested logit models, and there are specialized programs to estimate mixed logit and multinomial probit models based on McFadden's (1989) simulation estimator.

Despite these advances, complex models run the risk of asking the data to say more than they can. Their flexibility is useful only if it can be disentangled from randomness and data errors. A similar risk exists with very flexible functional forms for the systematic utility. Ultimately the ability to distinguish subtle effects is limited by the size, accuracy, range of variation, and other properties of the data set (Stern, 1997). In the following section, we examine more closely the nature of transportation demand data.

Transportation Demand Data

Virtually all travel-demand analysis uses survey data. It is hard to overemphasize the importance of collecting reliable data, and there is a large body of experience on ways to do so. We leave to other writers the task of reviewing practical methods of data collection.[28] In this section, we discuss instead the nature of the data sets that can be used for various purposes. Issues include measuring the transportation environment facing decision makers, using hypothetical questions to elicit preferences, and using data collected at more than one point in time.

Measuring the Transportation Environment

Most transportation demand models include one or more "generic" variables, that is, variables like travel time or cost that have the same meaning but different values on different alternatives. In the case of disaggregate models, one must know the value a generic variable takes for each individual in the sample, and for each of the possible modes. For example, to explain urban mode choices, Lave (1970) needed to know what times and costs members of his sample faced using either auto or transit.

One way of meeting this requirement is to use values reported by the user. Doing so, however, has severe weaknesses. People are likely to have poor knowledge of the attributes of travel options seldom chosen. Even worse, the values they report may be biased to justify the choice made. For example, people choosing to drive may believe bus service is very poor and so overstate the travel times by bus, while those who use transit exaggerate the severity of traffic congestion facing solo drivers. Such systematic misperceptions would cause serious bias in the estimated model.[29] Furthermore, because a variable constructed this way appears very powerful in the model, the analyst may be delighted with it — not realizing that the causation runs at least

---

[28] See, for example, Ampt, Richardson, and Meyburg (1992) and Richardson (forthcoming).

[29] MVA Consultancy et al. (1987, pp. 159-163) find such bias to be severe in a study of the Tyne River crossing in England. Some would argue that these perceived values are what determine people's actual behavior, so should be used in the model; but that does not eliminate the bias. Perceived values can be accounted for without biasing the results by estimating a joint model of perception formation and mode choice, with each influencing the other. Mannering and Winston (1987) provide an example of this type of model in the context of seat-belt use and the perceived effectiveness of seat-belts.

partly in the opposite direction from that assumed by the model.

A better way to meet the data requirements of disaggregate models is to obtain objective estimates of the values of the variables. For example, the McFadden, Talvitie, and Associates (1977) urban demand model used travel times and costs from computer-based network models of the highway and bus route systems, and the Morrison and Winston (1985) intercity demand model used travel times and costs from published airline, bus, and railroad guides.

Stated Preference Data.

Almost all of the empirical models presented in this paper have been estimated with data describing travelers' and shippers' preferences as revealed in actual decision making. Such data are said to portray *revealed preferences*. Another way to study decision making is to ask respondents about hypothetical scenarios, in which case the preferences displayed are called *stated preferences*. Stated preference analysis is especially useful when people cannot reveal their preferences because an alternative in not available on the market, as in the case of Brownstone and Train's analysis of the demand for vehicles using exotic fuels, and Hensher and Bradley's (1993) study of the potential demand for high-speed rail in Australia. Stated preference analysis is also useful when one wants to set up specialized decision-making situations that rarely occur in practice, as in the case of Calfee and Winston's (1998) study of commuters' willingness to pay congestion tolls to save travel time given hypothetical scenarios of how the toll revenue will be disbursed.

Stated preference data have some additional advantages. From a statistical point of view, explanatory variables generated from revealed preferences may not have a great deal of variation. If everyone faces the same bus fare, their choices cannot tell us what the effects of changing the bus fare would be. By contrast, when collecting stated preference data, the values for the explanatory variables can be varied widely and independently of each other, creating more opportunity to observe how decision makers respond to them. Another advantage of state preferences is that people can provide rankings of several alternatives rather than just stating their first choice, providing additional information that can be used to improve precision of estimates (Beggs, Cardell, and Hausman, 1981).

Nevertheless, many researchers are rightly cautious about believing people's responses concerning situations about which they have little experience. People may make implicit assumptions not intended by the researcher, or they may attempt to influence policy or demonstrate a particular set of values. Extensive experimentation has taught survey designers how to minimize such biases, but some danger remains.[30]

An ideal solution in some situations may be to combine revealed and stated preference data so as to reap the advantages of both. An illustrative example is provided by Ben-Akiva and Morikawa (1990), who examine survey data from the Netherlands. They measure the effects of price and service quality on the use of rail service from Nijmegen, a city near the German border, to the capital region, a trip of about two hours. A principal objective of their analysis is to estimate travelers' value of travel time in this market. This example illustrates the type of applied study often encountered by local planning agencies, as well as a case where limited variation in the travel environment hampers inference.

Each respondent first provided revealed preference (RP) data based on an actual recent trip by either car or train. The same respondent was then given descriptions of two hypothetical trips, one by car and one by train, and asked about his or her preference. By careful survey design, these stated preference (SP) data could provide accurate values and independent variation of a few key modal characteristics: cost, time, number of transfers, and a comfort indicator.

Binary probit estimation results of the choice between rail or car are presented in the first column of Table 1, based on the RP data. The coefficient of line-haul time is statistically negligible because it exhibited little variation across the sample. The rail constant indicates that,

[30] For surveys of this work see MVA Consultancy et al. (1987), Bradley and Kroes (1992), and Hensher (1994). For a discussion of practical issues of data collection, especially in a less developed nation, see Ortúzar and Garrido (1994).

other things equal, people taking work trips strongly prefer rail (utility increment 1.74), while people taking non-work trips prefer rail somewhat less strongly (utility increment 1.74-0.90 = 0.84). Transfers have a marked deterrent effect.

The second column shows results using the SP data. Two modifications have been made to the original model. First, the SP model includes an "inertia" variable equal to one for choosing the same mode as was used on the actual trip (known from the RP data), and zero for choosing the other mode. Second, people were not actually asked to choose one mode or the other, but rather to rate the strength of their likelihood of either choice: "definitely choose rail," "probably choose rail," "not sure," and so forth. Thus each answer is in one of five categories, which can be ordered from most likely to choose car (category 1) to most likely to choose rail (category 5). The utility in this case can be estimated using an *ordered probit* model which assumes that the higher the systematic utility for rail relative to car, the more likely the respondent will select a category that strongly indicates choosing rail.[31]

The results in the second column of the table show that line-haul time is now statistically significant, in fact quite large — it implies a value of time of 0.45 Guilders per minute or about $13/hour. The SP data also indicate far less tendency to favor rail for work trips, given identical trip characteristics, than do the RP data.[32]

The authors next present a model combining the RP and SP data. To do so they make three assumptions. First, the RP data are assumed to reflect actual behavior. Second, the SP data are assumed to be biased (relative to actual behavior) only in their portrayal of absolute modal preference and the influence of trip purpose. This bias is accounted for by postulating that the SP

[31]Greene (1993, section 21.7.2) provides a good textbook treatment of this model. The probability of choosing category i (ranging from 1 to 5) is $P_i = \Phi(\mu_i\text{-}\beta X) - \Phi(\mu_{i-1}\text{-}\beta X)$, where $\Phi(\cdot)$ is the cumulative standard normal distribution function, βX is the systematic utility difference between rail and car, μ_1-μ_4 are parameters to be estimated, $\mu_0=-\infty$, and $\mu_5=\infty$. If the model contains a constant term in βX, as this one does, one of the μ_j's can be normalized to an arbitrary value. Because of the symmetry in the categories, the authors in this case can normalize two of the μ_j's, which they do by assuming $\mu_2=-\mu_3$ and $\mu_1=-\mu_4$. See Lester Johnson (1990) for a discussion of other models for ordered data.

