3783

DEMAND ESTIMATION FOR EXPRESS BUS-FRINGE PARKING SERVICES

Volume II

of

Express Bus-Fringe Parking Planning Methodology

by

Fuat Can Kavak
Graduate Assistant

and

Michael J. Demetsky
Faculty Research Engineer

(The opinions, findings, and conclusions expressed in this report are those of the authors and not necessarily those of the sponsoring agencies.)

Virginia Highway & Transportation Research Council
(A Cooperative Organization Sponsored Jointly by the Virginia
Department of Highways & Transportation and the University of Virginia)

In Cooperation with the U.S. Department of Transportation
Federal Highway Administration

Charlottesville, Virginia

May 1975
VHTRC 75-R60

ABSTRACT

The conception, calibration, and evaluation of alternative disaggregate behavioral models of the express bus-fringe parking travel choice situation are described. Survey data collected for the Parham Express Service in Richmond, Virginia, are used to define the service market area and to construct binary and n-dimensional choice models. The performance of these models is tested using a set of comprehensive evaluation criteria. Finally, the Parham Express model is applied to another fringe parking service (Princess Anne Plaza in Virginia Beach, Virginia) to evaluate the transferability of such models for planning applications. It is concluded that a model calibrated for a given urban subarea can be transferred and applied only to other areas which exhibit similar population, service, and urban development characteristics. The requirements of a generalized model methodology are described.

3786

3767

TABLE OF CONTENTS

3768

3789

SUMMARY AND CONCLUSIONS

A data collection procedure was developed and implemented in Richmond, Virginia, to enable the calibration of behavioral choice models for an express bus-fringe parking service — the Parham Express. Both binary and n-dimensional models were constructed with the logistic function and alternate ways for mathematically specifying the system time and cost measures were tested. The resulting models were formally evaluated against accepted criteria. In addition, sensitivities and elasticities of travel behavior were measured, and values of time were calculated. The transferability of the Parham Express model to the Plaza Express in Virginia Beach-Norfolk, Virginia was examined. Finally, a generalized planning procedure for express bus-fringe parking services was described, assuming that a comprehensive set of models for different areas was available.

The results of this investigation support the following conclusions:

1) The variations in travel behavior found among tripmaker groups that were specified according to the accessibility of their residence zone to a fringe parking lot are significant, and can be used to determine the service area for proposed lots and to assist in the design of local feeder transit.

2) Disaggregate behavioral models can be constructed which accurately describe existing travel behavior towards a subareal service.

3) The accuracy of the model is sensitive to the manner in which the transportation system variables are specified. In this study a measure of the difference divided by the average of a system measure (time or cost) for competing modes proved most successful among the alternate measures tested.

4) The binary choice model was able to describe observed travel behavior much better than did the n-dimensional model. This outcome may have been due to insufficient data for describing choices in more detail than a basic auto-transit split. More information is required before a firm conclusion can be made on this issue.

5) The primary explanatory variables proven significant in the models were age, sex, travel time, cost, household autos/licensed drivers, and the accessibility of the residence zone to the lot.

6) Income data are important in establishing the transferability of a model and for validating value of time estimates.

7) A diagnostic analysis of the travel survey data, system measures, and areal characteristics is helpful in selecting variables for the models and for making inter-area comparisons for subarea model classifications.

8) Sensitivities and elasticities of choice with respect to certain independent variables and values of time based on both modeling strategies were consistent with theory and the findings in related studies. The confidence intervals of the elasticity measures were wider in the n-dimensional model than in the binary model. The values of time associated with the n-dimensional model were approximately 20-30% less than those in the binary model.

9) The survey design wherein data were collected directly from travelers on the competing modes proved adequate for the model development.

10) A model calibrated for a given urban subarea can be transferred and applied only to other areas which exhibit similar population, service, and urban development characteristics.

RECOMMENDATIONS

In order to develop a generalized planning procedure for express bus-fringe parking services, the following extensions of this research are required:

1) Improvement of the problem oriented survey used here, and testing of subarea origin-destination surveys. Both surveys should obtain psychological data on trip-maker perceptions of comfort, convenience, and other nonquantifiable service measures. Also, the survey respondents should be asked questions about competing modes as well as their chosen mode. These additional data should improve the behavioral accuracy of the model.

2) Investigation or the addition of psychological system measures in the models, i.e., comfort, convenience, reliability, etc.

3) Establishment of relationships between the perceived measures obtained through the surveys and engineering measures of the same parameters.

4) Comparative analyses of binary vs. n-dimensional modeling strategies for the same choices.

5) Calibration of an extensive set of similar models from a wide range of travel, population, and urban conditions. Synthesis and analysis of this model set and explanation of the variation of the given parameters among the various models. Establishment of a continuous range for each coefficient and guidelines for selecting coefficient values for different study area classes.

6) Documentation of the methodology in a handbook which includes case study examples.

DEMAND ESTIMATION FOR EXPRESS BUS-FRINGE PARKING SERVICES

Volume II

of

Express Bus-Fringe Parking Planning Methodology

by

Fuat Can Kavak
Graduate Assistant

and

Michael J. Demetsky
Faculty Research Engineer

INTRODUCTION

This report documents the development of mathematical models designed to predict travel choices relative to express bus-fringe parking services. Volume I of this two-volume report, entitled Planning Criteria for Express Bus-Fringe Parking Operations, provides an analysis of general tripmaker comments and aggregate travel behavior and includes a set of planning guidelines for express bus-fringe parking operations. The interested reader is also referred to Volume I for information concerning the study areas and services which provided the data for the models described herein.

The express bus-fringe parking concept is an example of a short-term transit improvement in selected urban subareas where area-wide travel models which represent an arbitrary auto-transit choice do not apply. Also, models based on aggregate zonal behavior are not sensitive to the travel choices under consideration because this transit operation serves only a segment of the travel market along a corridor and provides varying levels of service to different residential zones. The express bus-fringe parking choice problem, therefore, provides an opportunity to apply disaggregate behavioral modeling concepts to represent travel behavior for a well-defined subarea. While the express bus-fringe parking concept is being widely researched[1, 2, 3, 4] and implemented throughout the country, there is no objective means available to forecast the usage for alternative locations of anticipated services.

SCOPE OF THE RESEARCH

This report focuses on the conceptualization of choice processes, the formulation and calibration of a mathematical model, and testing of the model for practical planning applications. Accordingly, the specific objectives of this research are (1) to develop a methodology for modeling travel choice behavior concerning express bus-fringe parking transit services, and (2) to evaluate the application of the derived procedures for planning express bus-fringe parking services.

Initially, a historical review of models of mode choice is made leading to the state of the art. The properties which make disaggregate behavioral models preferable to the earlier, more aggregated models are explained. Choices available to a typical commuter residing within a generalized corridor are discussed and the modeling strategies implied by his evaluation of these alternatives are stated. Survey data collected for the Parham Express service in Richmond, Virginia, are examined to determine a set of variables for building models and to define the service-market area. Binary and n-dimensional choice models are developed and calibrated using alternative methods for specifying the transportation system variables. The performance and reliability of these models are tested using a set of comprehensive evaluation criteria. Finally, the Parham Express model is applied to another fringe parking service (Princess Anne Plaza in Virginia Beach, Virginia) and the results of this effort are used to recommend a methodology for planning such services.

REVIEW OF MODE CHOICE MODELS

Aggregate Models

Since 1955, when modal-split methodology was first introduced in a major region-wide study,[5] there have been many attempts to model the modal choice process. The earlier models were classified with respect to their placement in the transportation planning process either as trip-end or trip-interchange models.[6]

The earliest efforts,[5,7,8,9,10] which were trip-end type models, estimated modal split before trip distribution. Accordingly, these models were not sensitive to the relative characteristics of alternative transportation options. They primarily employed trip and tripmaker attributes and, in some cases, accessibility ratios were used.[7,8,9] These models were of little value in forecasting because they were not sensitive to changes in system characteristics, such as reductions in cost and time of the transit mode. Thus, as stated by Reichman and Stopher, "...because the socio-economic measures incorporated are generally increasing (e.g., income, car ownership, and level of education), predictions of future modal shares from these models suggest that transit will be used by a dwindling proportion of the population, irrespective of any changes in mode characteristics".[11]

By the late fifties, trip-interchange models were developed to correct this lack of sensitivity to system changes in the trip-end models. These models were employed after trip distribution and, therefore, could be responsive to changes in system characteristics for travel between specific zones. Early models of this type were "diversion curves" which related transit usage to either travel time differences or ratios. The "diversion curve" technique had two major drawbacks.[6] It did not include trip and tripmaker characteristics and could not be used in the planning of an entire transportation system at one time. In 1961, Quinby suggested that total volume of trips should be stratified into those with or without Central Business District (CBD) orientation by trip purpose and into those with and without peak-period peak-direction status.[12] He also used a Gompertz exponential curve formulation in his diversion curves. Following Quinby's ideas, a large set of diversion curves stratified by trip purpose, time of day, relative travel time and cost, relative level of service, and economic status of the trip-maker were developed by the National Capital Transportation Agency.[13] However, even these models used zones for grouping observations and neglected the fact that there might be as much variation among individual observations within a zone as among those between different pairs of zones.[14] Thus, they were extremely sensitive to the selection of traffic zones and, therefore, could not be transferred geographically.

The utility model developed by R. H. Pratt Associates, Inc.[15] represents the final step towards the present state of the art. This model is established on the basis of a meaningful theoretical framework which was lacking in prior models. First, it was assumed that the individual choice of mode was utilitarian and based on minimizing the disutility involved in making a trip. Second, a probabilistic approach was introduced which related the probability of choice of mode to the normal distribution. Finally, deviations from this normal distribution were attributed to predictable causes such as captivity and resistance to long trips. The model structure was, however, still aggregate as it employed zonal averages as explanatory variables. The only disaggregation attempt was to stratify trips by three purposes, three income groups, and sixteen captivity levels. In addition, the values of the parameters of the Pratt model were based on judgment rather than statistical estimation.

Current Developments

In an attempt to improve upon the limited predictive power and lack of theory of the aforementioned models, current research is directed towards building disaggregate behavioral models.[16,17,18,19,20,21] These models are disaggregate in the sense that they take the individual as the primary unit of decision making; they are behavioral in character since they are based on theories of individual behavior. Most disaggregate behavioral models are also probabilistic because they predict the probabilities of mode choice.

Current probabilistic mode choice models can be classified into three groups depending upon the modeling approach: discriminant, probit, or logit analysis. Linear multiple regression, on the other hand, has been considered an inferior approach due to various deficiencies inherent in its structure. Behavioral researchers believe that the response of individuals to changes in system characteristics varies in different ranges of the choice curve; therefore, the linearity assumption is inadequate.[17,22,23] Furthermore, the predictions of the linear model are unbounded and may not fall in the (0, 1) probability interval.

While a recent study by Talvitie[24] indicates that any three of the aforementioned methods can be used with equal success, Stopher and Lavender[25] found that discriminant analysis was clearly inferior to probit and logit models. The latter finding seems to be more acceptable mainly due to conceptual shortcomings inherent in discriminant analysis and is supported also by researchers like Watson[23] and Warner.[21] In terms of statistical characteristics, probit and logit models yield comparable results, however, the logit methodology is easier to use and interpret and consumes less computer time.[25] For the above reasons, the logit methodology was used for this research.

Warner[21] was the first to apply logit analysis to modal choice analysis.[26] Theil[26] extended this technique to deal with more than two modes at a time, but application has generally been restricted to binary choice situations; Stopher[18], Demetsky and Hoel[27], Wigner[28], and Watson[23] have built various disaggregate mode choice models that deal with only two modes at a time. Recently there have been attempts to use the logit model in a multimodal sense as well. Rassam, Ellis, and Bennett developed an n-dimensional logit model and used it to build models for Washington Airport Access[29] and the city of San Diego[30]. Inglis[31] derived a multimodal logit model for a short journey starting from the binary choice model.

