DEVELOPMENT OF WORK-TRIP MODE CHOICE MODEL: ANALYZING THE EFFECT OF CONGESTION PRICING

AHMED NADER KURSHID

(2010 – NUST - MS PhD - Tn - 03)

A thesis submitted in the partial fulfillment of

the requirements for the degree of

MASTER OF SCIENCE

in

TRANSPORTATION ENGINEERING

NATIONAL INSTITUTE OF TRANSPORTATION (NIT)

SCHOOL OF CIVIL AND ENVIRONMENTAL ENGINEERING (SCEE)

NATIONAL UNIVERSITY OF SCIENCE AND TECHNOLOGY (NUST)

SECTOR H-12, ISLAMABAD, PAKISTAN

(2014)

Certified that the contents and form of thesis titled

"Development of Travel Mode Choice Model: Analyzing the Effect of Congestion pricing"

Submitted by **Ahmed Nader Khurshid** have been found satisfactory for the requirement of degree.

Supervisor: ___________________________

Dr. Muhammad Irfan, PhD
National Institute of Transportation (NIT)
School of Civil and Environmental Engineering (SCEE)
NUST, Islamabad

DEDICATED

TO

MY PARENTS, TEACHERS AND COLLEAGUES

ACKNOWLEDGEMENTS

I pay gratitude to Allah Almighty, who gave me strength and knowledge to complete this Thesis.

I am very grateful to my research supervisor, Dr. Muhammad Irfan for continues guidance, help and motivation at every stage of research. In addition, thanks to Dr. Asif Fiaz for providing text for this research and faculty of National Institute of Transportation (NIT) for corporation and help in completing research work.

I pay my earnest gratitude to my parents for their encouragement and support for completion of my MS.

DISCLAIMER

The contents of this article reflect the views of the authors who are responsible for the facts and the accuracy of the data and results presented herein. This is a technical article and does not constitute a standard or a regulation.

Abstract

Increase in automobile ownership in last decade has prompted congestion, delays and environmental pollution on urban road network. Though, infrastructure interventions have proved effective, but can potentially cause inefficient corridor progression due to improved infrastructure/ segment mobility triggering rapid accumulation of traffic at intersections/ bottlenecks. A comprehensive policy and planning is needed to overcome the urban congestion and meet future transportation demand with sustainable solutions taking due cognizance of the traveler's behavior/ mode choice. This research is designed to investigate and develop a travel behavioral model for work trip mode using revealed and stated choice data collected through a questionnaire survey. Different model specifications were tested to predict the demand for the competing modes in order to analyze the effect on the mode choice due to the change in attributes such as income, cost, and travel time. Multinomial Logit (MNL) model specification was found best suited to develop a disaggregated modal-split model, and build the traveler's perceived expectation utility functions. Direct and cross elasticities were computed and pricing variable was found invariably elastic for all the considered choice models. The developed model was also used to calculate value of time and demand response to the policies of improvement in transit/ Bus Rapid Transit (BRT) and implementation of congestion pricing on major arterials of an urban road network. It is concluded that improvement in transit services by introducing BRT alone, do not induce major change in share proportion of auto demand, however on the other hand, congestion pricing has significant effect on reduction of auto demand. Also, combination of two policies has induced more modal-split than congestion pricing alone do. This research highlights traffic congestion pricing as one of the means of traffic demand management by demonstrating its contribution to releasing the urban traffic congestion.

Table of Contents

List of Figures

List of Tables

Chapter 1

INTRODUCTION

1.1 Background

Increased travel demand and auto ownership in the recent decades has induced congestion on urban road network causing reduction in mobility and environmental degradation. Congestion leads to increased travel time and travel cost. Infrastructure intervention is effective in reducing congestion but it is not a long term solution for reducing congestion. Therefore it has become necessary to find other measure to improve transport infrastructure to meet the travel demand in future.

