BEHAVIORAL MODELLING OF TRAVEL DEMAND - AN EMPIRICAL VERIFICATION OF UTILITY MAXIMIZATION APPROACHES IN THE CONTEXT OF AN INDIAN CITY, KANPUR

Sulur PALANISWAMY
Professor of Civil Engg.
Indian Inst. of Technology
Kanpur - India

Nair VALSALA
Research scholar
Indian Inst. of Technology
Kanpur - India

INTRODUCTION

Past research in India in the area of urban travel demand analysis focused on the application of aggregate models. The major criticism of such approaches is that they are least policy sensitive. Attempts are currently underway in behavioral modelling using individual observations, towards realistic analysis of the travel decisions. In this paper, an attempt is made to investigate individual travel choice in the context of a fast growing medium sized city whose transport system is dominated by nonmotorized vehicles. The emphasis is on the mode choice for both work and non-work travel. Models developed in this regard is based on certain assumptions about the regularity of the urban environment i.e. in urban economics, urban sociology and also in modal performance characteristics. In the Indian context, the situation is vastly different in the sense that unlike highly developed countries, population structure as well as traffic composition are highly heterogeneous. The difference between the rich and poor is very marked with a continuum in between.

Regarding the traffic composition, intermediate public transport and nonmotorized transport such as bicycle, cycle rikshaw and travel by foot dominate the transportation scene. Car owning group forms a very small percentage of the total population. The public transport system exists only in name. There is a filler in the form of IPT to partially meet the demand which otherwise need an efficient public transport system. Majority of the population are poor and they depend on nonmotorized personal modes for their daily commuting. Also on the other hand, scooters and car ownership are increasing at a fast rate resulting in frequent modal shifts.

Under these circumstances, it is very essential to know the individual travel decisions, and the factors which affect it for the identification and design of an economical infrastructure. Individual travel demand models play a significant role in answering some of the problems of the supply side management. They are useful in prediction of the actual choice, when faced with widely varying alternatives. Due to complexity of vehicle ownership and use pattern, identification of choice set for an individual is rather fuzzy, thus making the modelling process a complex task.

1.RANDOM UTILITY MODEL OF MODE CHOICE

Random utility models provide an appealing behavioral framework for modelling choice processes. These models which are based on the principle of utility maximization, assume that an individual's preferences among the available alternatives can be described with a utility function, and that the individual selects the alternative whose utility is greater than the utilities of all other alternatives.

Logit and probit models are familiar examples of discrete choice random utility models. Mathematically,

$$U_j = V(X_j,\beta) + \varepsilon_j(X_j,\beta) \qquad \ldots\ldots(1.1)$$

where,

U_j = utility of an alternative j

X_j = vector of observed attributes(individual + alternative)

β_j = vector of constant parameters

V = deterministic function

ε_j = random variable, whose mean is independent of X_j.

Based on the assumptions of the probability distribution of the random utility components, different models are obtained. The simplest assumption that leads to useful models is that the random variables are independent and identically distributed with Gumbel Type I extreme value distribution. Then the choice probabilities are related to the deterministic components of utility through the well known multinomial logit model(McFadden,1974):

$$P(j/X,\beta,C) = \exp[V(X_j,\beta)]/\sum_{j\in C}\exp[V(Xj,\beta)] \quad \ldots\ldots \quad (1.2)$$

If the error terms ε_i have a joint multivariate normal distribution with zero mean and an arbitrary variance-covariance matrix, multinomial probit model(MNP) results (Albright, Lerman and Manski,1978; Hausman and Wise,1978; Daganzo, Bouthelier and Sheffi,1977).

The work presented in the paper focuses on multinomial logit models(MNL) of mode choice. They are the only forms of random utility models that are widely used in practical policy analysis. In most of the earlier studies, the objective of the empirical effort was to illustrate the application of the theory. Hence, data base developed was very limited. Also the studies limited the modes available into two or three alternatives. Thus, models developed were mostly binary, in which private cars and transit are taken as the alternatives.

The current attempt, in the case study illustrated below, a variety of alternatives have been included. This was made possible by the availability of a large data base for a whole city context(Palaniswamy,1989). The case study along with empirical results and validation are presented in the sequel.

2.CASE STUDY

The information on travel data of Kanpur, a typical north Indian city, is used in this study. The data required for the analysis was taken from the home interview survey conducted by the Transportation Centre, Indian Institute of Technology, Kanpur (Palaniswamy,1989). Table1 shows the study area and its characteristics.