[32] From Table 1, second column, people who actually use rail show only a mild tendency to favor rail in the hypothetical scenarios (utility increment 1.49-0.97 = 0.52), while those who actually use car show a distinct tendency in the opposite direction (rail utility increment -0.97).

data are generated from a preference structure with its own separate values for the rail constant and for the non-work dummy coefficient. Finally, the random error in the SP model is assumed to have a standard deviation σ_{SP} different from that for the RP model, σ_{RP}, thus allowing for either greater or less dispersion in people's preferences when answering hypothetical questions than when making actual choices.

The combined estimates are shown in the last three columns of the table.[33] They confirm that respondents answering the hypothetical (SP) questions were far less likely to favor rail than they did in actual (RP) situations. Furthermore, people exhibited much more dispersion in their random preferences when answering SP questions. The combined model yields a value of time of roughly $4.20/hour, which appears more plausible than that obtained from either data set alone.

Ortúzar and Iacobelli (1998) also combine RP and SP data in their study of intercity travel in Chile. They find that the SP responses show less variance than the RP responses, just the opposite of the Ben-Akiva-Morikawa study, perhaps indicating that people felt more certain of their responses in this application. Recent work by Brownstone, Bunch, and Train (1998) uses the combined RP-SP methodology to better control for response bias in the SP questions used for the study of alternative fuels described earlier. Generally, when RP and SP data are combined to estimate the demand for an alternative not yet available in the market, the RP data help measure the degree of dispersion in random utility and the utility constants relating to existing alternatives, while the SP data help refine the estimates of tradeoffs and provide the only estimates of the utility constant(s) for the new alternative(s).

Panel Data

Thus far our discussion has focussed on studies that use data from a single cross-sectional sample. Use of these data assumes that respondents have had time to adjust to their current

[33] These estimates are obtained using a maximum-likelihood routine written specifically for this model; however, Bradley and Daly (1997) show how they can be obtained from standard nested-logit software by some clever manipulations of the data and tree structure.

situation, or if not that the effects of incomplete adjustment vary randomly across the population. Cross-sectional studies are therefore appropriate for understanding long-run behavior.

Sometimes we also need to know the transitional dynamics that people follow when things change. These dynamics can be analyzed by following the behavior of the same individuals over time. A data set collected this way is called a *panel.*

By capturing dynamic behavior at the individual level, panel data permit a more detailed understanding of the factors governing people's changing behavior including response lags and learning by experience (Raimond and Hensher, 1997). However, observed persistence in behavior can arise from two quite different causes. One is true behavioral inertia (adjustment lags), caused by impediments to changing behavior; this condition is also known as "state dependence" because behavior at any one time depends on the state in which one has been placed by past decisions. The other cause of persistent behavior is the existence of persistent idiosyncratic factors that make one person regularly lean toward one choice and another person toward another; this situation is called "unobserved heterogeneity" because the persistence in behavior arises from factors unknown to the analyst that vary across the population.

Collecting panel data poses special estimation problems that arise from respondents' initial failure to respond to surveys and from their attrition as the survey evolves. Statistical techniques designed to minimize such "nonrespondent" and "attrition" biases are described by Heckman (1981a, 1981b) and Pendyala and Kitamura (1997).

Mannering and Winston (1991) use the National Family Opinion panel to estimate the effect of consumers' previous experience with a particular brand of automobile on their future automobile purchases—that is, the extent of their brand loyalty. Each member of the panel kept records of their entire vehicle ownership history. The authors used these data to estimate multinomial logit models of vehicle-type choice before and after 1980, specifying the number of previous GM, Ford, Chrysler, Nissan, Honda, and Toyota purchases as independent variables. Their main finding was that brand loyalty toward American cars, particularly those manufactured by GM, had fallen substantially since 1980 while brand loyalty toward Japanese cars had risen. For example, before 1980 a previous GM purchase increased the probability that a consumer's next purchase would be a GM car by 6.3 percentage points, but after 1980 the increase was only 3.1 percentage points. In contrast, the effect of prior Toyota ownership on Toyota purchase probability increased, from 7 percentage points before 1980 to 14.3 percentage points after 1980.

Did the propensity for repeat purchases of a brand of car arise from true brand loyalty (state dependence) or persistent idiosyncratic factors (unobserved heterogeneity)? Mannering and Winston tested this question statistically and concluded that brand loyalty was the dominant factor. This finding has implications both for manufacturers' marketing strategies and for government policies toward motor vehicle imports.

One of the most extensive panel data sets is the Dutch Mobility Panel, a stratified random survey of households in The Netherlands (Van Wissen and Meurs, 1989; Meurs and Ridder, 1997). It has been used for many studies, well illustrated by Kitamura and Bunch's (1990) study of the number of cars owned by a household. In one of their models, state dependence is measured by including, among the explanatory variables for car ownership at time t, measures of car ownership at an earlier time t-1 (about six months earlier). Heterogeneity is measured by assuming that random utility has two components: one that varies only by individual, and another that varies each time the individual is observed. The first component represents persistent idiosyncratic factors (unobserved heterogeneity). Their results indicate a great deal of inertia in the system, but very little heterogeneity. The implication is that as incomes, fuel prices, or other factors affecting car ownership change, people will adjust only partially over a period of six months, but that eventually they will adjust because few have strong idiosyncracies favoring a particular car ownership level. Unfortunately, this finding was not very robust to variations in the assumed model structure, so it remains tentative.

Illustrative Empirical Findings

What do these models tell us about transportation behavior? Here we summarize some basic findings about travelers' and shippers' behavior by presenting two kinds of estimates: price and service elasticities of demand, and decision makers' values of travel time.

Elasticities.

Demand responsiveness is often summarized in terms of demand elasticities, defined as the percent change in use of a particular service resulting from a one percent change in an attribute such as price, trip time, or frequency of service offerings. Because use results from several related decisions, as described earlier, it is sometimes helpful to decompose this elasticity into those resulting from identifiable decision components. For example, the demand for rail freight service from Houston to Los Angeles reflects the effects of Houston-LA rail tariffs on the number and size of shipments originating in Houston, the proportion of them destined to Los Angeles, and the proportion of those sent by rail. Thus the total price elasticity for such service is the sum of a trip generation elasticity, a destination diversion elasticity, and a modal diversion elasticity. The latter is usually the largest.