One of the main reasons of road infrastructure failure in mitigating travel demand is increased auto ownership and poor transit facilities. Improving transportation facilities by providing high capacity transit services can reduce congestion. Also restricting car users by implementing pricing system on major urban roads to derive them from car to transit services is effective solution. A very comprehensive policy is needed to implement these types of solutions. Before implementing any policy or planning for mitigating the urban transportation problems, it is necessary to understand the traveler’s behavior with respect to travel variables for economical and efficient transportation planning and decision making. Traveler’s decision towards mode choice is affected by mode characteristics like price, time and mode specific attributes.

In Rawalpindi, being the one of the populated economic center of Pakistan, transportation problems are very extensive. Delay and congestion problems are observed on its major arterials; Murree road, IJP road and Mall Road. Due to high population growth in this city, it is anticipated that in future the transportation problems will be worse. Government cannot afford building new infrastructure or expansion of existing infrastructure because of budget constraints. Alternative solutions are the improvement of the transit network and pricing but question is how to predict the effect of such policies on user attitude and demand? This can be done by developing a behavioral model.

Congestion on road occurs when traffic volume or model split generates a demand for space greater than the capacity of the road. In economics it is defined as “congestion occur when the quality of service of a facility depends on the intensity of use where quality for transportation has following aspects; expected travel time, expected arrival time, reliability and convenience of travel.” Congestion leads to inefficient use of roads as it leads to increased delay and higher travel cost. Each additional auto on the facility will increase congestion resulting in increased cost of travel known as marginal cost. The cost of travel includes increase fuel consumption, increased travel time than the perceived travel time of travelling and reduced comfort perceived by the user. Reducing travel time for work trips and goods transport will have higher impact on economic growth of the country. Congestion also cause higher fuel consumption and environmental pollution both noise and air. Reducing congestion by pricing and mass transit system will improve environment quality; reduce travel cost and travel time, and increase economic efficiency, the three components of sustainable transportation system.

Pricing is found to be effective solution in reduction of congestion in develop countries. Pricing the auto users equal to the additional (marginal) cost they imparts on the system. If congestion pricing is implemented the user who cannot afford additional cost of toll will either tend to move on other alternative routes or shift the mode from auto to transit. It has been observed that congestion pricing alone is not an efficient tool for reducing congestion, providing better alternative transit mode is also necessary. High occupancy vehicles saves fuel, protect environment, prevent congestion and improve quality of life. People are unsatisfied with transit services in our country. Congestion pricing has always faced people opposition and political constraints. It will only be successful if a good alternative mode is also available.

This research is carried to develop a behavioral model for work trip mode choice. This model will help in predicting the demand for the competing modes and effect on the mode demand due to change in attributes of other mode or its own attribute such as price, increase in travel time, etc. The model will also be used for analysis of two strategies for reducing congestion on road, which are; introduction of Bus Rapid Transit (BRT) as new improved mode of travel and congestion pricing (toll and parking fee).

1.2 Policies Justification as Optimum Solution to Congestion

Worldwide experiences shows that traffic congestion may actually can never be solved and strategy for developing, widening and building more roads to reduce congestion will be ineffective ultimately. Flyovers/ interchanges build to reduce congestion actually speeds up traffic to next bottleneck creating more problems and congestion. Infrastructure like these will always have negative impact on community environment and fails. Sustainable transportation infrastructures are the only ways for better, improved and cost effective solutions to congestion needs to improve road management and utilization by improving Transit operations and improve relative space for walking, cycling and communities to enjoy public space. Improving the quality of public transit can help to make changes in choices to travel thus reducing tendency to increasing car use. Efficient Transport systems like BRT can absorb demand to very high level and reduce congestion. Using road and congestion pricing to manage road use is also a mechanism to balance the use of road, while raising revenue to invest in public transportation. Road-user charging is a good option to raise funds for road upkeep and to support more sustainable and efficient travel modes such as public transport. Ultimately, traffic congestion can be regarded as incentive to motorist to switch to faster and more efficient public transport system. A chart in Figure 1.1 shows the benefit incurred by implementing pricing and improving transit services.