The logit model relates the probability of mode choice to a linear function of explanatory variables. The relation is of a nonlinear type which restricts the probability to the (0, 1) interval while the function can assume values from $-\infty$ to $+\infty$. The maximum likelihood technique is the common method for estimating the parameters of the logit model. Finally, these models can be used to specify aggregate group behavior based on observed choices rather than rely on the forced assumption of common zonal behavior that was typical of the earlier aggregate based models. A mathematical description of the logit model is given in Appendix I.

THE CHOICE PROCESS AND DATA ANALYSIS

Choices Available Within a Generalized Corridor

The express bus-fringe parking choice problem is associated with the typical commuter residing within a defined service area and having real travel choices. The travel decisions at the zone of residence concern either the use of transit (local bus or the express bus) or the exclusive use of the automobile. The local bus is assumed to run from the zone of residence to the CBD, while the express bus commuters must first travel to the fringe lot. Accordingly, there are potentially various means available for traveling to the fringe lot to access the express service including parking at the lot, a collector bus, walking, kiss-'n-ride, car pool, bicycle, and motorcycle. Those who use the automobile exclusively for the trip to the CBD also have a route choice.

Modeling Strategies

There is considerable uncertainty as to how commuters evaluate the choices discussed above. One approach assumes that the commuter simultaneously considers all of the choices at his zone of residence. This conceptualization suggests a multimodal choice situation at the corridor level and is illustrated in Figure 1. Figure 2 represents another approach wherein it is assumed that the commuter makes his decisions in a sequential manner. All secondary choices are conditional upon a primary auto-transit decision and are considered as the submodal split.[32,33] With the exception of the express bus access modes, all decisions are binary which require aggregation of transit and auto characteristics to provide average system attributes for input to the model.[34]

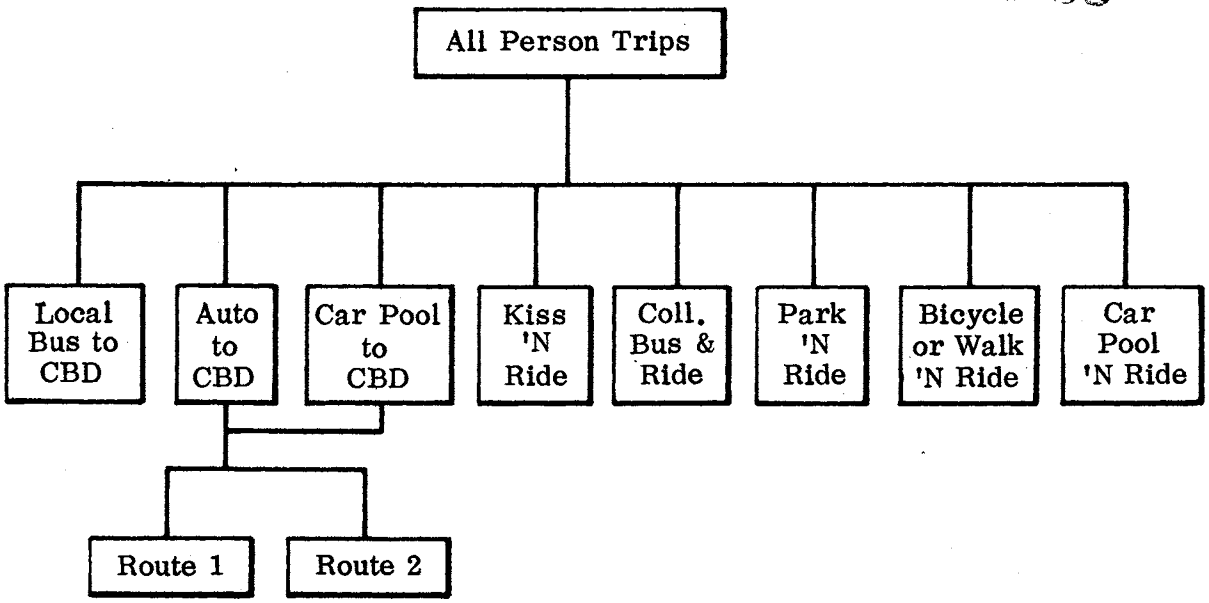


Figure 1. Flow chart for the n-dimensional choice model.

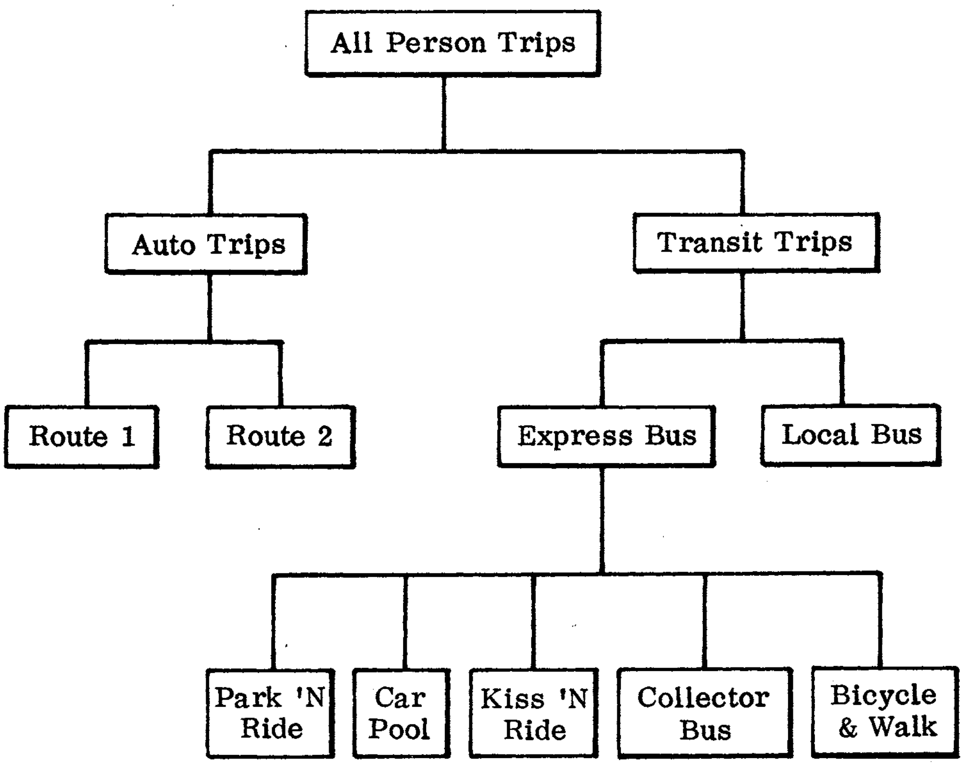


Figure 2. Flow chart for the binary choice model.

5796

Data Reduction

The description of the Parham Express service was given in Volume I, and the system and tripmaker data employed in this analysis of travel behavior include the following:

1. System Data

   (a) Highway travel distances
   (b) Highway travel times
   (c) Transit costs
   (d) Transit running times
   (e) Excess times (i.e., transit access, from parking lot to destination, etc.)

2. Behavioral data

   (a) Bus survey
   (b) Auto survey

The questionnaire used for the bus survey is shown in Figure 3. It was distributed on a weekday at the beginning of the bus trip and collected as riders left the bus, or it was returned by mail. The license numbers of auto travelers entering the expressway during the same time period (7 a.m. to 9 a.m.) on the two ramps in the vicinity of the fringe lot were recorded and questionnaires mailed. The auto survey form is shown in Figure 4.

In urban areas, the most regularly made trips are of the home based work type. Due to this regular trip pattern, the individual tripmaker is very likely to be familiar with many facets of his current and alternative modes of transportation, the available routes, etc. Thus, he would be expected to make his mode choice decisions in conformity with the commonly made behavioral assumption concerning complete knowledge of alternatives. Accordingly, only home based work trips are considered here, and since this study deals with a service catering only to work trips (on the day of the survey 96.6% and 98.7% of auto and bus trips, respectively, were work trips), the reduction in the data set due to the exclusion of other than home based work trips is negligible.

In the bus survey 302 questionnaires were handed out and 285 were returned. After incomplete forms were eliminated, 229 usable responses remained. Due to the fact that the license numbers of all vehicles entering the freeway could not be recorded, traffic counters were employed to provide a control total for the population. This figure was determined to be 4,030 auto trips, from which 1,165 valid questionnaire responses were obtained, or a 28.9% sample. Of this sample 381 responses concerned work trips to the CBD. It was further assumed that the sample was representative of the trip end distribution of the total population and, accordingly, the 381 responses were assumed to be a 28.9% sample of CBD destined work trips by auto.

This Survey is Sponsored by the Virginia Department of Highways

THE FOLLOWING QUESTIONS CONCERN THE BUS TRIP YOU ARE NOW MAKING

If possible, please fill out this questionnaire during this trip and return it to our personnel who are on board this bus. If this is inconvenient, please fill out this questionnaire at your pleasure and return it in the postage-paid envelope.

FOR OFFICIAL USE ONLY

1. Where did you initially begin your trip?

____
(specify address - number and street name)

2. Was the place you came from: (check one)
___ home
___ work ___ other (specify) ______________

3. Trip purpose. The reason for this trip was: (check one)
___ return home ___ shopping
___ work ___ recreation
___ school ___ other (specify) ______________

4. Time you began your trip: _______ A.M.

5. How did you get to the Parham Road Lot to board this bus?
___ drove and parked ___ another bus
___ car passenger-car parked ___ walked, how many minutes ___
___ dropped off-car not parked ___ other (specify) __________

6. What time did this bus leave the Parham Road Lot? ________ A.M.

7. Where will you get off this bus? (check one)
___ 8th & Clay ___ Main & 11th
___ 9th & Broad ___ Main & 10th
___ Broad & 10th ___ Main & 8th
___ Broad & 12th ___ 7th & Franklin
___ Broad & 14th ___ 7th & Grace
___ 14th & Franklin ___ 7th & Broad
___ 14th & Main ___ 7th & Clay

8. How will you get to your destination after leaving this bus? (check one)
___ walk, how many minutes _____ ___ taxi
___ another bus ___ other (specify) __________

9. What is your final destination?

____
specify address (number and street name) or building

10. Time you expect to arrive at your destination: ________ A.M.

11. If this bus service were not available, how would you make this trip?
___ drive a car ___ another bus
___ ride as a car passenger ___ other (specify) ________
___ participate in a carpool

12. If you drove a car or rode as a car passenger for this trip in the past, why did you switch to this bus? ______________________________

13. Do you have any recommendations as to how this bus service could be improved? ______________________________

14. How many licensed drivers reside in your household? (count yourself) ___________

15. How many cars are owned by members of your household? ___________

16. Could you have used one of the cars to make this trip? ___yes ___no

17. Please indicate your: Sex: ___Male ___Female
Age Group: ___ under 16 ___ 16-24 ___ 25-44 ___ 45-65 ___ over 65

18. What is the combined annual income of all members of your household?
___$0-$4000 ___$4000-$8000 ___$8000-$12000 ___over $12000

THANK YOU

Figure 3. Bus survey questionnaire.

3793

This Survey is Sponsored by the Virginia Department of Highways

A vehicle registered in your name was observed entering I-64 eastbound at Parham Road between 7:00 a.m. and 2:00 p.m. on August 21, 1973 . It would be appreciated if you or the person who drove that vehicle on this trip would answer the following questions and return the questionnaire in the postage-paid envelope.

FOR OFFICIAL USE ONLY

Errors in recording license plates do occur. If this form was sent to you by error, please check here and return ___. Otherwise, please continue.