In table 2 we present some estimates of demand elasticities, with respect to both price and service quality, for several major forms of transportation. Those derived from a translog cost function are long-run total elasticities because the cost function accounts for all three decision components and allows for choice of capital equipment. Those derived from a vehicle utilization model are short-run total elasticities; they again account for all three decision components, but constrain the household's number of vehicles to be constant. The others elasticities shown are based on mode choice only, so they are modal diversion elasticities.

Elasticity estimates in freight transportation vary widely by commodity group. The table indicates the range of variation and, in some cases, the commodity groups with the smallest and largest elasticities. It is interesting that service-time elasticities can be as large as price elasticities, particularly in the case of perishable commodities.

For urban passenger travel, price and in-vehicle-time elasticities are less than one in absolute value. Public policies that increase automobile costs or reduce transit in-vehicle times only modestly are therefore likely to have only small effects on automobile usage and transit ridership, respectively. This conclusion is consistent with comprehensive studies of urban transportation policy such as those by Meyer, Kain, and Wohl (1965) and Winston and Shirley

(1998). It also means that transit revenues can be increased by raising fares, a fact that is well known by transit managers though sometimes contested by user groups.

For intercity trips, a low travel-time elasticity also characterizes the auto and air modes, probably because these modes have highly captive markets — air has a large share of long distance intercity trips, auto has a large share of short distance intercity trips. In contrast, intercity bus and rail travel are highly elastic with respect to travel time; thus these modes could significantly increase their market shares if service times could be improved. Intercity bus and air travel are price-inelastic (elasticity less than one in absolute value), suggesting that either competition or regulation is working to prevent carriers from charging monopoly fares. Rail service, in contrast, is price-elastic which is consistent with the possibility that Amtrak, the national carrier for rail passengers, is acting like a monopolist and that lower prices would generate substantial new passenger traffic.

Utilization of a given automobile tends to be cost-inelastic, indicating that even large increases in fuel prices or other costs will not reduce annual automobile travel very much. This is especially true for two-vehicle households because they can respond to an increase in fuel costs by shifting some driving to their most fuel efficient vehicle. The low cost-elasticity of automobile utility is consistent with studies showing that the consumer response to higher gasoline prices during the 1970s and early 1980s was primarily to purchase smaller cars rather than to drive them less.

Values of travel time.

We have previously shown how the parameters of transportation demand models can be used to calculate the value of travel time. In the case of passenger travel, this value depends on the utility or disutility that a decision maker attaches to time spent in a particular mode, as well as the opportunity cost of time used in travel (M. Bruce Johnson, 1966; Oort, 1969). Thus a high value of time could arise from a high opportunity cost of time or from great disutility of time spent on a particular mode.

In the case of freight, the value of time arises from the opportunity cost of having goods tied up in transit, which can reflect perishability, risk of theft, and capital carrying costs. If the value per day of transit time is expressed as a percentage of the shipment's value, it can be interpreted as a daily discount rate.

Table 3 presents illustrative estimates. For freight, shippers of perishable agricultural goods naturally have a very high value of time. The opposite is true of shippers of low-value manufactured products, such as primary and fabricated metals, that are not subject to spoilage or damage.

The value-of-time estimates for urban transportation are drawn from the study of commuting in the San Francisco Bay Area described earlier, but using a more elaborate specification of the systematic utility function. One surprising finding is that the value of in-vehicle time is higher for auto than for transit. Time spent in an automobile involves more privacy but also more effort (for the driver, at least), and apparently the latter is dominant — a result that may have changed with the subsequent spread of air conditioning, hi-fidelity sound, and cellular telephones in automobiles. Other studies of urban commuters in major industrialized cities have found values of in-vehicle time in the range of 20 to 100 percent of the pre-tax wage rate, leading Small (1992) to conclude that a typical value is 50 percent, with walking and waiting time valued two to three times higher.

The value of time for intercity vacation trips probably reflects differing degrees of urgency and enjoyment of the trip by people using different modes. Auto travelers may enjoy side trips that take extra time, thus accounting for auto's low value of time. (This may be the one exception to the principle that travel is a derived demand rather than desired for its own sake.) Air travelers, in contrast, want to cover long distances quickly and do not derive much pleasure from time spent on the airplane, thus they have a very high value of time. Rail and bus travelers fall in between. Brand et al. (1992, table 2) similarly report a much higher value of time for air than auto in the case of non-business travel.

Practical Applications

The parameter estimates, implied values of time, and elasticities obtained from transportation demand models are critical inputs into public policy toward such issues as congestion relief, infrastructure investment, and industry regulation. They are also used to assist urban planning and to forecast the demand for new travel options. Most of these issues ave covered in detail in other chapters in this volume, so here we provide only a brief overview.

Welfare Measures and Public Policy Issues.

Evaluations of public policies often involve calculating their effects on economic welfare. A simple but important example is the efficiency loss when prices deviate from marginal costs. The usual measure of that loss accounts for both profits to firms (producer surplus) and the value of consumption to travelers (consumer surplus). It is approximately $\frac{1}{2}\Delta P \Delta Q$ where ΔP is the price deviation and ΔQ is the resulting change in quantity. Expressed in elasticity form, the measure is:

$$\Delta W = \tfrac{1}{2} R E_{\mathrm{p}} (\Delta P / P)^2 \tag{5}$$

where $R{=}PQ$ is revenue and E_{p} is the absolute value of the price elasticity of demand.[34] The more elastic the demand, the greater the distortion resulting from non-marginal-cost pricing and the greater the resulting loss of efficiency.

A more general measure involves the *compensating variation*, which measures the amount of money consumers would have to be given after a policy change to make them as well off as before. Under certain conditions it is identical to consumer surplus (the area under the demand curve and above the current price). In the case of a logit model of demand, the compensating

[34] Equation (5) is the area on a demand diagram known as a "Harberger triangle," after Harberger (1964).

variation can be expressed as:

$$CV = -\frac{1}{\mu}\left[\ln\sum_{j}\exp(\beta X_j)\right]_{X^0}^{X^1} \tag{6}$$

where β denotes the set of coefficients estimated from the demand model, X_j denotes the corresponding set of explanatory variables for alternative j, μ is a conversion factor (related to the price coefficient) to put the results in monetary units, and the notation X^0 and X^1 indicates that the expression in square brackets is to be evaluated at the initial and final values of the variables and the difference taken.[35] This expression permits evaluation of even very complex policies so long as their effects on the variables X can be accurately predicted.

We now turn to some examples of welfare calculations, beginning with urban transportation. Mohring (1965) estimates the welfare effects of several urban highway investments, using consumer surplus measures analogous to those leading to equation (5). Kraus, Mohring, and Pinfold (1976) use similar techniques to evaluate the cost of non-optimal pricing and investment policies on urban expressways. Small (1983a) uses a logit model of commuting mode choice to estimate compensating variations from alternative highway pricing strategies and from high-occupancy vehicle lanes. Because these policies affect the price and service times of the various modes, their welfare effects can be calculated from equation (6). In a related paper, Small (1983b) uses the same equation to identify population subgroups that would gain, and those that would lose, from congestion pricing. Winston and Shirley (1998) use an aggregate urban mode choice model to estimate compensating variations from charging optimal congestion tolls, imposing marginal-cost transit fares, and optimizing transit frequency. They conclude that an efficient urban transportation policy calls for more automobile travel spread more evenly throughout the day.