1.2.1 BRT

Bus Rapid Transit (BRT) has become increasingly popular as a mass transit mode as it addresses the full range of planning principles, which are:

a) Increased mobility

b) Cost effective

c) Environmentally friendly

d) Balance road use

e) Lower Space requirements

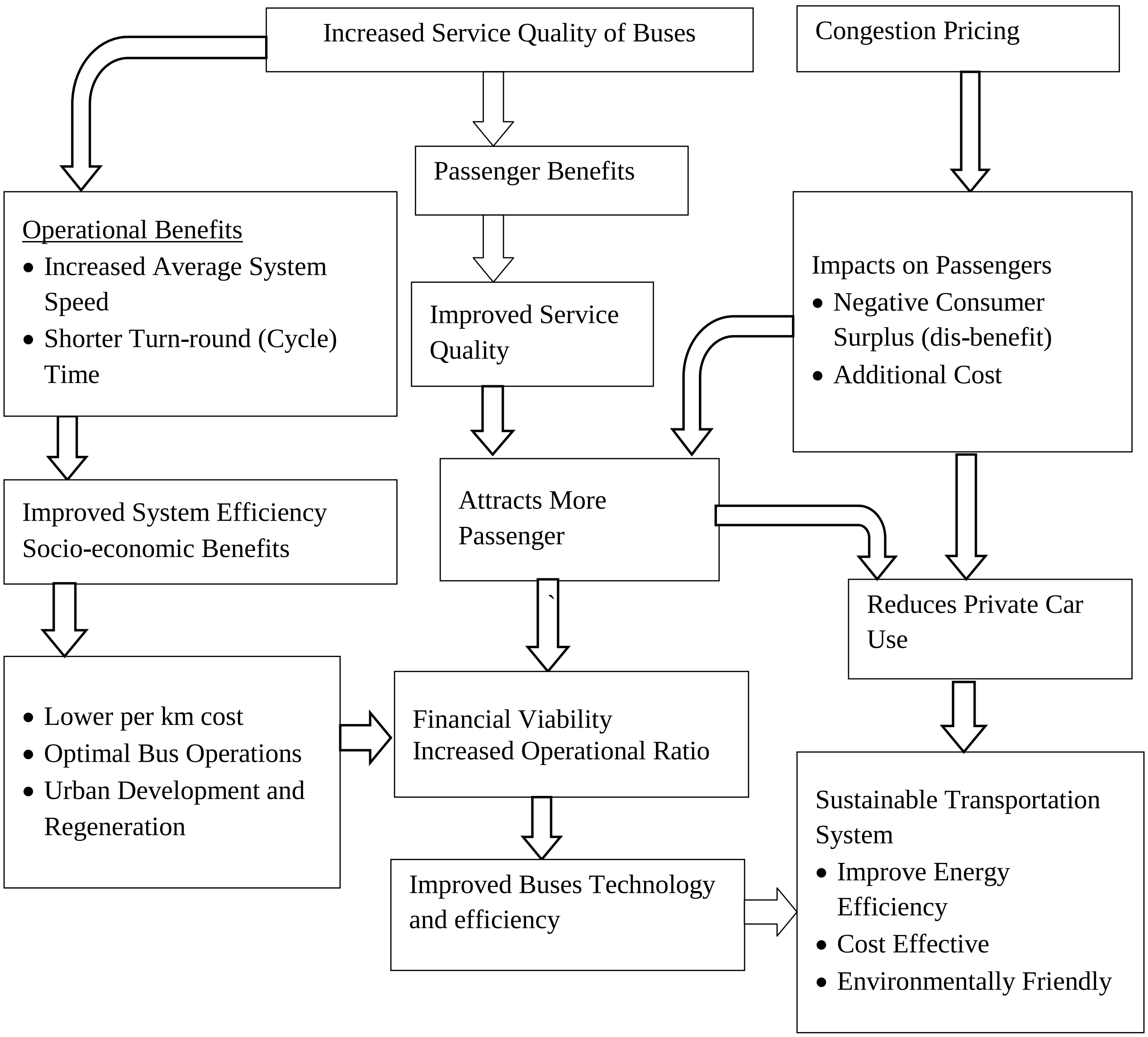


Figure 1.1 Benefits of congestion pricing and improved transit operations

BRT provides more efficient service than ordinary buses and mini-bus transit systems achieved through improvement of infrastructure, scheduling and comfortable vehicles. BRT is has exclusive right of way provided either by dedicated lanes on roads or grade separated infrastructure. BRT provides improved service quality with optimum cost and easy accessibility compared to rail transits. High accessibility is one of the main characteristics that make BRT more attractive compared to other high speed mass transit systems.

Figure 1.2 Bus Rapid Transit (Source: Wikipedia)

Trains, rapid transit, high speed rails and buses are the mass transit modes available in most of cities of developed countries. Construction of rail infrastructure within populated is very difficult and expensive. A relative cheaper and fast mode that can be easily introduced is Bus Rapid Transit. BRT has been successfully launched in Lahore. Existing transit mode “van” has poor service facilities and in the recent times a Bus Rapid Transit (BRT) project has been started in the city which will be completed by end of year 2014. The other project is being under consideration for Karachi BRTs, paperwork for which has been completed but the project has not been started yet. BRT has three supporting pillars as shown in Figure 1.3.

1.2.2 Congestion Pricing

Pricing is the method of penalizing auto users for creating congestion on roads which includes methods of road pricing and car parking charges. Charging auto users with extra cost equal to additional cost (known as Marginal cost) they impart on system will results in reduce demand for travel by auto and mode shift to public transit modes thus reducing congestion. Congestion Pricing is discussed in detail in chapter 2.