1. Where did you begin this trip?

   ____
   specify address (number and street name)

2. Was the place you came from: (check one)
   ___ home
   ___ work ___ other (specify) ____________

3. Trip purpose. The reason for this trip was: (check one)
   ___ return home ___ shopping
   ___ work ___ recreation
   ___ school ___ other (specify) ____________

4. Time you began your trip: ________ A.M./P.M.

5. What was your final destination?

   ____
   specify address (number and street name) or building

6. Time you reached the above address: ________A.M./P.M.

7. What was the vehicle parking cost? $_____ per ________

8. After you parked the automobile, how did you get to your final destination?
   ___ walk, how many minutes ___ taxi
   ___ bus ___ other(specify)____________

9. Do you use your car during the business day? ___ yes ___ no

10. Do you usually make this trip: (check one)
    ___ alone
    ___ carrying passengers, how many? _______
    ___ within a carpool, how many members (count yourself)? _______

11. Could you have used the express bus from the Parham Road Lot for this trip?
    ___ yes, but I chose not to because ____________
    ___ no, because ____________
    ___ not aware of this service

12. Are there any improvements possible regarding the Parham Express bus service which would make it acceptable enough to influence you to use it? ___ yes ___ no If yes, what might they be? _______

13. How many licensed drivers reside in your household (count yourself)? ____________

14. How many autos are owned by members of your household? ________

15. Please indicate your: Sex: ___Male ___Female
    Age Group: ___under 16 ___16-24 ___25-44 ___45-65 ___over 65

16. What is the combined annual income of all members of your household?
    ___$0-$4000 ___$4000-$8000 ___$8000-$12000 ___over $12000

THANK YOU

Figure 4. Auto survey questionnaire.

Because the usable auto responses constitute a 28.9% sample, a similar proportion of bus user responses was used in order that the data set be proportionately representative of the auto and bus populations, as would be the case in a home interview survey. Since such a requirement may result in statistical bias, a program was used to randomly select a 28.9% bus sample.

Since the model is designed to reflect only real choices, captive riders were removed from the data set. Individuals were classified as transit captives if their alternative mode choice was another bus and if they indicated that they could not have used a household automobile to make the trip. A tripmaker was considered to be an auto captive if he needed a car for his job or worked at a location in the CBD which was remote from a transit stop. The development of the data set is summarized in Table 1. The transportation system data were obtained from the transit operator and the Virginia Department of Highways and Transportation, and were supplemented with traffic engineering measurements.

Table 1

Data Set Summary

Sample Description	Bus Trips		Auto Trips	
	Number	Percent	Number	Percent
1. Total trips	302	100	4030	100
2. Number of valid questionnaires	229	94	1165	29
3. CBD trips	229	76	381	
4. Choice CBD trips	222	74	223	
5. Number calibration used for model	87	29	223	29

The data analysis provided in Volume I was interpreted to develop basic hypotheses for stratifying the travel market into homogeneous choice groups and to assist in specifying explanatory variables for structuring a model. The initial observations concerning the appropriateness of specified explanatory variables are summarized in Table 2.

Table 2

Initial Observations on Relevant Variables

Variables Examined	Significant Variables (denoted by x) Primary Choice	Access Choice
Auto Ownership		x
No. Autos/No. Licensed Drivers	x	x
Sex	x	x
Household Income		
Age	x	x
Travel Cost	x	
Residence Zone (location)	x	
Travel Time	x	

Due to data limitations only two access modes were considered — park and ride and kiss and ride.

MODEL DEVELOPMENT

Disaggregate behavioral models were calibrated for the choice processes illustrated in Figures 1 and 2. The binary choice strategy assumes that tripmakers make a basic choice between the private and public modes of transportation, while the multimodal model shows that all potential modes or modal combinations are considered simultaneously. The multimodal choice model is conceptually superior to a binary choice consideration, however, there exists no evidence as to which model would perform best in this situation. Therefore, both modelling concepts were applied and comparative evaluations performed using the test criteria given in Appendix II.

Binary Choice Model

The basic form of the binary logit model used here is

$$P_b = \frac{e^{G(x)}}{1 + e^{G(x)}} \tag{1}$$

where P_b is the probability of chosing the express bus, and G(x) is a linear function of explanatory variables. The parameters of this function were estimated using a computer program developed by J. G. Cragg, University of British Columbia, and adapted to the CDC 6400 by P. R. Stopher of Northwestern University (see references 22, 35 and 36 for a detailed description of the estimation procedure).

Three primary split models and a sub-modal split model were tested. Similar socioeconomic variables were used in each of the three primary split models, but the nature of the specification of the time and cost measures was varied. Since the accessibility of the lot from the residential zone proved to be an influential factor on travel behavior a surrogate measure of accessibility was initially entered as a discrete variable taking on values of 0, 1 or 2 for Accessibility Groups 1, 2 and 3, respectively. Zones located adjacent to the zone with the lot comprised Accessibility Group 1. If a zone's minimum travel time route to the CBD fell in close proximity to the fringe lot it was classified as Accessibility Group 2. Accessibility Group 3 included those zones whose shortest route to the CBD did not come close to the lot (see Volume I for derivation of Accessibility Groups). This discrete variable had the second highest correlation with the probability of choice (0.289) and its coefficient exhibited a significant t-statistic. Furthermore, when a separate model was calibrated for each accessibility group it was found that the coefficients of the time and cost variables differed considerably among the models. In the following applications, separate models are calibrated for each accessibility level as well as a single model based on all of the data.

A listing and definition of all of the variables used in developing the models is given in Table 3. The three types of models presented are named according to the manner by which the time and cost measures are entered: the difference, log of ratios, and relative values models.

The Difference Model

The system characteristics used in the difference model shown in Table 4 include the running time, excess time, and cost differences. The values for the reported mode choice were obtained directly from the survey responses concerning perceived times and costs, while the measures for the alternative mode were estimated by averaging the perceived data for each zone. The use of averaged data for the alternate mode presents potential problems; but, since the survey provided no information on the alternative choice, this was essentially the only option available.

The estimated coefficients exhibited the expected signs. All of the system variables were significant at the 0.05 level with the exception of the excess time, which was significant at the 0.10 level for Accessibility Group 3. The chi-square test rejected the hypothesis that all of the coefficients, except the constant, were equal to zero at the .005 level. Probabilities of choice at zero difference were in agreement with the assumptions concerning the bias of the accessibility groups as stated in Appendix II. The model predicted the original data almost perfectly; however, the value of e_2 was the highest among the three models (11.18%).

Table 3

Variables Used in Models

Independent Variable		Symbol
Sex	0 = female; 1 = male	x_1
Age	0 = (25-44); 1 = otherwise	x_2
$\frac{\text{No. household autos}}{\text{No. licensed drivers}}$		x_3
Running time difference		$x_4 = (RT_a - RT_b)$
Excess time difference		$x_5 = (ET_a - ET_b)$
Total cost difference		$x_6 = (C_a - C_b)$
Natural log of ratios of total times		$x_7 = \text{Ln}\ (T_a/T_b)$
Natural log of ratios of total costs		$x_8 = \text{Ln}\ (C_a/C_b)$
Total time difference divided by average total time		$x_9 = \frac{T_a - T_b}{(T_a + T_b)/2}$
Total cost difference divided by average total cost		$x_{10} = \frac{C_a - C_b}{(C_a + C_b)/2}$

Accessibility Groups

Group 1. Trips from zones adjacent to zone where lot is located.

Group 2. Trips from zones whose minimum time route to the CBD passes through the area where the lot is located.

Group 3. Trips from zones whose minimum time routes to the CBD are out of the way from the lot.

Dependent Variable

Calibration:	$P_b = 0$ for auto trips
	$P_b = 1$ for bus trips
Application:	P_b = probability of bus choice

Note: a = auto measure; b = express bus measure

Table 4

The Difference Model (Binary Case)

Estimated Model Coefficients

Independent* Variable	Accessibility Group 1	Accessibility Group 2	Accessibility Group 3	All Data
X_1	-1.1080	-1.3083	0.7016**	-0.4901**
X_2	1.1720**	0.3846**	1.5550	1.0520
X_3	-2.1763	-4.3375	-3.4558	-3.2798
X_4	0.1083	0.2383	0.2326	0.1891
X_5	0.0378	0.0490	0.0591	0.0369
X_6	0.1530	0.3752	0.5803	0.2262
Constant	2.1544**	4.5191	0.9981**	2.6365
Evaluative Measures				
x^2	23.51	28.77	35.84	80.04
e_1	0.08%	0.77%	0.26%	0.40%
P_b at zero diff.	0.573	0.500	0.251	0.480
e_2	--	--	--	11.18%

* Variables are defined in Table 3.
** Indicates the variables or constant was found to be nonsignificant at the .05 level.

The Log of Ratios Model

The difference model makes the assumption that the mode choice decision is based on the absolute values of the differences in times and costs. In this respect the model implies that the choice between travel times of 15 and 20 minutes is equivalent to a choice between 35 and 40 minutes when all other variables are kept constant. The log of ratios model shown in Table 5 was introduced to correct this fault and it predicted two significantly differing transit choice probabilities for the hypothetical travel times indicated above (0.214 and 0.430, respectively). The time and cost variables were calculated by taking the natural logarithm of the ratio of auto time or cost to bus time or cost. Also, since the auto data included some observations where excess time was equal to zero (i.e., Ln 0 = negative infinity), total time figures rather than a running time and excess time breakdown were necessary for this model.

In the log of ratios model all coefficients exhibited the hypothesized signs. All the system variables were significant at the 0.05 level. Age and sex failed the significance test for the Accessibility Group 2 and Group 3 models, respectively. The chi-square test was satisfactory at the 0.05 significance level. Probabilities of choice at zero difference were as hypothesized. The model predicted the original data almost perfectly, and the value of e_2 was the second best among the four models.

Table 5

The Logarithm of Ratios Model (Binary Case)

Estimated Model Coefficients

Independent* Variable	Accessibility Group 1	Accessibility Group 2	Accessibility Group 3	All Data
X_1	-1.3291	-1.2840	0.8103**	-0.5259**
X_2	1.1447	0.3235**	1.4357	1.0838
X_3	-2.3681	-3.8899	-4.6697	-3.5466
X_7	4.1488	10.5250	8.3734	6.4931
X_8	3.3688	4.4247	4.5293	3.3654
Constant	2.3994	4.030	2.0240**	2.7782
Evaluative Measures				
x^2	29.60	32.41	35.96	93.7
e_1	0.13%	0.15%	0.18%	0.61%
P_b at zero diff.	0.559	0.543	0.245	0.455
e_2	--	--	--	3.2%

* Variables are defined in Table 3.
** Indicates variable or constant was found to be nonsignificant at the 0.05 level.

The Relative Values Model

A further model form, given in Table 6, used time and cost differences relative to a base cost and time. Since it was not known whether the actual mode taken or the alternate mode was considered as a base by tripmakers, the average of the total times and costs of the alternative choices was used as a reference measure.

The general characteristics of this model, although slightly better, were similar to those of the log of ratios model. The values of the estimated coefficients were within 8% of those of the latter model and the same variables were significant. The relative values model satisfied the expected sign test and had the lowest e_2 value. Probabilities of choice at zero difference complied with the hypothesized trend.[2]

A ranking of the resulting models in view of their performance with respect to the test criteria discussed in Appendix II is shown in Table 7. The relative values model scored highest and was used to derive the various descriptive measures of group travel behavior.

Table 6

Relative Values Weighted by Average Model (Binary Case)

Estimated Model Coefficients

Independent* Variable	Accessibility Group 1	Accessibility Group 2	Accessibility Group 3	All Data
X_1	-1.3416	-1.3092	0.8207**	-0.5294**
X_2	1.1430	0.3443**	1.4384	1.0883
X_3	-2.3536	-3.9319	-4.7517	-3.5738
X_9	4.2932	10.8990	8.5377	6.6795
X_{10}	3.3990	4.7533	4.7783	3.5717
Constant	2.3732	4.3230	2.0465**	2.7839
Evaluative Measures				
x^2	30.05	33.03	36.20	94.8
e_1	0.21%	0.22%	0.24%	0.88%
P_b at zero diff.	0.554	0.532	0.236	0.451
e_2	--	--	--	2.22%

* Variables are defined in Table 3.
** Indicates variable or constant was found to be nonsignificant at the 0.05 level

Table 7

Binary Choice Models Ranked by Performance and Reliability Criteria

Performance Tests	Model		
	Relative Val.	Log of Ratios	Difference
Compatibility	1	2	3
Significance* of Variables	1	2	3
Chi-square test	1	2	4
Expected sign	OK	OK	OK
Prediction	1	2	4
Probability, zero diff.	OK	OK	OK
Final Ranking	1	2	3

* Refers to significance of individual variables.