For intercity transportation, one of the most significant questions has been the effects of industry regulation on the welfare of travelers, shippers, and carriers. Levin (1978, 1981) and

[35] See Williams (1977) and Small and Rosen (1981).

Winston (1981b) use freight demand models to calculate the net welfare loss from freight transportation regulation, using equation (5). Other studies have considered the welfare effects of the subsequent deregulation of airlines and surface freight transportation, using equation (6) (see Morrison and Winston's chapter in this volume).

An important response by many carriers to deregulation has been to merge with another carrier. Mergers confer costs to travelers if they enable the merged firm to raise prices, but they also confer benefits if they enable the merged firm to improve service. Transportation demand models have been used to estimate the potential benefits from improved service due to mergers of airlines (Carlton, Landes, and Posner, 1980) and of railroads (Harris and Winston, 1983).

Introducing New Travel Options.

One of the common tasks asked of a travel demand analyst is to forecast the demand for a new transportation option. Examples include rapid-rail urban transit, high-speed intercity rail, supersonic air transport, and even the space shuttle. More mundane examples include door-to-door demand-responsive transit service to elderly or handicapped populations, shared-ride taxi service, and airport shuttles.

Overall, the models have not been very successful on this score. Probably this is because the new travel options have unique characteristics that cannot be included in existing models, either because they lie outside current experience (like three-hour transatlantic travel times) or because they are hard to measure (like the fear that shared-ride taxis will pick up unsavory passengers). For example, Train (1978) investigated the ability of mode choice models like those described earlier, calibrated on bus and auto modes, to predict patronage for the new Bay Area Rapid Transit (BART) service introduced to the San Francisco region in 1973. He found the models tended to overpredict BART use, perhaps because they failed to account fully for the difficulties of accessing a rail station.

One of the hopes for stated preference data is that they will enable researchers to better account for novel characteristics of proposed alternative transportation arrangements. For example, Brand et al. (1992) propose a way to forecast the demand for high-speed intercity rail service, using both revealed preference and stated preference data. First, a direct demand model (based on revealed preference data) is estimated for existing modes. Then, based on stated preference surveys, the diversion from each existing mode is predicted. Finally, induced trip generation is estimated by assuming the number of trips will respond to the new service in the same way as to upgraded existing service, based on conventional revealed preference models. This procedure allows for a flexible substitution pattern between the existing modes and the new one, and also combines revealed preference and stated preference data in much the same spirit as the methods discussed earlier. We are not aware of any before-and-after studies of predictions using such methods.

Meanwhile, forecasts of the demand for new facilities are of necessity undertaken. But as noted in chapter 5, the record of such forecasts is dismal, especially in the case of urban rail transit. While some of this failure can be blamed on deficiencies in the demand models, it is probably indicative of deeper problems in the way funding decisions are made for public projects. Too many people have strong incentives to misrepresent the viability of a project that will bring large amounts of money to an area. The problem is aptly reviewed by Wachs (1986, 1990).

Assessment

How well do models of transportation demand meet their objectives? We have lauded the technical progress in demand modelling on the grounds that it has enabled us to address new questions. But has it produced correct answers?

If the objective is to predict the use of a particular transportation service at some date in the future, one is justified in taking a cynical view. Forecasts for new travel options, whether conventional or exotic, have often been far from the mark. In large part this is because models are asked to do what is impossible: predict accurate values for each of the many uncertainties in economic conditions, technology, administrative capabilities, logistical innovations, and other factors affecting demand. As argued in Chapter 5, it is better to view projections as an exercise in understanding alternative possibilities than as forecasts of what is going to happen. In this respect, the ability of current demand models to elucidate the effects of numerous exogenous and policy variables makes them valuable aids in evaluating transportation investments and policies.

One indicator of how much trust can be placed in model outputs is their transferability across space and time. To what extent do models fit on data from St. Louis in 1985 help us to understand urban travel in Denver in 1998? This type of question has been studied quite extensively (Koppelman and Rose, 1985). The answer seems to be that the "generic" parts of disaggregate demand models — those that explain the response of decision makers to measurable traits that have similar meanings in many situations — transfer quite well, so long as the range of conditions in the new location is not too different from that in the old. Thus, for example, the relationship between value of time and income seems to be fairly general. In contrast, factors reflecting non-generic influences do not transfer well. These include preferences for unmeasurable characteristics, as captured in mode-specific constants, and idiosyncratic preferences, as measured by the variance of error terms (or, when that variance is normalized, by the scale of all the other coefficients).

These observations have led to some well-defined strategies for transferring a model from one location or time period to another. One is simply to adjust the alternative-specific constants so as to predict the correct aggregate shares for the various alternatives in the new area (Koppelman and Wilmot, 1982). Another is to collect a small survey sample in the new location in order to re-estimate the alternative-specific constants and the overall scale of the utility function, which measures the strength of idiosyncratic preferences. A third is to combine data sets, or to use special "Bayesian" techniques on the new data set, in order to reestimate some parameters while giving weight to the original estimates of other parameters (Ben-Akiva and Bolduc, 1987).

We may also ask how well existing models account for transportation as a derived demand, arising from the desire to undertake varying activities distributed over time and space. For the most part, they do so only indirectly. Attempts to model activities directly has led to only modest gains in practice. For example, Kim and Mannering (1997) show how the duration of a shopping trip depends on the time of day, vehicle occupancy, gender, trip distance, and whether it is part of a work trip. Unfortunately most of these variables are themselves determined simultaneously within an interrelated system of decisions, including activity duration; so we are still a long way from being able to derive the demand for transportation from first principles. It remains to be seen whether the current effort to build such models, as part of a microsimulation strategy to demand modeling (Wachs, 1996), will have more success. Axhausen and Gärling (1992) and Miller and Salvini (forthcoming) review the state of the art.

Another example of limited but successful research into the fundamental determinants of travel behavior is the literature on how telecommunications have affected travel. Many people have asserted that the ability to cheaply transmit data, including video images in real time, will make much travel obsolete. Yet the telecommunications revolution goes back at least to Alexander Graham Bell and no noticeable drop in travel has occurred. The issue is really whether telecommunications and travel are substitutes or complements. There is much evidence for the latter: apparently, people take advantage of their greater ability to contact others by forming wider networks that are accompanied by even more travel to cement those relationships. Of course, the nature of that travel is considerably affected. For a thorough review, see Mokhtarian and Salomon (forthcoming).