3.MODAL CHOICE ANALYSIS

Work trips as well as shopping trips are analyzed. As the population and traffic composition are highly heterogeneous, market segmentation has been carried out to identify homogeneous groups. Income, vehicle ownership and distance commuted are the variables considered for obtaining homogeneous groups. The groups identified are

Income groups : 1)Economically weaker section(EWS)
2)Low income group(LIG)
3)Middle income group(MIG)
4)High income group(HIG)

Vehicle ownership : No vehicles, cycle only, scooter only, car only and car and scooter.

Length of trip : Short distance and long distance trips.

Table 1. Study area and its characteristics.

Income levels	Distn. of Household income	Household Vehicle ownership		Modal Usage Distribution	
EWS (<Rs 1000)	47%	Car	4%	Walk	44%
				Cycle	20%
LIG (Rs 1000-2000)	33%	Scooter	26%	Rikshaw	15%
				Scooters	10%
MIG (Rs 2000-4000)	15%	Cycle	30%	Tempo	2%
				Car	1%
HIG (> Rs 4000)	5%	Nil	41%	Others	8%

Table 2. List of variables included in the models

Level of service variables	Notation	User Variables	Notation
Travel time(generic)	TT	Family income	FI
Travel cost(generic)	TC	Wage of traveller	I
Distance to boarding point	DS	Age of traveller	A
		Sex-dummy*	SD
		Frequency-dummy#	FD
		Number of cycles	NCY
		Number of scooters	NS
		Occupation-dummy+	OD
		Family size	FS

(* - '0' for male and '1' for female)
(# - '0' for daily trips and '1' for others)
(+ - '1' for business trips and '0' for others)

4. MODEL SPECIFICATION AND EMPIRICAL RESULTS

Once homogeneous groups were identified, choice set for each group is determined on the basis of the vehicle usage. The utility function specified for the model consists of (a)variables which reflect user characteristics (b)level of service variables.

The parameters, 'beta', are calculated by the maximum likelihood method. The estimates obtained in this way are consistent, and are the best possible. In the analysis, the deterministic component is assumed as a linear function of the parameter vector 'β'. The following section deals with the calibration results.

Table 3 consists of binary logit models of two types. Model 1 deals with the population who does not own any vehicle and Model 2 describes the behavior of the group who own both car and scooter. In the first model both work trips and shopping trips are dealt with, and the choice set for this category consists of two modes, walk and rickshaw. In model 2, both short and long haul results are shown. The t statistics of the parameters are shown in italics below the parameter values. ρ^2 statistic, whose equation is given below is also included in the tables.

$$\rho^2 = (1 - L^* / L^0), \quad \text{where} \qquad \ldots (1.3)$$

L^* is the value of the likelihood function at convergence.
L^0 is the value of the likelihood function at zero.

Fig 1.1 to 1.3 show the effect of travel cost and travel time difference of walk and rikshaw for the EWS, LIG and MIG respectively for short (<4 Km) work trips. It can be seen from these figures, that the probability reduces as the cost increases (refer Model 1(a)). From Fig 1.1, it can be observed that the probability of choosing rikshaw is very small compared with the other income groups. Walking is predominant irrespective of distance. In Fig 1.2 the pattern is closer to that of EWS, but the usage of rikshaw is slightly more. MIG on the other hand (Fig 1.3) prefer both modes equally. As the distance increases, there is a modal shift to rikshaw(probability 0.5-0.8).