Descriptive Measures of Travel Behavior

The models were used to derive fundamental descriptive measures of the travel behavior namely, sensitivities, elasticities of choice, and the tripmaker's value of time. Sensitivity analysis measures the change in the probability of choice of a given mode relative to a change in one of the explanatory variables. Table 8 shows the sensitivity of the bus choice to a 10% change in each of the system variables and the ratio of number of household autos to the number of drivers. Since sensitivity depends on the units of the variables used, it is not a direct measure of tripmakers' responsiveness to changes in system characteristics. The use of elasticity, a relative measure, can overcome this shortcoming. The elasticity, denoted by E, is a dimensionless number defined as the relative percentage change in the probability of the specified choice which results from a one percent change in any of the explanatory variables.[37] Mathematically, the elasticity of the probability of using mode m, p_m, with respect to a given variable X_k is stated as

$$E_{m,k} = (\partial p_m/p_m) \,/\, (\partial X_k/X_k) \qquad (2)$$

Table 8

Sensitivity Analysis
(Binary Case)

Change in Probability of Bus Choice due to 10%* Change in				
T_a	T_b	C_a	C_b	X_3
0.079	-0.079	0.039	-0.043	-0.042

T_i = Time, mode i

C_i = Cost, mode i

X_3 = Number of household autos/Number of licensed drivers

a = auto

b = bus

* keeping all other variables constant.

The probability of using the express bus was found to be elastic relative to all of the system variables and the auto/drivers measure, the elasticity of auto choice was found to be elastic only with respect to time (i.e., $E_{m,k} > 1$). The aggregate elasticities computed for each mode are given in Table 9. These results support the hypothesis that auto users are more attached to that mode than are users of the express bus service to their mode. Also, the high values of time elasticities indicate that tripmakers weight travel time more than travel cost in mode choice decisions. Both results agree with the theory and findings in other studies.[38] Ninety percent confidence intervals for the true values of elasticities are also provided in Table 9.

The value of time is found by calculating the change in cost due to a unit change in the time variable, keeping all other variables, including the choice probability, constant. Accordingly G(x) must remain unchanged if the choice probability remains constant. Using this fact, it has been shown that[37]

$$\frac{dC_i}{dT_j} = -\frac{\partial G(x)}{\partial T_j} \Big/ \frac{\partial G(x)}{\partial C_i} \qquad (3)$$

where, i = a, b   a = auto

j = a, b   b = bus

and dC_i/dT_j is the rate of commodity substitution, and the change in the value of the cost of mode i (dC_i) for a unit change in the travel time of mode j (dT_j) is the value of travel time.

3803

Table 9

Aggregate Elasticities of the Probability of Choice
(Binary Case)

Explanatory Measure	Transit	Auto
Auto Time	2.81	-1.11
	(2.03, 3.59)*	(-1.42, -0.80)
Transit Time	-2.80	1.11
	(-3.58, -2.02)	(0.80, 1.42)
Auto Cost	1.39	-0.55
	(1.00, 1.78)	(-0.71, -0.39)
Transit Cost	-1.51	0.60
	(-1.94, -1.08)	(-0.77, -0.43)
#Autos/#Licensed Drivers	-1.47	0.58
	(-2.05, -0.89)	(0.36, 0.80)

*90% confidence limits

The value of travel time for the study population was estimated by substituting the appropriate terms for each mode in the above relationship, which results in four expressions of the value of travel time for average sample values. These four values of time relate to changes in the cost associated with each of the two competing modes due to a unit time change in either mode. The average values of bus and auto time were calculated to be $2.10/hr. and $2.69/hr. respectively, showing that bus users value time differently than automobile travelers. These values of travel time were found to be 39.6% and 50.8% of the wage rate for the bus and auto users respectively.

Since travel time was not separated into the running and excess time components in the relative values model, the difference model was used to estimate individual values for excess time and running time. The values obtained were $2.33/hr. for the running time and $4.55/hr. for the excess time, which amounted to 44% and 85.8% of the wage rate respectively.

Submodal Split Model

The next step in the binary choice modeling strategy is the submodal split analysis of the access modes. Since only a very small representation of the pedestrian, bicycle, and auto passenger modes was obtained in the sample data, only the park n' ride and kiss n' ride access modes were considered. A single model without time and cost measures was investigated because both choices concerned auto travel, which made the accessibility and time and cost measures invariant.

Three independent variables — sex, age, and the ratio of autos to licensed drivers — were used in the model, and the variables were entered one by one to test their significance (see Table 10). Among the three variables only the aforementioned ratio was significant at the 0.05 level. The sign of the ratio variable indicates that as the number of cars increase in a household, the probability of driving the car to the fringe lot and parking it increases. The model reproduced the data almost perfectly with a negligible error of 0.03%. However, e_2 was considerably high at 7.68% but was still within a tolerable level.

Table 10

Submodal Split Model Coefficients and t-value

Model	Constant	X_3	X_1	X_2	x^2
1.	3.2231 (4.56)	-5.5835 (-5.83)			42.67
2.	3.5231 (4.26)	-5.6901 (-5.81)	-0.3500 (N.S.)		43.21
3.	3.4796 (4.09)	-5.7146 (-5.79)	-0.3259 (N.S.)	0.1001 (N.S.)	43.26

For Model No. 3 $e_1 = 0.03\%$ and $e_2 = 7.68\%$

N.S. specifies nonsignificance at the .05 level.

The N-Dimensional Choice Model

The n-dimensional choice model described in Appendix I was calibrated using a computer program developed by Peat, Marwick, Mitchell & Co. This program estimated the parameters of $G_k(X)$'s of the n-dimensional logit model using the method of maximum likelihood as applied to the case of m modes. The final model, the fully competitive model, was obtained by applying the variational technique described in equation 8 of Appendix I, with Q and a taken to be equal to 1/3 and 2, respectively.

The n-dimensional choice model analyzes the choice process among three modes: auto, park'n ride, and kiss'n ride. This development included only two models: the relative values model, since it had proven to be the best of the binary choice models; and the difference model, which provided separate estimates of excess time and running time. Definitions of the variables used in building these n-dimensional models are given in Table 11.

The Difference Model

The system variables used in the difference model are shown in Table 12 and include running time, excess time, and cost differences. The estimated coefficients exhibited the expected signs. All of the variables were significant at the 0.05 level and the chi-square test proved the hypothesis that some of the coefficients were significantly different from zero at the .005 level. The model predicted the following average probabilities of choice: 0.266 for park'n ride, 0.672 for auto and .062 for kiss'n ride, respectively. However, the observed split was considerably different, 0.187, 0.737 and 0.076, respectively, an indication that the model overestimates the park'n ride mode and underestimates the alternate modes. Accordingly, the values of e_1 (15.6%) and e_2 (14.0%) were substantially higher than those values obtained for the binary choice models.

The Relative Values Model

The relative values model, as shown in Table 13, employed time and cost differences relative to total time and costs. The estimated coefficients had the expected signs and all of the variables were significant at the .05 level, with the chi-square test satisfactory at the 0.005 significance level. The model predicted average probabilities of choice of 0.268 for park'n ride, 0.671 for auto, and .061 for kiss'n ride, which were considerably different than the observed values. The e_1 and e_2 values were 16.1% and 13.4%, respectively. The relative values model performed better than the difference model, which conformed with the results of the binary choice analysis.

Table 11

Variables Used in the n-dimensional Choice Models

Independent Variable		Symbol
Sex	0 = female; 1 = male	X_1
Age	0 = (25-44); 1 = otherwise	X_2
$\frac{\text{No. household autos}}{\text{No. lic. drivers}}$	0 if < 1; 1 if ≥ 1	X_3
Total time difference divided by avg. total time		$X_4 = \frac{T_a - T_t}{(T_a + T_t)/2}$
Total cost difference divided by avg. total cost		$X_5 = \frac{C_a - C_t}{(C_a + C_t)/2}$
Running time difference		$X_6 = RT_a - RT_t$
Excess time difference		$X_7 = ET_a - ET_t$
Total cost difference		$X_8 = C_a - C_t$

Note: a = auto measure; t = express bus measure

Table 12

The Difference Model
(Multimodal Case)

Estimated Model Coefficients

Base Mode (Park and Ride)

$G_d(X) = 0$

Auto Mode

$G_a(X) = -0.7922X_1 - 1.8985X_2 - 0.12078X_6 - 0.2256X_7 - 0.0374X_8 + 1.6400$

Kiss and Ride Mode

$G_k(X) = -1.8436X_1 - 1.8992X_2 - 3.4187X_3 + 1.9789$

and

$$Y_d = p_d\ (1 + Qu_d)$$
$$Y_a = p_a\ (1 + Qu_a)$$
$$Y_k = p_k\ (1 + Qu_k)$$

where Y_d, Y_a, and Y_k are the estimated probabilities of the fully competitive model, $Q = 1/3$ and $u_i = p_i - \sum_{j=1}^{M} p_j^2$

and

$$p_d = \frac{1}{1 + e^{G_a(X)} + e^{G_k(X)}}$$

$$p_a = \frac{e^{G_a(X)}}{1 + e^{G_a(X)} + e^{G_k(X)}}$$

$$p_k = 1 - p_d - p_a$$

Evaluative Measures

$x^2 = 142.86$ with 8 d.o.f.

$e_1 = 15.6\%$; $e_2 = 14.0\%$

Table 13

The Relative Values Model
(Multimodal Case)

Estimated Model Coefficients

Base Mode (Park and Ride)

$G_d(X) = 0$

Auto Mode

$G_a(X) = -0.8776X_1 - 1.9550X_2 - 3.8446X_4 - 4.9552X_5 + 1.8503$

Kiss and Ride Mode

$G_k(X) = -2.0600X_1 - 1.9900X_2 - 3.6907X_3 + 2.1623$

and

$$Y_d = p_d\,(1 + Qu_d)$$

$$Y_a = p_a\,(1 + Qu_a)$$

$$Y_k = p_k\,(1 + Qu_k)$$

where Y_d, Y_a and Y_k are the estimated probabilities of the fully competitive model, $Q = 1/3$ and $u_i = p_i - \sum_{j=1}^{M} p_j^2$

and

$$p_d = \frac{1}{1 + e^{G_a(X)} + e^{G_k(X)}}$$

$$p_a = \frac{e^{G_a(X)}}{1 + e^{G_a(X)} + e^{G_k(X)}}$$

$$p_k = 1 - p_d - p_a$$

Evaluative Measures

$x^2 = 157.97$ with 7 d.o.f.

$e_1 = 16.1\%$; $e_2 = 13.4\%$

Descriptive Measures of Travel Behavior

The multimodal choice model was used to derive measures of travel behavior similar to those obtained with the binary choice model, i.e., sensitivities, elasticities of choice, and the traveler's value of time. Table 14 shows the sensitivities for the three modes considered here.

The elasticities of choice given in Table 15 were derived by applying equation 2 to a multimodal situation. Of the fifteen cases examined, the probability of choice was shown to be inelastic in only three: Park 'n ride choice to the ratio of automobiles to licensed drivers, and auto choice to auto cost and transit cost. The probability of transit choice was highly elastic with respect to travel time. Ninety percent confidence intervals for the true values of the aggregate elasticities are shown in Table 15.