Because transportation demand is derived from activity patterns, people care about the time of day they travel and the predictability of their travel arrangements. We have seen an example of the latter in the influence of transit-time reliability on freight mode choice. It is at least as important in urban transportation. Driving a congested highway may be a great choice most of the time, but not if the occasional delay would result in missing an important meeting. As a result, the choices of mode, route, and time of day may be sensitive to the time pattern of congestion and to system reliability. Small (1982) and others have estimated models of time of day choice, which have begun to be integrated into standard modeling practice (e.g. Bates et al., 1996). Reliability has been harder to handle because good measures of it are scarce, but some progress has been made.[36]

[36] See, for example, Mahmassani, Caplice, and Walton (1990); Abdel-Aty, Kitamura, and Jovanis (1995); Calfee and Winston (1998); and Noland et al. (1998).

Conclusion

Practical experience suggests that transportation demand models have contributed accurate and informative evidence to public policy debates. In assessing policy issues as diverse as urban pricing and investment, treatment of heavy trucks, and regulation of intercity transportation, such models have been the basis for welfare estimates in accord with the beliefs of informed observers using other methods. In some cases, such as congestion pricing, the demand models have enabled researchers to highlight certain political pitfalls in advance by identifying how various groups of travelers are affected. In others, such as airline deregulation, they have helped deflect spurious interpretations of events by demonstrating convincingly how things might have gone in the absence of deregulation.

Confidence in transportation demand models has stimulated the search for further technical advances and has encouraged applications to public policy and planning. Many of the contributions in these areas will be apparent to readers of other chapters in this volume. Additional contributions will undoubtedly appear in the handbook produced by the next generation of transportation researchers.

TABLE 1
Choice of Rail or Car for Intercity Trips in The Netherlands

	RP Model	SP Model	Combined Model: Common coefficients	Combined Model: RP only	Combined Model: SP only
Rail constant	1.74 (0.32)	-0.97 (0.12)		1.61 (0.29)	-2.96 (0.86)
Cost per person	-0.0257 (0.0058)	-0.0072 (0.0014)	-0.0240 (0.0049)		
Line-haul time	0.0005 (0.0035)	-0.0032 (0.0012)	-0.0046 (0.0024)		
Terminal time	-0.0263 (0.0060)	-0.0066 (0.0021)	-0.0250 (0.0053)		
Number of transfers	-0.344 (0.133)	-0.053 (0.032)	-0.245 (0.090)		
Non-work dummy	-0.90 (0.23)	-0.02 (0.08)		-0.90 (0.22)	-0.13 (0.26)
Inertia dummy		1.49 (0.02)			4.84 (1.16)
Thresholds:					
μ_3		0.080 (0.010)			0.080 (0.010)
μ_4		0.478 (0.022)			0.476 (0.022)
Relative dispersion:					
σ_{RP}/σ_{SP}			0.294 (0.069)		

Source: Ben-Akiva and Morikawa (1990), Tables I, II, IV.

TABLE 2
Transportation Price and Service Time Elasticities

Freight

	Rail	Truck
Aggregate mode split model[a]		
Elasticity with respect to:		
Price	-0.25 to -0.35	-0.25 to -0.35
Transit time	-0.3 to -0.7	-0.3 to -0.7
Aggregate model from translog cost function[b,c]		
Elasticity with respect to:		
Price	-0.37 (mineral products) to -1.16 (petroleum products)	-0.58 (petroleum products) to -1.81 (mineral products)
Disaggregate mode choice model[b,d]		
Elasticity with respect to:		
Price	-0.08 to -2.68	-0.04 to -2.97
Transit time	-0.07 to -2.33	-0.15 to -0.69

Urban Passenger[e]

	Auto	Bus	Rail
Elasticity with respect to:			
Price	-.47	-.58	-.86
In-vehicle time	-.22	-.60	-.60

Intercity Passenger[f]

	Auto	Bus	Rail	Air
Elasticity with respect to:				
Price	-.45	-.69	-1.20	-.38
Travel time	-.39	-2.11	-1.58	-.43

Automobile Utilization[g]

	One-Vehicle Household	Two-Vehicle Household
Elasticity with respect to:		
Short-run operating cost	-.228	-.059
Long-run operating cost	-.279	-.099

[a] Levin (1978)
[b] These estimates vary by commodity group; we report the largest and smallest.
[c] Friedlaender and Spady (1981)
[d] Winston (1981a)
[e] McFadden (1974), multinomial logit mode choice model for work trips in the San Francisco Bay Area.
[f] Morrison and Winston (1985), multinomial logit mode choice model for vacation trips in the U.S.
[g] Mannering and Winston (1985)

TABLE 3
Values of Time

Freight[a] (as percentage of shipment value per day)		Rail	Truck	
		6% (primary and fabricated metals) to 21% (perishable agriculture)	8% (primary and fabricated metals) to 18% (perishable agriculture)	
Urban work trips[b] (as percentage of after-tax wage rate)	Auto	Bus		
In-vehicle time	140%	76%		
Walk access time	273%	273%		
Transfer wait time	----	195%		
Intercity Passenger[c] (as percentage of pre-tax wage rate)	Auto	Bus[d]	Rail[e]	Air
Total travel time	6%	79%-87%	54%-69%	149%

[a] Winston (1979)
[b] Calculated from McFadden, Talvitie, and Associates (1977, p. 116).
[c] Morrison and Winston (1985). Estimates for vacation trips.
[d] The lower value applies to low-income travelers, the higher value to high-income travelers.
[e] The lower value applies to high-income travelers, the higher value to low-income travelers — just the reverse of bus. (But recall these are % of wage, so value of time generally still rises with income.)

References

Abdel-Aty, Mohamed A., Ryuichi Kitamura, and Paul P. Jovanis. 1995. "Investigating Effect of Travel Time Variability on Route Choice Using Repeated-Measurement Stated Preference Data." *Transportation Research Record* 1493: 39-45.

Ampt, Elizabeth S., Anthony J. Richardson, and Arnim H. Meyburg, eds. 1992. *Selected Readings in Transport Survey Methodology*. Melbourne: Eucalyptus Press.

Axhausen, Kay W., and Tommy Gärling. 1992. "Activity-Based Approaches to Travel Analysis: Conceptual Frameworks, Models, and Research Problems." *Transport Reviews* 12 (no. 4): 323-41.

Bates, John, Ian Williams, Denvil Coombe, and James Leather. 1996. "The London Congestion Charging Research Programme: 4. The Transport Models." *Traffic Engineering and Control*, 37 (May): 334-39.

Becker, Gary S. 1965. "A Theory of the Allocation of Time." *Economic Journal* 75 (September): 493-517.

Beesley, Michael E., and Michael A. Kemp, "Urban Transportation." 1987. In Edwin S. Mills, ed., Handbook of Regional and Urban Economics, Volume II: Urban Economics. Amsterdam: North-Holland.

Beggs, S., S. Cardell, and J. Hausman 1981. "Assessing the Potential Demand for Electric Cars," *Journal of Econometrics* 16 (January): 1-19.

Ben-Akiva, Moshe, Denis Bolduc, and Mark Bradley. 1992. "Estimation of Travel Choice Models with Randomly Distributed Values of Time," working paper, M.I.T.

Ben-Akiva, Moshe, and Steven R. Lerman. 1974. "Some Estimation Results of a Simultaneous Model of Auto Ownership and Mode Choice to Work." *Transportation* 3 (November): 357-76.