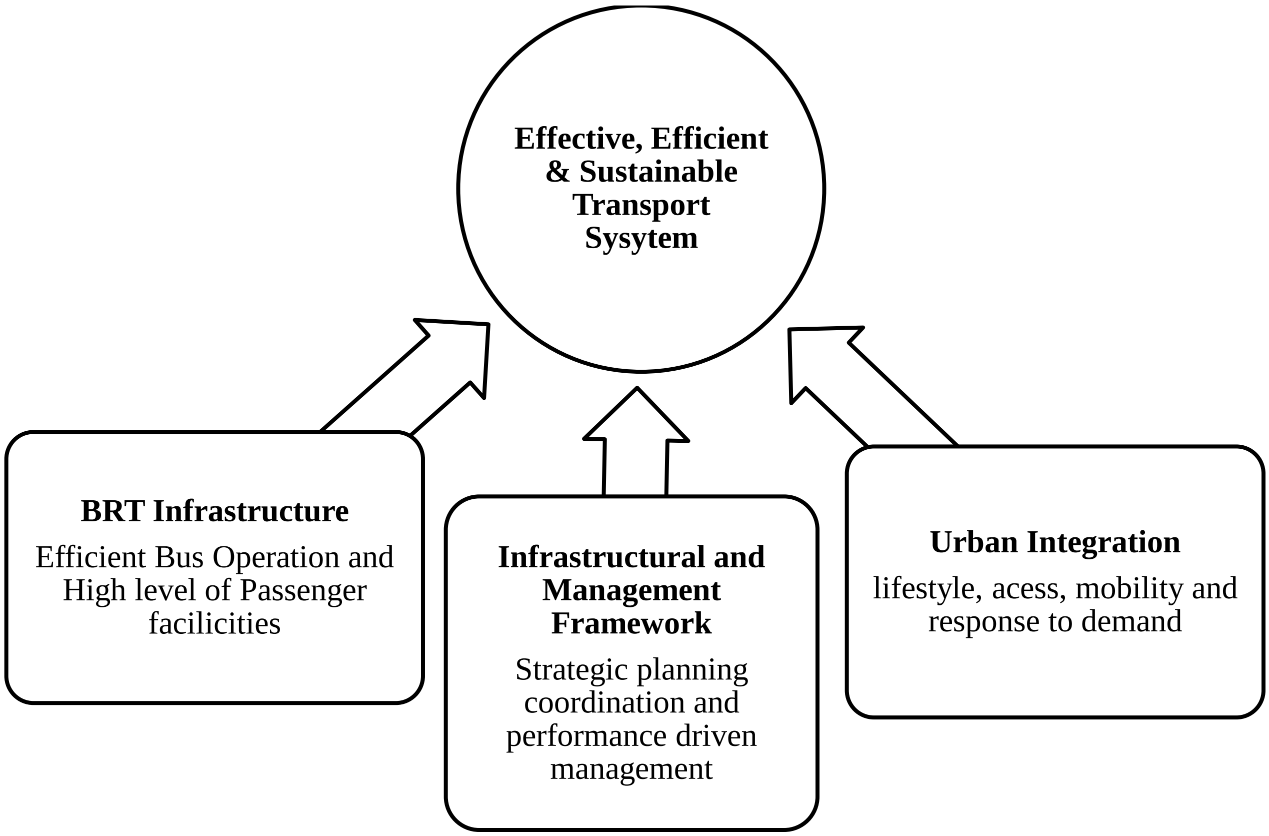


Figure 1.3 Bus Rapid Transit (BRT) supporting Pillars (Source: JICA Study Team)

1.2 Problem statement

Traffic situation in Rawalpindi city has become worse because increased travel demand has created congestion on major roads network. Extensive delay is experienced by the people on major arterials of the city like Murree Road, IJP road and Mall Road. Even on small roads traffic jams are observed due to extensive parking. Expansion of these roads is impossible because of budget limitations and political constraint. Recent improvement of road infrastructure has also proved inefficient in reduction of congestion. Transit improvement and pricing strategies should be devised to solve congestion problems.

1.3 Objective

The objectives of this study are:

1. To develop a mode choice model for work trips and determine the variables explaining mode choice.

2. To determine the demand elasticities (direct and cross) for modes.

3. To analyze the effect of pricing and new transit mode on auto demand.

4. To find the value of travel time.

1.4 Scope

The study will cover the analyzing the variables which affect modal choice behavior, development of modal choice behavioral model and estimation of mode demand direct and cross elasticities. Behavioral model will then be used for analyzing the congestion pricing (toll and parking fee) on auto demand and case of introducing new mode on modal split. The result of this research will made a platform for future research and planning of transportation infrastructure.

1.5 Thesis Organization