The values of bus and auto time were calculated to be \$1.46/hr. and \$2.01/hr., respectively, or 27.5% and 37.9% of the wage rate.[39] The difference model was used to estimate the values of excess time and running time separately. The values obtained were \$3.62/hr. and \$1.94/hr., respectively, which amounted to 68.3% and 36.6% of the wage rate.

Table 14.

Sensitivity Analysis
(n-dimensional Model)

Explanatory Measures	Change in Probabilities Due to 10% Change in		
	Park 'n Ride	Auto	Kiss 'n Ride
Auto Time	0.084	0.072	0.013
Transit Time	0.056	0.068	0.013
Auto Cost	0.040	0.049	0.009
Transit Cost	0.044	0.053	0.010
#Autos/#Licensed Drivers	0.014	0.082	0.016

Table 15

Aggregate Elasticities of the Probability of Choice
(n-dimensional Model)

Explanatory Measure	Park 'n Ride (90% conf. int.)	Auto (90% conf. int.)	Kiss 'n Ride (90% conf. int.)
Auto Time	2.16	-1.07	2.14
	(1.29, 3.03)	(-0.64, -1.50)	(1.28, 3.00)
Transit Time	-2.09	1.01	-2.14
	(-1.25, -2.93)	(0.60, 1.41)	(-1.28, -3.00)
Auto Cost	1.49	-0.73	1.47
	(1.03, 1.95)	(-0.50, -0.96)	(1.01, 1.93)
Transit Cost	-1.64	0.79	-1.64
	(-1.13, -2.15)	(0.55, 1.03)	(-1.13, -2.15)
#Auto/#Lic. Drivers	-0.52	1.22	-2.63
	(-0.38, -0.66)	(0.88, 1.56)	(-1.90, -3.36)

Comparison of Binary and Multimodal Choice Models

Both the binary and the n-dimensional choice models exhibited satisfactory statistical performance. The estimated coefficients in each model were all shown to be different from zero at the .05 level, with the exception of sex in the binary models. Similarly, both models had high chi-square values. The elasticity figures were comparable but the confidence intervals were wider for the n-dimensional model and the values of time for the n-dimensional model were 20% to 30% less than the corresponding values for the binary choice model.

Both models satisfied the expected sign test. However, the n-dimensional model failed to reproduce the data as well as did the binary choice model. While the binary choice model had negligible e_1 and reasonable e_2 values, the percentage of misplaced trips amounted to 16.1% in the n-dimensional case, which overestimated the park'n ride and underestimated the other modes. This fact suggests that the decision process shown in Figure 1, i.e., all available modes are simultaneously evaluated by the commuter at his zone of residence, might not be valid for the fringe parking situation. However, this should be considered as a tentative conclusion, since data limitations might have affected the performance of the multimodal choice model. Thus, the verification of the superiority of the binary choice models in the general case requires further study.

PLANNING APPLICATIONS

The models developed from the Parham Express data were examined for their transferability in predicting the usage of a similar service in another city. Data from the Princess Anne Plaza service in the Virginia Beach-Norfolk Area were used for this test. The set of zones comprising the potential market area for the Plaza Express is given by Figure 5. Analysis of the data revealed that all 23 of the zones produced a majority of the auto (73.8%) and express bus trips (89.2%) and, accordingly, the test data were restricted to the 23 zones underlined in Figure 5.

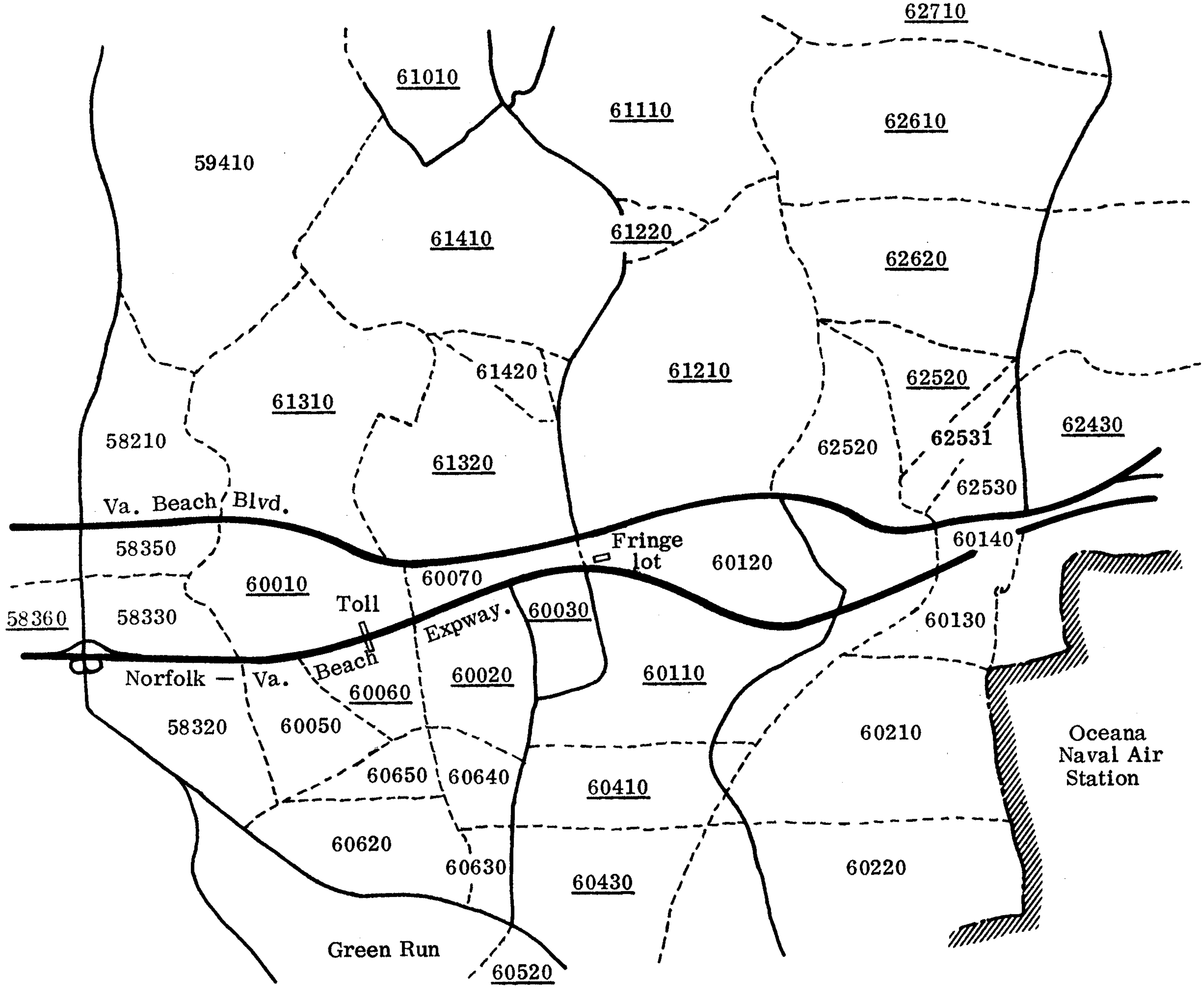
The primary assumption underlying the transferability of models from one study area to another is that both maintain similar land use activity and transportation systems. In this respect, a preliminary analysis of various aggregate descriptions of travel behavior and urban development is helpful in deciding when a model can be transferred from one area to another. A comparison of the market area and service characteristics of the Richmond and Virginia Beach services revealed the following differences.

1) 32.7% of the auto trips originating within the market area of the Parham Road Lot were destined to the CBD, while the same statistic was only 16.6% for the Virginia Beach area.

2) Average household income was about 25% higher in the Parham Road market area.[40]

3) The Virginia Beach service appears to be less satisfactory than the Parham Express relative to the frequency of service, (the express bus headways were 10 and 15 minutes in Richmond compared to 30 minutes in Virginia Beach) longer travel times, insecurity, and inconvenience at the lot and the downtown end of the trip.

4) Parking costs in the CBD are lower in Virginia Beach compared to Richmond. In Norfolk 75.9% of the downtown parkers pay less than 50 cents a day compared with 55.1% in Richmond.



Underlined numbers indicate zones included in the analysis.

Figure 5. Plaza Express potential market area.

Based on the above information and the Parham Road lot experience, the following three hypotheses regarding application of the Richmond model to the Princess Anne Plaza lot were tested.

1) The models calibrated with the Parham Express data will fail to reproduce Virginia Beach data within a reasonable accuracy due to different market area and service characteristics.

2) The value of travel time in Virginia Beach will be less than that of Richmond, since the average income is less.

3) The probability of choice will be biased in favor of the automobile mode in Virginia Beach such that even when the values of the system characteristics of the competing modes are equal, the probability of choosing the bus will be lower than for the Parham Express market area. Furthermore, the choice elasticities of automobile with respect to time and cost variables should be lower than in Richmond.

The first hypothesis was tested by applying the Parham Express binary relative values model (Table 6). Since only a small data base was available for the Plaza Express and trips could not be realistically stratified by accessibility levels, the Richmond model based on the entire data set was used. This model overstated the number of bus riders on the Plaza Express by 39.6%. Next, the Parham model for Accessibility Group 3 was applied because the data analysis revealed similar model split levels for this group of Richmond area tripmakers and commuters in Virginia Beach. The resulting prediction was an improvement over the first, but an error of 27.2% was reported. From these results it was concluded that models developed for the Parham market area could not be directly applied to market areas with different area characteristics and transport services.

Difference and relative values models were calibrated from the Virginia Beach data, wherein sex and age were found to be insignificant at the 0.05 level. The relative values model is shown in Table 16. Table 17 shows that the values of the coefficients of the variables in this model are considerably different from those of a similar model based on the Richmond data.

The second hypothesis stated that the value of travel time would be lower for the Virginia Beach commuters than for their counterparts in Richmond. The estimated values of travel time for the Virginia Beach sample were \$1.92/hr. and \$1.27/hr. for the time spent in auto and bus, respectively. These values were 28.6% and 39.5% less than the corresponding values of \$2.69 and \$2.10 for the Parham Express study area. These findings thus support the hypothesis that the value of time in the Plaza Express market area is less than that for the Parham Express area.

Table 16

Relative Values Model Calibrated with Virginia Beach Data

(Estimated Binary Choice Model Coefficients)

X_3	X_9	X_{10}	Const.	X^2	e_1	e_2
-3.2961	2.8514	2.0156	1.2444	15.85	0.12%	16.0%

Probability of choosing bus at equal system variables = 0.196

Note: These variables are as defined in Table 3.

Table 17

Comparison of Coefficients obtained from Richmond and Virginia Beach Models

Explanatory Variable	Richmond Model Accessibility Group 3	Virginia Beach Model
X_1	N.S.	N.S.
X_2	1.4834	N.S.
X_3	-4.7517	-3.2198
X_9	8.5377	2.9728
X_{10}	4.7783	1.9312
Const.	2.0465	1.1625

Note: These variables are as defined in Table 3.

For the Plaza Express the probability of choice of bus at the indifference level was estimated to be 0.196, much less than that of the Parham area model (0.451). This finding agrees with the stated hypothesis. The sensitivities and elasticities were estimated using previously described methodology, and are given in Tables 18 and 19, respectively. As hypothesized, the elasticities for automobile were much less than the values obtained for the Parham area, which supports the third hypothesis which stated that the bias in favor of the auto mode was considerably higher in Virginia Beach than in the Parham Express market area.

The preceding analysis indicates that a model based on a single lot in a given area is biased by a number of factors which influence the local travel behavior such as the income and population distributions, parking policy and availability at the CBD, the scheduled hours of service, the accessibility of the lot, and so forth. In order to provide a meaningful planning methodology for forecasting the usage of anticipated express bus-fringe parking services, locally biasing variables must be accounted for. Accordingly, comparisons must be made among similar models calibrated from projects in different urban areas to derive hypotheses concerning variability in choice behavior relative to area characteristics and local transportation policy. This strategy will also assist in showing the effect of lot size and location on usage. Ultimately it is envisioned that a planner should be able to select a specific model from an available set which was derived under circumstances similar to those of his study area.