---------. 1985. *Discrete Choice Analysis: Theory and Application to Travel Demand*. Cambridge, Mass.: MIT Press.

Ben-Akiva, Moshe, and Takayuki Morikawa. 1990. "Estimation of Travel Demand Models from Multiple Data Sources." In Koshi, Masaki, ed., *Transportation and traffic theory*. New York: Elsevier.

Bhat, Chandra R. 1998. "Analysis of Travel Mode and Departure Time Choice for Urban Shopping Trips." *Transportation Research* 32B (August): 361-71.

Boyce, David E., 1984. "Urban Transportation Network-Equilibrium and Design Models: Recent Achievements and Future Prospects," *Environment and Planning*, 16A, pp. 1445-74.

Boyce, David E., and Bin Ran. 1996. *Modeling Dynamic Transportation Networks: An Intelligent Transportation System Oriented Approach.* New York: Springer-Verlag.

Boyd, J. Hayden, and Robert E. Mellman. 1980. "The Effect of Fuel Economy Standards on the U.S. Automotive Market; An Hedonic Demand Analysis," *Transportation Research,* 14A (Oct.-Dec.), pp. 367-78.

Bradley, M.A., and A.J. Daly. 1997. "Estimation of Logit Choice Models Using Mixed Stated-Preference and Revealed-Preference Information." In Stopher, Peter, and Martin Lee-Gosselin, eds., *Understanding Travel Behaviour in an Era of Change.* Oxford, UK: Elsevier Science Ltd.

Bradley, M.A., and E.P. Kroes. 1992. "Forecasting Issues in Stated Preference Survey Research." In Ampt et al. (1992).

Brand, Daniel, Thomas E. Parody, Poh Ser Hsu, and Kevin F. Tierney. 1992. "Forecasting High-Speed Rail Ridership." *Transportation Research Record* 1341: 12-18.

Brownstone, David, David S. Bunch, and Kenneth Train. 1998. "Joint Mixed Logit Models of Stated and Revealed Preferences for Alternative-Fuel Vehicles." Working, paper, Department of Economics, University of California at Irvine.

Brownstone, David, and Kenneth Train. Forthcoming. "Forecasting New Product Penetration with Flexible Substitution Patterns." *Journal of Econometrics.*

Bruzelius, Nils. 1979. *The Value of Travel Time.* London: Croom Helm.

Calfee, John, and Clifford Winston. 1998. "The Value of Automobile Travel Time: Implications for Congestion Policy." *Journal of Public Economics* 69 (July): 83-102.

Cardell, N. Scott, and Frederick C. Dunbar. 1980. "Measuring the Societal Impacts of Automobile Downsizing," *Transportation Research,* 14A (Oct.-Dec.), pp. 423-34.

Carlton, Dennis, and William Landes, and Richard Posner. 1980. "Benefits of Airline Mergers." *Bell Journal of Economics* 11 (Autumn): 65-83.

Chiang, Yu-Sheng, Paul Roberts, and Moshe Ben-Akiva. 1981. "A Short-Run Freight Demand Model: The Joint Choice of Mode and Shipment Size," Presented at the 60th meeting of the Transportation Research Board, Washington, D.C.

Chu, Chaussie. 1981. *Structural Issues and Sources of Bias in Residential Location and Travel Mode Choice Models.* Ph.D. Dissertation, Northwestern University. Ann Arbor, Michigan: University Microfilms (1981).

Daughety, Andrew F. 1979. "Freight Transport Demand Revisited: A Microeconomic View of Multimodal Multicharacteristic Service Uncertainty and the Demand for Freight Transport." *Transportation Research* 13B: 281-88.

Daughety, Andrew F., and Fred S. Inaba. 1978. “Empirical Aspects of Service-Differentiated Transport Demand.” *Motor Carrier Economic Regulation: Proceedings of a Workshop*, National Academy of Sciences: 329-49.

Domencich, Thomas A., and Gerald Kraft. 1970. *Free Transit.* Lexington, Mass.: Heath Lexington Books.

Domencich, Thomas, and Daniel McFadden. 1975. *Urban Travel Demand: A Behavioral Analysis.* North Holland Press. Amsterdam.

Dubin, Jeffrey, and Daniel McFadden. 1984. “An Econometric Analysis of Residential Electric Appliance Holdings and Consumption,” *Econometrica* 52 (March): 345-62.

Friedlaender, Ann F. and Richard Spady. 1980. “A Derived Demand Function for Freight Transportation.” *Review of Economics and Statistics* 62 (August): 432-41.

-------------. 1981. *Freight Transport Regulation.* MIT Press. Cambridge.

Gaudry, Marc. 1975. "An Aggrgate Time-Series Analysis of Urban Transit Demand: The Montreal Case." *Transportation Research* 9 (August): 249-58.

---------- and Michael J. Wills. 1978. "Estimating the Functional Form of Travel Demand Models." *Transportation Research* 12 (August): 257-89.

Gellman Research Associates. 1977. “An Annotated Bibliography of Shipper Attitude Studies.” Prepared for the Association of American Railroads (June).

Greene, William H. 1993. *Econometric Analysis.* New York: Macmillan.

Hajivassiliou, Vassilis, and Paul Ruud. 1994. "Classical Estimation Methods for LDV Models Using Simulation." In Engle, Robert, and Daniel McFadden, eds., *Handbook of Econometrics, Volume IV.* New York: North-Holland.

Harberger, Arnold C. 1964. "Taxation, Resource Allocation, and Welfare." In Due, John, ed., *The Role of Direct and Indirect Taxes in the Federal Revenue System.* Washington: Brookings.

Harris, Robert G. and Clifford Winston. 1983. “Potential Benefits of Railroad Mergers.” *Review of Economics and Statistics* 65 (February): 32-40.

Hausman, Jerry, and David Wise. 1978. “A Conditional Probit Model for Qualitative Choice.” *Econometrica* 46 (March): 403-26.

----------and Daniel McFadden. 1984. “Specification Tests for the Multinomial Logit Model.” *Econometrica* 52 (September): 1219-40.

Heckman, James J. 1978. "Dummy Endogenous Variables in a Simultaneous Equation System." *Econometrica* 46 (July): 931-59.

Heckman, James J. 1981a. "Statistical Models for Discrete Panel Data." In Manski, Charles F., and Daniel L. McFadden, eds., *Structural Analysis of Discrete Data with Econometric Applications*. Cambridge: MIT Press.

Heckman, James J. 1981b. "The Incidental Parameters Problem and the Problem of Initial Conditions in Estimating a Discrete Time-Discrete Data Stochastic Process." In Manski, Charles F., and Daniel L. McFadden, eds., *Structural Analysis of Discrete Data with Econometric Applications*. Cambridge: MIT Press.

Hensher, David. 1994. "Stated Preference Analysis of Travel Choices: The State of Practice." *Transportation* 21 (May): 107-33.

---------- and Bradley, Mark. 1993. "Using Stated Response Choice Data to Enrich Revealed Preference Discrete Choice Models." *Marketing Letters* 4 (April): 139-52.