Table 3. Binary Models

Var	ALT	MODEL: 1						MODEL: 2			
		ALT: 1)Walk 2)Rickshaw						ALT:1)Car 2)Scooter			
		Work trips (a)			Shopping trips (b)			Work trips			
								short		long	
		EWS	LIG	MIG	EWS	LIG	MIG	MIG	HIG	MIG	HIG
TT	1,2	-.08 *11.8*	-.11 *10.5*	-.07 *4.4*	-.18 *5.2*	-.16 *3.4*	-.12 *1.6*	-.09 *0.4*	-.43 *2.0*	-.72 *2.0*	-.56 *1.4*
TC	1,2	-.19 *4.4*	-.19 *3.2*	-.48 *2.9*	-.23 *1.1*	-.12 *0.8*	-1.0 *1.5*	-.64 *0.8*	-1.1 *1.8*	-1.4 *1.7*	-.88 *1.3*
I	1	+.64 *3.2*	+.94 *6.1*	+.59 *4.4*				+.32 *1.5*	+.07 *1.7*	+.56 *1.7*	+.01 *0.4*
SD	2	-.47 *1.9*	1.25 *1.3*	1.77 *4.0*	-.24 *0.7*	0.16 *0.4*	+1.2 *1.4*				
A	1 2#	-.01 *2.6*	-.01 *1.2*		.04 *0.3*	-.07 *0.6*	-.46 *1.6*	-.35 *1.7*	-.46 *4.0*	-.13 *0.5*	-.84 *4.6*
FD					-1.1 *1.5*	-1.9 *3.0*	-1.3 *1.1*				
FI	2				+.68 *1.0*	1.47 *2.5*	.23 *.35*				
NS	2							+1.2 *2.2*	+.49 *2.6*	+1.1 *1.3*	+.63 *2.3*
OD	1							-.06 *0.2*	+.72 *2.2*	-.69 *1.0*	-.09 *0.2*
CON ST1	1	3.43 *12.8*	3.86 *11.2*	1.62 *2.61*	4.2 *3.2*	6.44 *3.9*	1.88 *0.57*	-.42 *0.5*	-.78 *0.9*	-.27 *0.3*	-.59 *0.7*
ρ^2		0.64	0.59	0.41	0.58	0.31	0.37	0.20	0.21	0.24	0.22
L^*		-994	-510	-187	-87	-92	-28	-81	-132	-33	-76

\# For the model 2, variable age is included for the second alternative(scooter)

The effect of income, on the probability of rikshaw choice for the three groups are shown in Fig 1.5, which illustrates the well known behavior of travellers with respect to income.

The analysis of the shopping trips for the above group revealed that, both EWS and LIG prefer walk for shopping (refer Model 1(b)). Cost and travel time difference of

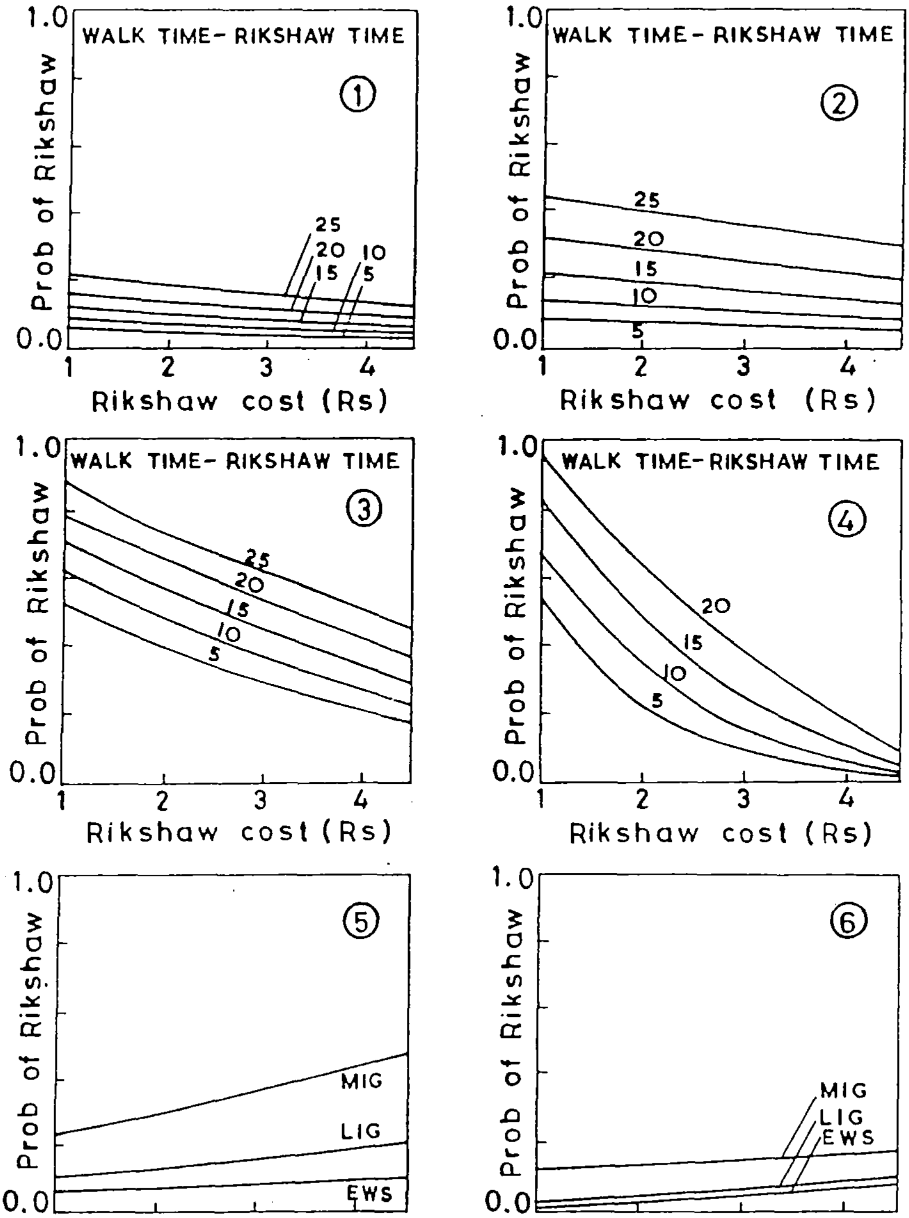
WALK TIME- RIKSHAW TIME
①
Prob of Rikshaw
Rikshaw cost (Rs)
25
20
15
10
5
WALK TIME- RIKSHAW TIME
②
WALK TIME- RIKSHAW TIME
③
WALK TIME-RIKSHAW TIME
④
⑤
MIG
LIG
EWS
⑥
Income (Rs)