Table 18

Sensitivity Analysis (Va. Beach Data)

	Change in Probability of Bus Choice Due to 10% Change* In
Auto Time	.032
Transit Time	-.033
Auto Cost	.023
Transit Cost	-.022
#Autos/#Licensed Drivers	-.035

* Keeping all other variables constant.

Table 19

Aggregate Elasticities of the Probability of Choice (Va. Beach Data)

Explanatory Variable	Transit	Auto
Auto Time	1.71	-0.39
Transit Time	-1.77	0.41
Auto Cost	1.23	-0.28
Transit Cost	-1.18	0.27
#Autos/#Licensed Drivers	-1.87	0.43

EXTENSIONS

The potential for widespread application of the technique developed in this research for planning new services is now addressed. It was shown earlier that for the methodology to be of practical value, it is necessary that models be transferable among subareas which show similar travel behavior. In this respect, it is assumed that a comprehensive set of models has been calibrated for a wide range of tripmakers, areas, and service characteristics. It is also assumed that a relationship which maps engineering measures of the service characteristics into perceived values is available. This is necessary since the models are developed with data relating the perceptions of tripmakers, whereas objective system measures must be used when planning new services. Finally it is assumed that the planner is concerned with a particular corridor and a set of feasible sites for developing the service.

The following analysis procedure is recommended for each potential site.

1) Define an approximate market area that will be served by the proposed service. A criterion based on the accessibility of the fringe parking lot from the zone of residence relative to the CBD is suggested. It can be assumed that the market area is made up of three hypothetical rings of residential zones. The first ring consists of those zones which are adjacent to the zone wherein the fringe lot is located. The second ring includes a set of zones whose minimum travel path to the CBD passes close to the lot and/or the travel time via the fringe lot to the CBD is reasonably close to the minimum direct travel time. For practical purposes, a third ring of residential zones can be assumed to include those zones which touch the first and/or the second rings but are not included in either category. The definition of such a market area, then, determines the boundaries of the study area.

2) Collect socioeconomic data and measures of the transportation system in the market area. The socioeconomic information needed includes the zonal sex and age distribution, automobile ownership, and the number of trips which terminate at the distination served by the transit service. Income data are also necessary for the value of time analysis, and for inter-area comparisons. The required transportation system data include the average cost and travel time per trip via each mode of transportation. Table 20 summarizes the data requirements and their potential sources.

A preliminary survey is suggested for the assessment of auto and transit captivity figures in the market area. A survey might also provide a better estimation of the number of zonal work trips terminating at the destination zone of the service than the census data. In a comprehensive transportation planning process a distribution model such as the gravity model can also furnish an estimate of trip end points.

3) Summary statistics of the data described above should be compared with those of the study areas for which models have been calibrated and an appropriate model selected. For example, if only the models calibrated for the two fringe parking-express bus situations discussed here (Parham Road and Princess Anne Plaza) were available, the former would be selected to represent a high income market area with a fringe parking lot located at a distance of 10 miles or less from the CBD and a planned frequency of service of 15 minutes or less. The model for the Princess Anne Plaza lot, on the other hand, could be applied to a situation where existing conditions are heavily biased in favor of the automobile. (For example, a fringe parking facility more than 10 miles from

the CBD with low parking rates, and located in an area where CBD work trip destinations comprise a relative small share of the areawide total.)

The elements of a generalized forecasting procedure for work trips originating at a given zone are summarized by Figure 6. Application of this methodology to each of a set of alternate lot sites will show which location optimizes patronage and/or best satisfies the planning objectives.

Table 20

Data Requirements for Evaluating Potential Lots

Data	Source
A. Socioeconomic	
1. No. of zonal work trips terminating at destination zone of service (e.g., no. of CBD work trips)	census survey or gravity model output
2. Estimates of captivity to either mode	preliminary survey
3. Zonal distribution of workers by sex	census or survey
4. Zonal distribution of workers by age	census or survey
5. Average zonal auto ratio; No. household autos/ No. licensed drivers	census or survey
B. Transportation System	
1. Average cost per trip via each alternative	network simulation
2. Average total travel time per trip via each alternative	network simulation
3. Zonal classification relative to lot accessibility (3 groups in Richmond model)	network simulation

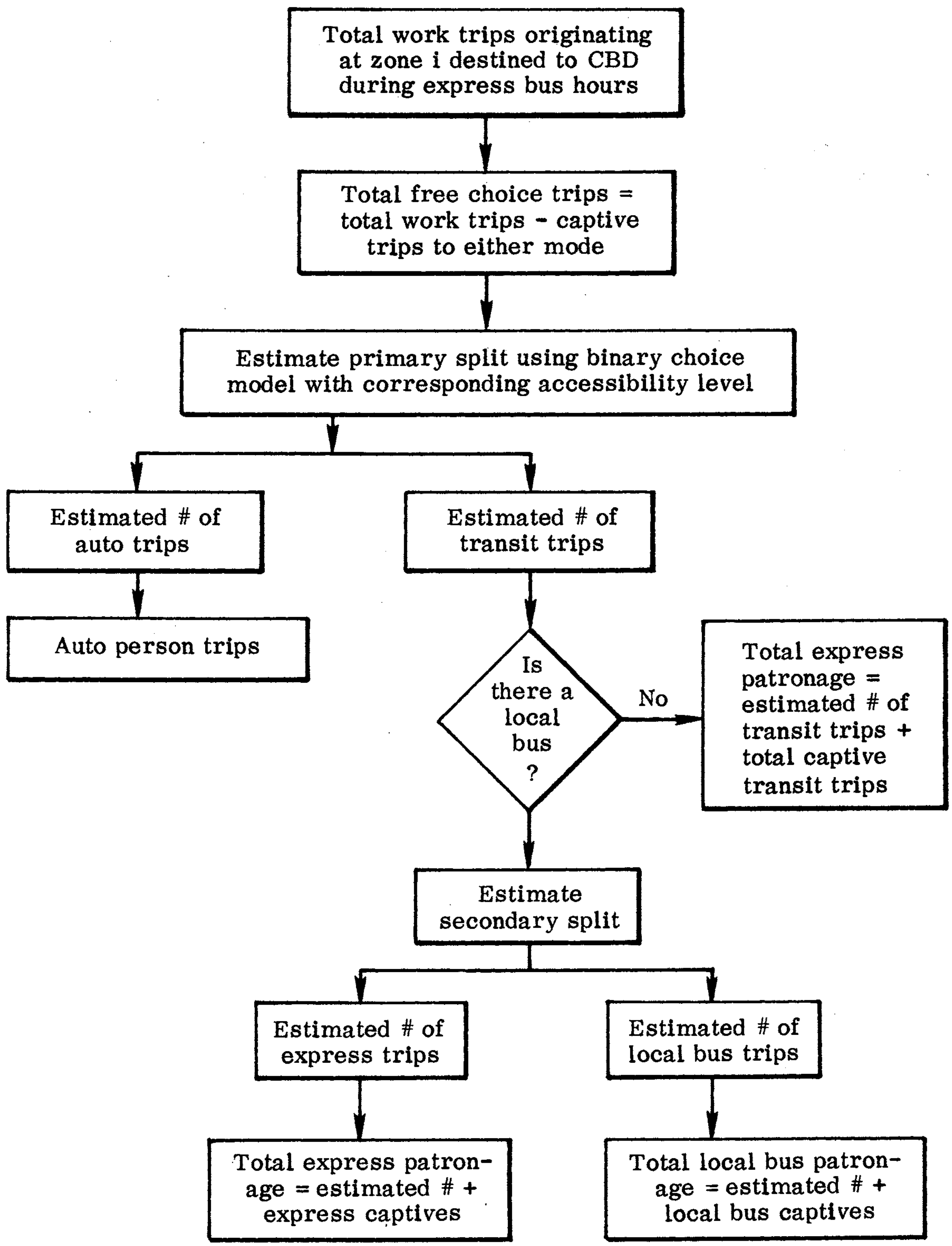


Figure 6. The forecasting procedure.

REFERENCES CITED

1. Algers, S., S. Hansen, and G. Tegner, "On the Evaluation of Comfort and Convenience in Urban Transportation — A Choice Analytic Approach". Proceedings, Transportation Research Forum, Vol. 15, No. 1, 1974, pp. 470-481.

2. Beesley, M. E., "The Value of Time Spent in Travelling: Some New Evidence," Economica, Vol. 32, 1965, pp. 174-185.

3. Beimborn, E. A., "Impedance Minimization Travel Choice Process," Transportation Engineering Journal of ASCE, Vol. 98, No. TE 2., 1972, pp. 177-190.

4. Berkson, J., "Why I Prefer Logits to Probits," Biometrics, Vol. 7, 1951, pp. 327-339.

5. ___________, "Application of the Logistic Function to Bio-Assay," Journal of American Statistical Association, Vol. 39, 1944, pp. 357-365.

6. ___________, "Maximum Likelihood and Minimum X^2 Estimates of the Logistic Function," Journal of American Statistical Association, Vol. 50, 1955, pp. 130-162.

7. Bock, F. C., Factors Influencing Modal Split Assignment, NCHRP Report. 57, 1968.

8. Boyce, D. E., Bruce Allen, Gene Desfor, and Richard Zoker, Impact of Access Distance and Parking Availability on Suburban Rapid Transit Station Choice, University of Pennsylvania, Philadelphia, Pennsylvania, November 1972.

9. Brand, D., "Travel Demand Forecasting: Some Foundations and a Review," Proceedings, Urban Travel Demand Forecasting Conference held at Williamsburg, Va., Dec. 3-7, 1972, pp. 239-282.

10. Charles River Associates, Inc., A Disaggregated Behavioral Model of Urban Travel Demand, Cambridge, Mass., March 1972.

11. Daly, A. J., "Research on Transport Demand Models," Proceedings, Transportation Research Forum, Vol. 15, No. 1, 1974, pp. 354-362.

12. De Neufville, R., and R. L. Keeney, "Multiattribute Preference Analysis for Transportation System Analysis," Transportation Research, Vol. 7, 1973, pp. 63-76.

13. ___________, and J. H. Stafford, System Analysis for Engineers and Managers (McGraw-Hill Book Co., 1971).

14. Demetsky, M. J., Analysis of Express Bus-Fringe Parking Operations, (VHRC 73-R23), Virginia Highway Research Council, Charlottesville, Virginia, November 1973, pp. 11-20.

15. Dobson, R., and G. C. Nicolaidis, "Preferences for Transit Service by Homogeneous Groups of Individuals," Proceedings, Transportation Research Forum, Vol. 15, No. 1, 1974, pp. 326-335.

16. Domencich, T. A., G. Kraft, and J. P. Valette, "Estimation of Urban Passenger Travel Behavior: An Economic Demand Model," Highway Research Record 238, 1968, pp. 64-78.

17. Edwards, W., "Theory of Decision Making," Psychology Bulletin, Vol. 51, No. 4, 1954, pp. 380-417.

18. Ergun, G., "Development of a Downtown Parking Model," Highway Research Record 369, 1971, pp. 118-134.

19. Fisher, R. A., "The Use of Multiple Measurements in Taxanomic Problems," Ann Eugen., London, 1936, Vol. 1.

20. Goldberger, A. S., Econometric Theory (John Wiley & Sons, Inc., 1964).

21. Hartgen, D. T., The Influence of Attitudinal and Situational Variables on Urban Mode Choice, Preliminary Report, PRR 41, New York State Department of Transportation, Albany, New York, March 1973.

22. Horton, F. E., "Behavioral Models in Transportation Planning," Transportation Engineering Journal of ASCE, Vol. 98, No. TE2., 1972, pp. 411-419.

23. Kavak, C. F., and M. J. Demetsky, Behavioral Modeling of Express Bus-Fringe Parking Decisions, a paper presented at the 54th Annual Meeting of the Transportation Research Board, January 1975. Also accepted for subsequent publication by the Transportation Research Board.