Johnson, Lester W. 1990. "Discrete Choice Analysis with Ordered Alternatives." In Fischer, Manfred M., Peter Nijkamp, and Yorgos Y. Papageorgiou, eds., *Spatial Choices and Processes*. Amsterdam: North-Holland.

Johnson, M. Bruce. 1966. "Travel Time and the Price of Leisure," *Western Economic Journal* 4 (Spring): 135-45.

Kim, Soon-Gwan, and Fred L. Mannering. 1997. "Panel Data and Activity Duration Models: Econometric Alternatives and Application." In Golob, Thomas F., Ryuichi Kitamura, and Lyn Long, eds., *Panels for Transportation Planning: Methods and Applications*. Boston: Kluwer Academic Publishers.

Kitamura, Ryuichi, and David S. Bunch. 1990. "Heterogeneity and State Dependence in Household Car Ownership: A Panel Analysis Using Ordered-Response Probit Models with Error Components." In Koshi, M., ed., *Transportation and Traffic Theory*. Amsterdam: Elsevier.

Koppelman, Frank S., and Geoffrey Rose. 1985. "Geographic Transfer of Travel Choice Models: Evaluation and Procedures." In Hutchinson, Bruce G., Peter Nijkamp, and Michael Batty, eds., *Optimization and Discrete Choice in Urban Systems*, vol. 247 of *Lecture Notes in Economics and Mathematical Systems*, Heidelberg: Springer-Verlag.

Koppelman, Frank S., and Chester G. Wilmot. 1982. "Transferability Analysis of Disaggregate Choice Models," *Transportation Research Record*, 895, pp. 18-24.

Kraft, John, and Arthur Kraft. 1974. "Empirical Estimation of the Value of Travel Time Using Multi Mode Choice Models." *Journal of Econometrics* 2 (December): 317-26.

Kraus, Marvin, Herbert Mohring, and Thomas Pinfold. 1976. "The Welfare Costs of Nonoptimum Pricing and Investment Policies for Freeway Transportation," *American Economic Review* 66 (Sept.): 532-47.

Lave, Charles A. 1969. "A Behavioral Approach to Modal Split Forecasting." *Transportation Research* 3 (December): 463-480.

Lee, Lung-Fei. 1979. "Identification and Estimation in Binary Choice Models with Limited (Censored) Dependent Variables." *Econometrica* 47 (July): 977-96.

Lerman, Steven R. 1981. "Location, Housing, Automobile Ownership, and Mode to Work: A Joint Choice Model." *Transportation Research Record* 610: 6-11.

Levin, Richard C. 1978. "Allocation in Surface Freight Transportation: Does Rate Regulation Matter?" *Bell Journal of Economics* 9 (Spring): 18-45.

----------.1981. "Railroad Rates, Profitability, and Welfare Under Deregulation." *Bell Journal of Economics* 12 (Spring): 1-26.

Lisco, Thomas E. 1967. *The Value of Commuters' Travel Time: A Study in Urban Transportation.* Ph.D. dissertation, University of Chicago. Ann Arbor, Michigan: University Microfilms.

MVA Consultancy, Institute for Transport Studies of the University of Leeds, and Transport Studies Unit of the University of Oxford. 1987. *The Value of Travel Time Savings.* Newbury, England: Policy Journals.

Maddala, G.S. 1983. *Limited-Dependent and Qualitative Variables in Econometrics.* Cambridge, U.K.: Cambridge University Press.

Mahmassani, Hani S., Christopher G. Caplice, and C. Michael Walton. 1990. "Characteristics of Urban Commuter Behavior: Switching Propensity and Use of Information." *Transportation Research Record*, 1285: 57-69.

Mandel, Benedikt, Marc Gaudry, and Werner Rothengatter. 1994. "Linear or Nonlinear Utility Functions in Logit Models? The Impact on German High Speed Rail Demand Forecasts." *Transportation Research* 28B (April): 91-101.

Mannering, Fred, and David A. Hensher. 1987. "Discrete/Continuous Econometric Models and Their Application to Transport Analysis." *Transport Reviews* 7 (July-Sept.): 227-44.

Mannering, Fred, and Clifford Winston. 1985. "A Dynamic Empirical Analysis of Household Vehicle Ownership and Utilization." *Rand Journal of Economics* 16 (Summer): 215-36.

-----------. 1987. "Recent Automobile Occupant Safety Proposals." In Clifford Winston and Associates, *Blind Intersection? Policy and the Automobile Industry.* Washington DC: Brookings.

-----------. 1991. "Brand Loyalty and the Decline of American Automobile Firms." *Brookings Papers on Economic Activity: Microeconomics*: 67-114.

McFadden, Daniel. 1973. "Conditional Logit Analysis of Qualitative Choice Behavior." In Paul Zarembka, ed., *Frontiers in Econometrics*. Academic Press. New York: 105-42.

------------. 1974. "The Measurement of Urban Travel Demand." *Journal of Public Economics* 3 (April): 303-28.

------------. 1978. "Modelling the Choice of Residential Location." In A. Karlquist, L. Lundquist, F. Snikars, and J. Weibull, eds., *Spatial Interaction Theory and Planning Models*. North-Holland Press. Amsterdam: 75-96.

------------. 1981. "Econometric Models of Probabilistic Choice."In Manski, Charles F., and Daniel L. McFadden, eds., *Structural Analysis of Discrete Data with EconometricApplications*. Cambridge: MIT Press.

------------. 1987. "Specification Tests for the Multinomial Logit Model." *Journal of Econometrics* 34 (January): 62-82.

------------. 1989. "A Method of Simulated Moments for Estimation of Discrete Response Models." *Econometrica* 57 (September): 995-1026.

------------, Antii P. Talvitie, and Associates. 1977. *Demand Model Estimation and Validation*, Urban Travel Demand Forecasting Project, Phase I Final Report Series, Vol. V. Berkeley: University of California Institute of Transportation Studies, Special Report UCB-ITS-SR-77-9.

McFadden, Daniel, and Kenneth Train. 1997. "Mixed MNL Models for Discrete Choice." Working paper, University of California at Berkeley (May).

-------------, Clifford Winston, and Axel Boersch-Supan. 1985. "Joint Estimation of Freight Transportation Decisions Under Nonrandom Sampling." In Andrew F. Daughety, ed., *Analytical Studies in Transport Economics*. Cambridge University Press. Cambridge: 137-57.

McLynn, J. and R. Watkins. 1967. "Multimode Assignment Model." In *Approaches to the Modal Split: Intercity Transportation*. U.S. Department of Commerce. Washington, D.C.

Meurs, Henk and Geert Ridder. 1997. "Attrition and Response Effects in the Dutch National Mobility Panel." In Golob, Thomas F., Ryuichi Kitamura, and Lyn Long, eds., *Panels for Transportation Planning: Methods and Applications*. Boston: Kluwer Academic Publishers.

Meyer, John R., John F. Kain, and Martin Wohl. 1965. *The Urban Transportation Problem*. Cambridge, Mass.: Harvard University Press.