Fig. 1

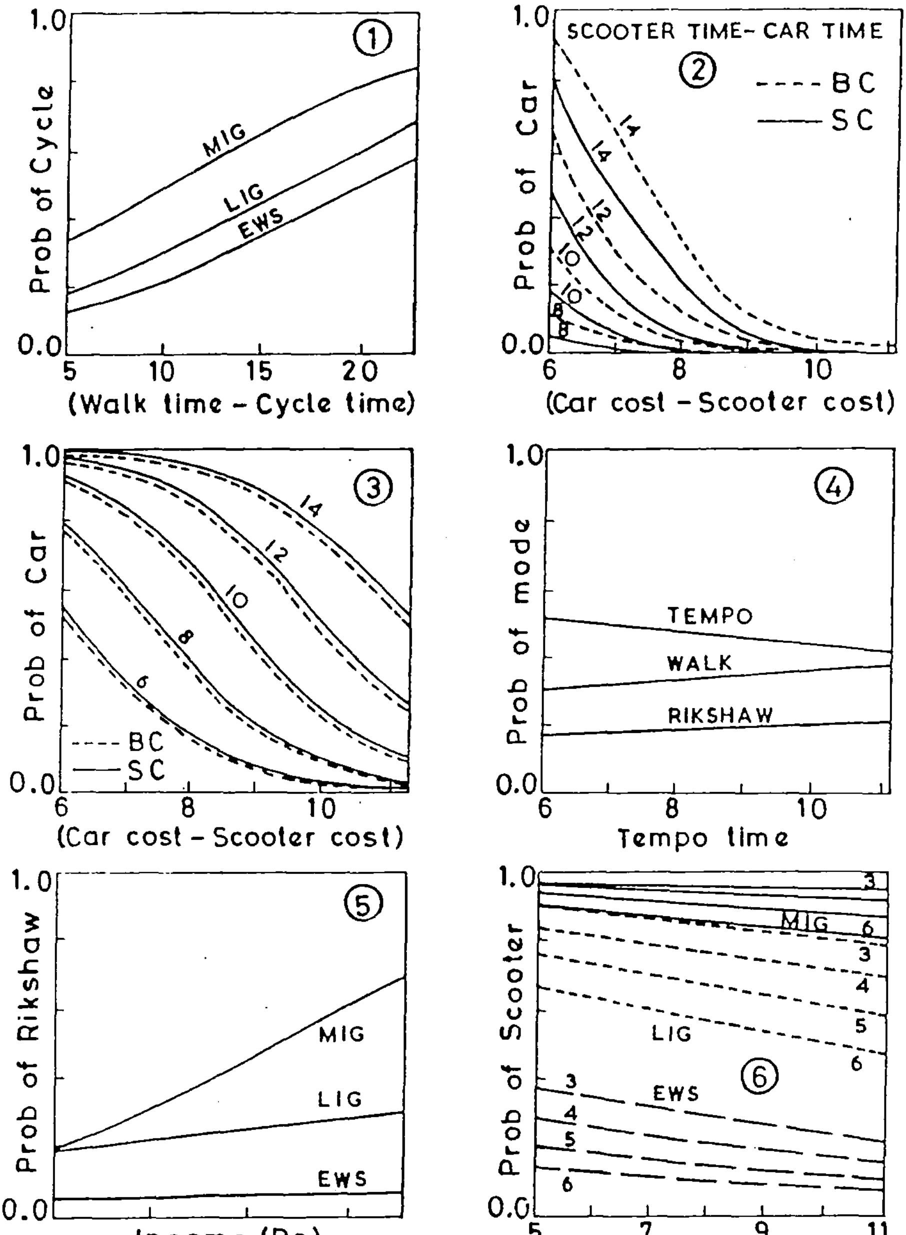
1.0
0.0
Prob of Cycle
MIG
LIG
EWS
5
10
15
20
(Walk time - Cycle time)
SCOOTER TIME- CAR TIME
BC
SC
Prob of Car
14
12
10
8
6
8
10
(Car cost - Scooter cost)
Prob of Car
14
12
10
8
6
BC
SC
6
8
10
(Car cost - Scooter cost)
Prob of mode
TEMPO
WALK
RIKSHAW
6
8
10
Tempo time
Prob of Rikshaw
MIG
LIG
EWS
Income (Rs)
Prob of Scooter
3
MIG
6
3
4
5
6
LIG
EWS
3
4
5
6
5
7
9
11
Scooter time