24. Kmenta, Jan, Elements of Econometrics (Macmillan Book Co., 1971).

25. Kutter, E., "A Model for Individual Travel Behavior," Urban Studies, Vol. 10, 1973, pp. 235-258.

26. Lancaster, K. J., "A New Approach to Consumer Theory," Journal of Political Economy, Vol. 74, 1966, pp. 132-157.

27. Le Boulanger, H., "Research into the Urban Traveller's Behavior," Transportation Research, Vol. 5, 1971, pp. 113-125.

28. Levinson, L. M., and M. C. Gersten, Transportation Attitude Survey for Modal Split Forecasting as a Part of Long-Range Transit Planning, a paper presented at the 53rd Annual Meeting of the Highway Research Board, January 1974.

29. Lovelock, C. H., Consumer Oriented Approaches to Marketing Urban Transit, Stanford University, Stanford, California, March 1973.

30. McGillivray, R. G., "Some Problems with Urban Transportation Planning Models," Traffic Quarterly, Vol. 26, No. 4, 1972, pp. 547-559.

31. McGillivray, R. G., "Binary Choice of Transport Mode in the San Francisco Bay Region," Econometrica, Vol. 40, No. 5, 1972, pp. 827-848.

32. ________________, "Mode Split and the Value of Travel Time," Transportation Research, Vol. 6, 1972, pp. 309-316.

33. Peat, Marwick, Mitchell and Co., Fringe Parking and Intermodal Passenger Transportation: Operational Experience in Five Cities, Washington, D. C., November 1971.

34. Quandt, R. E., and W. J. Baumol, "The Demand for Abstract Transport Modes: Theory and Measurements," Journal of Regional Science, Vol. 6, No. 2, 1966, pp. 13-26.

35. Rao, C. R., Advanced Statistical Methods in Biometric Research (John Wiley & Sons, 1952).

36. Stopher, P. R., and T. E. Lisco, "Modeling Travel Demand: A Disaggregate Behavioral Approach Issues and Application," Proceedings, Transportation Research Forum, Vol. 11, No. 1, 1970, pp. 195-214.

37. ____________, and A. H. Meyburg, "User and Non-User Perceptions of a Small Urban Area Bus System: An Exploratory Investigation," Proceedings, Transportation Research Forum, Vol. 14, No. 1, 1973, pp. 539-551.

38. Talvitie, Antti, "Aggregate Travel Demand Analysis with Disaggregate or Aggregate Travel Demand Models," Proceedings, Transportation Research Forum, Vol. 14, No. 1, 1973, pp. 583-603.

39. Theil, Henri, "The Information Approach to Demand Analysis," Econometrica, Vol. 33, No. 1, 1965, pp. 67-87.

40. Warner, S. L., "Multivariate Regression of Dummy Variates under Normality Assumptions," Journal of the American Statistical Association, Vol. 58, 1963, pp. 1054-63.

41. Watson, P. L., "Problems Associated with Time and Cost Data Used in Travel Choice Modeling and Valuation of Time," Highway Research Record 369, 1971, pp. 148-158.

42. ____________, and P. R. Stopher, "The Effect of Income on the Usage and Valuation of Transport Modes," Proceedings, Transportation Research Forum, Vol. 15, No. 1, 1974, pp. 460-469.

43. Weiner, Edward, "Modal Split Revisited," Traffic Quarterly, Vol. 23, No. 1, 1969, pp. 5-28.

44. Zellner, A., and T. H. Lee, "Joint Estimation of Relationships Involving Discrete Random Variables," Econometrica, Vol. 33, No. 2, 1965, pp. 382-394.

SELECTED REFERENCES

1. Deen, T. B., "A Study of Transit Fringe Parking Usage," Highway Research Record 130, 1966, pp. 1-19.

2. Abdus-Samad, U. R., and W. L. Grecco, Predicting Park 'n Ride Parking Demand, Purdue University, West Lafayette, Indiana, December 1972.

3. Hartgen, D., Forecasting Remote Park-and-Ride Transit Usage, (New York State Department of Transportation), Albany, New York, December 1972.

4. Tanner, G. H., and R. Barba, Park-and-Ride Transit Service: Some Guidelines and Considerations for Service Implementation, PRR 44, (New York State Department of Transportation), Albany, New York, April 1973.

5. Howe, J. J., "Modal Split of CBD Trips," C. A. T. S. Research News, Chicago Area Transportation Study, Vol. 2, No. 42, 1958.

6. Fertal, M. J., et al., Modal Split, Office of Planning, Bureau of Public Roads, U. S. Department of Commerce, Washington, D. C., 1966.

7. Alan M. Voorhees and Associates, Inc., Modal Split Model, Erie Area Transportation Study, (Staff Report No. 3), 1963.

8. Basmaciyan, H., and J. W. Schmidt, Development and Application of a Modal Split Model for the Puget Sound Region, Puget Sound Regional Transportation Study (Staff Report No. 12), Seattle, Washington, 1964.

9. Weiner, E., A Modal Split for Southeastern Wisconsin, Technical Record, Vol. II, No. 6, Southeastern Wisconsin Regional Planning Commission, 1966.

10. Keefer, L. E., "Predicting the Modal Split in Pittsburgh," Jour. Highway Div., ASCE, Vol. 89, No. HW1, 1963, pp. 13-25.

11. Reichman, S., and P. R. Stopher, "Disaggregate Stochastic Models of Travel-Mode Choice," Highway Research Record 369, 1971, pp. 91-103.

12. Quinby, H. D., "Traffic Distribution Forecasts — Highway and Transit," Traffic Engineering, Vol. 31, No. 5, 1961, 11. 22-29.

13. Deen, T., W. Mertz, N. Irwin, "Application of a Modal Split Model to Travel Estimates for the Washington Area," Highway Research Record 38, 1963, pp. 97-123.

14. Quarmy, D. A., "Choice of Travel Mode for the Journey to Work: Some Findings," Jour. of Transport Economics and Policy, Vol. 1, No. 3, 1967, pp. 273-314.

15. Pratt, R. H., "A Utilitarian Theory of Travel Mode Choice," Highway Research Record 322, 1970, pp. 40-53.

16. McGillivray, R. G., "Demand and Choice Models of Modal Split," Journal of Transport Economics and Policy, Vol. 4, No. 2, 1970, pp. 192-207.

17. Lisco, T. D., The Value of Commuter's Travel Time: A Study in Urban Transportation, Ph.D. Dissertation, Dep't of Economics, Univ. of Chicago, Chicago, Illinois, June 1967.

18. Stopher, P. R., "A Probability Model of Travel Mode Choice for the Work Journey," Highway Research Record 283, 1963, pp. 57-65.

19. Lave, C. A., "A Behavioral Approach to Modal Split Forecasting," Transportation Research, Vol. 5, 1971, pp. 113-125.

20. Thomas, T. C., and G. I. Thompson, "Value of Time Saved by Trip Purpose," Highway Research Record 369, 1971, pp. 104-115.

21. Warner, S. L., Stochastic Choice of Mode in Urban Travel: A Study in Binary Choice, (Northwestern University Press, 1962.)

22. Neter, J., and E. S. Maynes, "On the Appropriateness of the Correlation Coefficient with a 0,1 Dependent Variable," Journal of the American Statistical Association, Vol. 65, No. 330, 1970, pp. 501-509.

23. Watson, P. L., The Value of Time; Behavioral Models of Modal Choice, (Lexington Books, 1974).

24. Talvitie, A., "Comparison of Probabilistic Modal Choice Models: Estimation Methods and System Inputs," Highway Research Record 392, 1972, pp. 111-120.

25. Stopher, P. R., and J. O. Lavender, "Disaggregate Behavioral Travel Demand Models: Empirical Tests of Three Hypotheses," Proceedings, Transportation Research Forum, Vol. 11, No. 1, 1970, pp. 321-336.

26. Theil, H., "A Multinomial Extension of the Linear Logit Model," International Economic Review, Vol. 10, No. 3, 1969, pp. 251-259.

27. Demetsky, M. J., and L. A. Hoel, "Modal Demand: A User Perception Model," Transportation Research, Vol. 6, 1972, pp. 293-308.

28. Wigner, M. F., "Disaggregated Modal-Choice Models of Downtown Trips in the Chicago Region," Highway Research Record 446, 1973, pp. 49-65.

29. Rassam, P. R., R. H. Ellis, and J. C. Bennett, "The n-Dimensional Logit Model: Development and Application," Highway Research Record 369, 1971, pp. 135-147.

30. Peat, Marwick, Mitchell & Co., Implementation of the n-Dimensional Logit Model, Final Report, Washington, D. C., May 1972.

31. Inglis, P., "A Multinomial Logit Model of Modal Split for a Short Journey," Highway Research Record No. 446, 1973, pp. 12-20.

32. Pratt, R. H., T. B. Deen, Alan M. Voorhees and Associates, Inc., "Estimation of Sub-Modal Split Within the Transit Mode," Highway Research Record 205, 1967, pp. 20-30.

33. Schultz, G. W., and R. H. Pratt, "Estimating Multimode Transit Use in a Corridor Analysis," Highway Research Record 369, 1971, pp. 39-46.

34. Ben-Akiva, M. E., Structure of Passenger Travel Demand Models, Ph. D. Dissertion, Department of Civil Engineering, M.I.T., Cambridge, Massachusetts, 1973.

35. Finney, D. J., Probit Analysis (Third Edition, Cambridge University Press, 1971).

36. Tobin, J., Application of Multivariate Probit Analysis to Econometric Survey Data, Cowles Foundation Discussion Paper No. 1, 1955.

37. Henderson, J. M., and R. E. Quandt, Microeconomic Theory, (2nd Ed., McGraw-Hill Book Co., 1972).

38. Moses, L. N., and H. F. Williamson, "Value of Time, Choice of Mode, and the Subsidy Issue in Urban Transportation," Journal of Political Economy, Vol. 71, 1963, pp. 247-264.

39. 1970 Census of Population and Housing Census Tracts, Richmond, Va., Standard Metropolitan Statistical Area, U. S. Department of Commerce, Bureau of Census, 1972.

40. 1970 Census of Population and Housing Census Tracts, Norfolk-Portsmouth, Va., Standard Metropolitan Statistical Area, U. S. Department of Commerce, Bureau of Census, 1972.

APPENDIX I

THE LOGISTIC MODEL

The Binary Choice Model

Let $X_i = (X_{1i}, X_{2i}, \ldots X_{ni})$ be the ith observation vector of explanatory variables where X_{ki} specifies the kth attribute of observation i. Then, by Bayes Theorem the posterior probability that an observation came from the bus population (b), given the values of the ith observation vector, X_i, becomes:

$$P(b|X_i) = \frac{P(X_i|b)\ P(b)}{P(X_i|b)\ P(b) + P(X_i|a)\ P(a)} \tag{I-1}$$

where:

$P(b)$ = prior probability of bus choice

$P(a) = 1 - P(b)$, and

$P(X_i/m)$ = probability of observing the ith vector of explanatory variables, X_i, given that the observation came from mode m (m = a for auto, m = b for bus). If this expression is divided by $P(a/X_i)$ and the natural logarithm of both sides is taken, it becomes:

$$\ln \frac{P(b|X_i)}{P(a|X_i)} = \ln \frac{P(X_i|b)}{P(X_i|a)} + \ln \frac{P(b)}{P(a)} \tag{I-2}$$

The right hand side of equation I-1 has been shown to be a linear function of the observation vector in the multivariate normal case.[1] The model developed in this study employs discrete variables as well as continuous variables, and therefore the joint distribution of the explanatory variables is not multivariate normal. However, a linear functional form can still be assumed in this model where a maximum likelihood approach has to be used to estimate the unknown parameters. Under this assumption, Equation I-2 becomes:

$$\ln \frac{P(b|X_i)}{1 - P(b|X_i)} = G(X_i) \tag{I-3}$$

where $G(X_i)$ is the function which is linear in parameters to be estimated. Equation I-3 can be further simplified to obtain the well-known logit model for individual i:

$$P(b|X_i) = \frac{e^{G(X_i)}}{1 + e^{G(X_i)}} \tag{I-4}$$

For a group of people this equation can be written as:

$$P_b = \frac{e^{G(X)}}{1 + e^{G(X)}} \tag{I-5}$$

where P_b is the proportion choosing the bus and G(X) is the function of average characteristics of the group.