Meyer, John R., and Mahlon R. Straszheim. 1971. *Techniques of Transport Planning, Volume One: Pricing and Project Evaluation*. Washington: Brookings.

Miller, Eric J., and Paul A. Salvini. Forthcoming. "Activity-Based Travel Behavior Modeling in a Microsimulation Framework." In (IATBR CONFERENCE PROCEEDINGS)

Mohring, Herbert. 1965. "Urban Highway Investments," in Robert Dorfman, ed., *Measuring Benefits of Government Investment*. Washington: Brookings.

Mokhtarian, Patricia L., and Ilan Salomon. Forthcoming. "Emerging Travel Patterns: Do Telecommunications Make a Difference?" In (IATBR CONFERENCE PROCEEDINGS)

Morrison, Steven A. and Clifford Winston. 1985. "An Econometric Analysis of the Demand for Intercity Transportation." *Research in Transportation Economics* 2: 213-37.

Noland, Robert B., Kenneth A. Small, Pia Maria Koskenoja, and Xuehao Chu. 1998. "Simulating Travel Reliability." *Regional Science and Urban Economics* 28 (September): 535-64.

Oort, C. J. 1969. "The Evaluation of Travel Time." *Journal of Transport Economics and Policy* 3 (September): 279-86.

Ortúzar, Juan de Dios, and Rodrigo A. Garrido. 1994. "A Practical Assessment of Stated Preferences Methods." *Transportation* 21 (August): 289-305.

Ortúzar, Juan de Dios, and Andrés Iacobelli. 1998. "Mixed Modelling of Interurban Trips by Coach and Train." *Transportation Research* 32A (June): 345-57.

Ortúzar, Juan de Dios, and Luis G. Willumsen. 1994. *Modelling Transport*. New York: Wiley.

Oum, Tae Hoon. 1979. "A Cross Sectional Study of Freight Transport Demand and Rail-Truck Competition in Canada." *Bell Journal of Economics* 10 (Autumn): 463-82.

-------------. and David Gillen. 1983. "The Structure of Inter-City Travel Demands in Canada: Theory, Tests and Empirical Results." *Transportation Research* 17B: 175-91.

-------------. and W.G. Waters, II, and Jong Say Yong. 1992. "Concepts of Price Elasticities of Transport Demand and Recent Empirical Estimates." *Journal of Transport Economics and Policy* 26 (May): 139-54.

Pendyala, Ram M., and Ryuichi Kitamura. 1997. "Weighting Methods for Attrition in Choice-Based Panels." In Golob, Thomas F., Ryuichi Kitamura, and Lyn Long, eds., *Panels for Transportation Planning: Methods and Applications*. Boston: Kluwer Academic Publishers.

Perle, Eugene. 1964. *The Demand for Transportation: Regional and Commodity Studies in the United States*. Department of Geography. University of Chicago. Chicago, Illinois.

Quandt, Richard, and William Baumol. 1966. "The Demand for Abstract Transport Modes: Theory and Measurement." *Journal of Regional Science* 6: 13-26.

Raimond, Timothy, and David A. Hensher. 1997 "A Review of Empirical Studies and Applications." In Golob, Thomas F., Ryuichi Kitamura, and Lyn Long, eds., *Panels for Transportation Planning: Methods and Applications*. Boston: Kluwer Academic Publishers.

Richardson, Tony. Forthcoming. "Current Issues in Travel and Activity Surveys." In (IATBR CONFERENCE PROCEEDINGS)

Small, Kenneth A. 1982. "The Scheduling of Consumer Activities: Work Trips." *American Economic Review* 72 (June): 467-79.

-------------. 1983a. "Bus Priority and Congestion Pricing on Urban Expressways." *Research in Transportation Economics* 1: 27-74.

-------------. 1983b. "The Incidence of Congestion Tolls on Urban Highways." *Journal of Urban Economics* 13 (January): 90-111.

-------------. 1987. "A Discrete Choice Model for Ordered Alternatives." *Econometrica* 55 (March): 409-24.

-------------. 1992. *Urban Transportation Economics.* Harwood Publishers. Philadelphia, Pennsylvania.

-------------. 1994. "Approximate Generalized Extreme Value Models of Discrete Choice" *Journal of Econometrics* 62 (June): 351-82.

-------------. and Cheng Hsiao. 1985. "Multinomial Logit Specification Tests." *International Economic Review* 26 (October): 619-27.

-------------. and Harvey Rosen. 1981. "Applied Welfare Economics with Discrete Choice Models." *Econometrica* 49 (January): 105-30.

Stern, Steven. 1997. "Simulation-Based Estimation." *Journal of Economic Literature* 35 (December): 2006-39.

Terza, Joseph V., and Paul W. Wilson. 1990. "Analyzing Frequencies of Several Types of Events: A Mixed Multinomial-Poisson Approach." *Review of Economics and Statistics* 72 (Feb.): 108-15.

Train, Kenneth. 1978. "A Validation Test of a Disaggregate Mode Choice Model." *Transportation Research* 12A: 167-74.

Train, Kenneth. 1986. *Qualitative Choice Analysis: Theory, Econometrics, and an Application to Automobile Demand.* Cambridge, Mass.: MIT Press.

Van Wissen, L.J.G., and H.J. Meurs. 1989. "The Dutch Mobility Panel: Experiences and Evaluation." *Transportation* 16 (May): 99-119.

Voith, Richard. 1997. "Fares, Service Levels, and Demographics: What Determines Commuter Rail Ridership in the Long Run?" *Journal of Urban Economics* 41 (March): 176-97.

Wachs, Martin. 1986. "Technique vs. Advocacy in Forecasting: A Study of Rail Rapid Transit." *Urban Resources* 4 (Fall): 23-30.

---------. 1990. "Ethics and Advocacy in Forecasting for Public Policy." *Business and Professional Ethics Journal* 9 (Spring/Summer): 141-57.

Wachs, Martin (ed.). 1996. *Special Issue: A New Generation of Travel Demand Models. Transportation* 23 (August).

Wardman, M. 1997. "Inter-Urban Rail Demand, Elasticities and Competition in Great Britain: Evidence from Direct Demand Models." *Transportation Research* 33E (March): 15-28.

Williams, Huw C.W.L. 1977. "On the Formation of Travel Demand Models and Economic Evaluation Measures of User Benefit." *Environment and Planning*, 9A (March): 285-344.

Winston, Clifford. 1979. "A Disaggregated Qualitative Choice Mode Choice Model for Intercity Freight Transportation." Working Paper SL 7904 UC Berkeley, Department of Economics.

-------------.1981a. "A Disaggregate Model of the Demand for Intercity Freight Transportation." *Econometrica* 49 (July): 981-1006.

-------------. 1981b. "The Welfare Effects of ICC Rate Regulation Revisited." *Bell Journal of Economics* 12 (Spring): 232-44.

--------------, and Chad Shirley. 1998. *Alternate Route: Toward Efficient Urban Transportation.* Brookings.

Wynter, Laura M. 1995. "Stated Preference Survey for Calculating Values of Time of Road Freight Transport in France." *Transportation Research Record* 1477: 1-6.