Fig. 2

walk and rikshaw on the probability of using rikshaw by the MIG are given in Fig 1.4. It is found that they are more sensitive to travel cost, for shopping trips than for work trips. Fig 1.6 shows the effect of household income on the usage of rikshaw. The travellers prefer walk irrespective of household income for short distance trips.

For the group who own both car and scooter (Model 2) the effect of time and cost difference between car and scooter on the probability of using car, for MIG and HIG are shown in Fig 2.2 and 2.3. MIG and HIG are further stratified into business(BC) and service(SC) classes. While HIG are least cost sensitive, there is a sudden shift from car to scooter for the MIG. Even if the travel time is more, usage of car is a necessity for the HIG, whereas MIG prefers scooter from affordability viewpoint.

Table 4 consists of three models. Model 3 explains the binary model developed for cycle owning group, whereas Model 4 describes the one developed for the population who does not own any vehicle, but the mode tempo, is available for commuting. The model becomes trinomial, as three alternatives are occuring in their choice set. Model 4 explains the behavior of scooter owning group, which also uses cycle and walk frequently, for commuting.

The effect of travel time difference of walk and bicycle on the probability of using cycle for EWS, LIG, and MIG (Model 3) are given in Fig 2.1. If the distance to work is less, then all the three groups prefer walking, and as the distance increases, they shift to bicycle.

Tempo is an intermediate public transport, which is available in certain corridors of the city. Fig 2.4 shows the change in probability of using walk, rikshaw and tempo as the tempo time increases for the LIG. As time increases probability of usage of tempo decreases, and that of walk and rikshaw increases, thus showing the interdependency of the choice of modes in the travel demand. Time and cost sensitivities of all the groups are given in Model 4. As the distance to tempo terminal increases, probability of using tempo decreases.