The graph of the logit model is S-shaped, which agrees with the common assumption made in behavioral models; i.e., the marginal utility of increments of a commodity, say time difference, is highest in regions where the difference between the two modes is close to zero, and conversely approaching zero in regions where the difference is substantial. The logit curve is shown in Figure I-1.

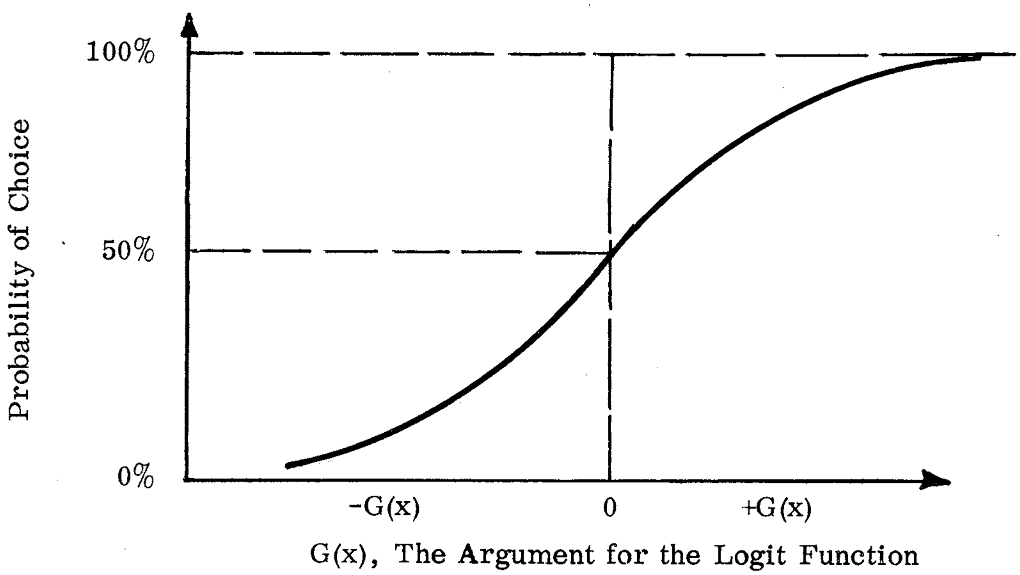


Figure I-1. Logit curve.

The Multimodal Choice Model

A natural extension of the binary logit model shown in Equation I-5 to a multimodal form is:

$$P_k = \frac{e^{G_k(X)}}{\sum_{i=1}^{M} e^{G_i(X)}} \tag{I-6}$$

where P_k is the probability of choosing mode k and $G_k(X)$ is a function of explanatory variables describing mode k which is linear in estimated parameters. The symbol M denotes the total number of modes in competition.

Equation I-6 is known as the n-dimensional logit model and has been developed to account for the limitations of the binary choice model.[2,3,4] However, the n-dimensional logit model, per se, is incomplete and violates two basic hypotheses pertaining to individual tripmakers.[5] The first of these concerns the property of independence from irrelevant alternatives which states that the ratio of the probability of choosing one mode to the probability of choosing another is independent of the total set of alternatives available.[6] The ratio of P_k/P_j reduces to $e^{G_k(X)}/e^{G_j(X)}$ and therefore depends only on variables that describe modes j and k. Consequently, the ratio will never be affected by an changes in the explanatory variables of other modes, which clearly violates rational behavior. Secondly, it can be shown that the inclusion of a new mode reduces the share of each mode by the same percentage.[5] This clearly contradicts behavioral theory[7,8] as noted by Amos Tversky.[9]

> ". . . it appears that the addition of an alternative to an offered set 'hurts' alternatives that are similar to the added alternative more than those that are dissimilar to it."

Therefore, in this context a new mode should compete most strongly with the mode that it most resembles and the use of an n-dimensional model should be restricted to distinct and/or dissimilar alternatives.

Some current research is concerned with the development of fully competitive choice models[5,10,11] which, in addition to conforming with the basic assumptions made in deriving models given in Equation I-6, satisfies the following condition that is essential in correcting the shortcomings of the n-dimensional logit models:

$$\frac{\partial}{D_{ti}} \left(\frac{p_k}{p_j}\right) \neq 0 \quad \text{for } i \neq j \text{ or } k \tag{I-7}$$

where D_{ti} denotes the tth attribute of mode i. McLynn[5,10] derived a general model starting from the n-dimensional logit model using a method similar to the variational technique. This model was related to P_k in Equation I-6 as follows:

$$Y_k = p_k\ (1 + Qu_k) \tag{I-8}$$

where Y_k is the modified probability of choosing mode k and Q is a constant such that $0 \leq Q \leq 1/3$. Furthermore, u_k is assumed to be a function of all explanatory variables, not just the variables used in describing mode k.

McLynn also found that for specific values of u_k, Equation I-8 conformed with the behavioral properties inherent in the assumptions previously made; i.e., independence from the irrelevant alternatives property does not hold and the introduction of a new mode does not reduce the share of the existing modes by the same proportion. This family of equations describing u_k were given as

$$u_k = p_k^{a-1} - \sum_{J=i}^{M} p_j^{a} \tag{I-9}$$

where a is a constant such that $a \geq 2$. The reader is referred to references (5, 10, and 11) for a more detailed description of the fully competitive models.

REFERENCES — APPENDIX I

1. Warner, S. L, Stochastic Choice of Mode in Urban Travel: A Study in Binary Choice, (Northwestern University Press, 1962)

2. Theil, H., "A Multinomial Extension of the Linear Logit Model," International Economic Review, Vol. 10, No. 3, 1969, pp. 251-259.

3. Rassam, P. R., R. H. Ellis, and J. C. Bennett, "The n-Dimensional Logit Model: Development and Application," Highway Research Record 369, 1971, pp. 135-147.

4. Inglis, P., "A Multinomial Logit Model of Modal Split for a Short Journey," Highway Research Record 446, 1973, pp 12-20.

5. McLynn, J. M., Fully Competitive Modal Choice Models, DTM, Inc., Bethesda, Maryland, August 1973.

6. Luce, R. D., Individual Choice Behavior, (John Wiley & Sons, Inc., 1959).

7. Becker, G. M., et al. , "Probabilities of Choices Among Very Similar Objects," Behavioral Science, Vol. 8, 1963, pp. 306-311.

8. Debreu, G., "Review of R. D. Luce, Individual Choice Behavior: A Theoretical Analysis," American Economic Review, Vol. 50, 1960, pp. 186-188.

9. Tversky, A., "Elimination by Aspects: A Theory of Choice," Psychological Review, Vol. 79, No. 4, 1972, pp. 281-299.

10. McLynn, J. M., Disaggregate Model Choice Models of Fully Competitive Types, DTM, Inc., Bethesda, Maryland, December, 1973.

11. McLynn, J. M., and K. M. Goodman, Modal Choice and the Shirley Highway Experiment, Final Report prepared for the National Bureau of Standards, Technical Analysis Division, November 1973.

3819

APPENDIX II

TEST CRITERIA

Measures used to evaluate the performance and reliability of both binary and multimodal choice models can be grouped into two categories. The first category relates to the structure of the models: compatibility of the models, probability of choice at one point of indifference, and statistical tests. The second category concerns the predictive power of the models, and the criteria based on the difference between the actual and predicted number of users.

Model Structure

Compatibility

The calibrated model should be compatible with the basic behavioral assumptions associated with disaggregate models of mode choice. This compatibility requires that the mathematical form of the variables entered in these models reflects the tripmakers' rationality, consistency, complete knowledge of alternatives and limited resources. Another important requirement is that the estimated parameters should have the expected signs. The sign of a parameter should be such that an increase in the time and/or cost of one mode, every other variable being kept constant, should result in an increase in the probability of choosing the alternate mode(s).

Probability of Choice at the Point of Indifference

Ideally, the binary logit curve should correspond to 50% probability of choice when the values of system characteristics of the competing modes are equal, since this is the point where the traveler should be indifferent to either mode. However, this figure is difficult to attain in situations where one mode is more compatible to the geographic area than the others. The express service, for instance, is not a viable alternative for the travelers who reside in zones that fall into Accessibility Group 3. The lot is out of way of their best route to the CBD, and therefore, the express is almost always considered to be an inferior mode, which creates a bias in favor of the automobile. Another difficulty arises due to the omission of some psychological variables, such as comfort and convenience, which are believed to play a major part in the decision making process of the travelers.[1, 2, 3]

Statistical Tests

The statistical tests used to evaluate the significance of the estimates are based on the distribution of maximum likelihood estimators when the sample size is large and approaching infinity. It has been shown that for a sufficiently large sample size the maximum likelihood estimators are normally distributed.[4] This property makes it possible to estimate the variance-covariance matrix of the sample and to perform the t test to evaluate the significance of each estimated parameter.

A second test is based on the property that minus twice the logarithm of a likelihood ratio has asymptotically a chi-square distribution. This property is used to test the hypothesis that all parameters except the constant are equal to zero against not all having zero values.[4]

Prediction Tests

A conventional way to test the predictive power of a model is to compare the expected number of users to the actual. The prediction error, e_1, is defined in percentages as

$$e_1 = \sum_{i=1}^{M} \left| \frac{\text{Actual no. - Expected no.}}{\text{Actual no.}} \right| \times 100 \qquad \text{(II-1)}$$

The expected number of express bus riders is estimated as follows: Let Z_i be a random variable indicating whether or not the ith person chose the express bus according to the following rule:

$$Z_i = \begin{cases} 1 \text{ if ith person chose the bus} \\ 0 \text{ otherwise} \end{cases}$$

Then, the expected value of Z_i becomes

$$E(Z_i) = 1.P_{bi} + 0 \cdot (1-P_{bi}) \qquad \text{(II-2)}$$

where P_{bi} denotes the probability of choosing the express bus for the ith individual and the expected number of express bus riders becomes

$$E(\sum_{i=1}^{N} Z_i) = \sum_{i=1}^{N} E(Z_i) = \sum_{i=1}^{N} P_{bi} \qquad \text{(II-3)}$$

In the case of the multimodal choice model the expected number of users of mode q can be obtained in a similar manner:

$$E_1 \text{ (number)} = \sum_{r=1}^{N} Y_{1r} \qquad \text{(II-4)}$$

Another relevant test used here is the methodology suggested by Watson,[5] which involves using one-half of the data to calibrate the model and the other half for the purpose of prediction. The prediction error, e_2, is defined similar to e_1.

REFERENCES — APPENDIX II

1. Hartgen, D. T., and G. H. Tanner, "Investigation of the Effect of Traveler Attitudes in a Model of Mode-Choice Behavior," Highway Research Record 369, 1971, pp. 1-14.

2. Golob, T. F., "Resource Paper on Attitudinal Models," Proceedings, Urban Travel Demand Forecasting Conference, Williamsburg, Va., December 3-7, 1972, pp. 130-145.

3. Sherret, A., and J. P. Wallace, "Resource Paper on Product Attributes," Proceedings, Urban Travel Demand Forecasting Conference, Williamsburg, Va., December 3-7, 1972, pp. 146-174.

4. Theil, H., Principles of Econometrics (John Wiley & Sons, Inc., 1971).

5. Watson, P. L., "Predictions of Intercity Mode Choice from Disaggregate Behavioral Stochastic Models," Highway Research Record 446, 1973, pp. 28-35.

3612