Table 4. Logit models

Var	ALT	MODEL: 3			ALT	MODEL: 4			ALT	MODEL: 5	
		1)Cycle 2)Walk Work trips				1)Walk 2)Rick- shaw 3)Tempo				1)Scooter 2)Walk 3)Cycle	
		EWS	LIG	MIG		EWS	LIG	MIG		LIG	MIG
TT	1,2	-.13 *20.9*	-.13 *21.8*	-.13 *16.1*	1,2 & 3	-.08 *7.8*	-.06 *7.3*	-.16 *6.2*	1,2 & 3	-.18 *14.9*	-.19 *8.7*
TC		----	----	----	2,3	-.09 *0.9*	-.35 *0.9*	-.49 *2.2*	1,2 & 3	-.68 *5.3*	-.96 *3.9*
I	1	+1.1 *5.1*	+.93 *11.0*	+.68 *5.9*	2	+.65 *0.7*	+.39 *1.2*	+1.2 *2.4*	1	1.50 *11.9*	0.88 *6.8*
SD	2	3.19 *7.1*	1.57 *5.7*	3.19 *4.5*	2	0.38 *0.6*	0.47 *0.5*	2.02 *1.9*	2	1.12 *1.8*	1.64 *3.1*
DS		----	----	----	3	-.59 *1.0*	-.09 *0.2*	-1.3 *1.1*			
FS									1	-.11 *3.9*	-.09 *2.6*
NS									1	0.90 *3.5*	1.32 *4.6*
NCY	1	+.79 *6.7*	+.79 *12.7*	+.78 *9.8*					3	0.91 *8.2*	0.66 *5.5*
CON ST1	1	-3.4 *18.8*	-3.9 *29.2*	-4.2 *17.4*	1	2.27 *3.4*	1.83 *2.4*	3.0 *3.4*	1	-1.13 *1.8*	-1.10 *1.6*
CON ST2					2	-.88 *1.2*	-.94 *1.2*	-1.4 *1.1*	2	2.82 *4.7*	-1.50 *2.3*
CON ST3					3	-1.4 *1.9*	-.88 *1.3*	-1.6 *1.5*	3	-1.68 *2.7*	2.60 *4.1*
ρ^2		0.28	0.31	0.34		0.47	0.27	0.41		0.44	0.33
L^*		-1990	-1901	-551		-219	-257	-41		-783	-367

Fig 2.6 shows the effect of time and cost on the probability of using scooter. When compared to HIG and MIG, usage of scooter is very less by the EWS. Middle income group mainly uses scooter, showing the other alternatives are not relevant for them(probability variation is negligible). They are the predominant scooter owning groups. The behavior of LIG resembles closely MIG.

5. STATISTICAL TESTS AND VALIDATION

The statistical test for the specification errors employed in this study is informal procedures which include checking signs, ratios, t-statistics of the estimated coefficients and computation of the ρ^2 statistics. Even though informal procedures can provide only rough indications of the quality of the model, they are the only diagnostic procedures that are carried out during model estimation. Tables 3 and 4 also give a list of statistics obtained for the above models.

A certain percentage of the data were kept as hold out sample for validation of the model, and the models discussed above are validated using that data. The statistics obtained during validation revealed that the estimated coefficients are quite satisfactory.

6. LIMITATIONS AND SCOPE

The major drawback of the MNL model is that it exhibits the property of 'independence from irrelevant alternatives' (Luce,1959). The model tends to overestimate the choice probability of correlated alternatives. The correlation among the utility functions cannot be captured, as the assumption is that the error terms are independent random variables. GEV models, probit models etc which overcomes this difficulty are being investigated using the above data and will be reported in the future.

7. CONCLUSION

A study of the above type is fundamental to the analysis of the impacts of a wide variety of changes in population characteristics and transportation services. A modest attempt which is presented in this paper establishes the efficacy of utility maximization approaches to the modal choice decision processes in a complex environment of multiplicities of modes and varied population groups. It will be worthwhile to use data from similar cities within India and other developing cities to validate the models for giving guidelines to policy makers of urban transport.

Also the work reported herein deals primarily with nonmotorized transport with the exception of a small percentage of car owners. The results of this study would be useful to the task of development of nonmotorized transport in cities of the developing countries.

BIBLIOGRAPHY

1. Albright R.L., Lerman S.R. and Manski C.E (1977) Report on the development of an estimation program for the multinomial probit model. Cambridge Systematics, Inc, Cambridge,Mass.

2. Adler T. and Ben-Akiva M.(1979) A theoretical and empirical model of trip chaining behavior. Transp.Res. 13B.,243-257.

3. Daganzo C.(1979) Multinomial Probit: The Theory and Its Application to Demand forecasting. Academic,New York.

4. Daganzo C., Bouthelier F. and Sheffi Y.(1977) Multinomial probit and qualitative choice:a computationally efficient algorithm. Transp.Sci.11,338-358.

5. Domencich T. and McFadden D.(1975) Urban Travel Demand. North-Holland,Amsterdam.

6. Horowitz J.L.(1982) Specification tests for probabilistic choice models. Trans.Res.16A,383-394.

7. Horowitz J.L.(1981) Identification and diagnosis of specification errors in the multinomial logit model. Transp.Res.15B,345-360.

8. Horowitz J.L.(1985)Travel and location behavior:State of the art and research opportunities. Transp.Res.19A, 441-453.

9. Palaniswamy S.P.(1989) Kanpur Metropolitan Area Transportation Modelling Study, Indian Institute of Technology, Kanpur.