The two solutions to congestion problems described before that are: Improvement of transit facilities by introduction of new improved transit alternative (BRT) and pricing the car user to increase travel cost to force them to change travel mode, fall in the domain of mode choice problems a third component of transportation demand forecasting. Traveler has to choose among several available modes depending upon his socio-economic constraints like percent of his income that he can spent on travelling. How these constraints effects individual travel mode choice is described by travel mode choice behavioural models. A mode choice model is concerned about individual behavior regarding the selection of mode. The choice is decided based on individual’s trip type, cost, travel time, quality of service and comfort. Attributes of mode choice models can be divided into two components;

- Traveler's attributes which include income, trip purpose, age etc.
- Mode specific which are mainly time, cost and level of service

These models are based on utility maximization theory and are calibrated using utility function. Utility functions are the mathematical representation of degree of satisfaction that people derive from choices made. It is impossible to measure degree of satisfaction but the degree of dissatisfaction can be measured because these are the directly experienced by the users. A disutility function represents the generalized cost associated with choice such as cost and time, which is also deterministic part of utility functions. A traveler will choose the mode which seems to provide maximum utility. Based upon utility theory, various form of probabilistic choice models are used for estimating the likelihood that given mode will be chosen by individual. The most common of these choice models are logit models. A detail discussion of utility theory and mode choice model is provided in chapter 2.Using utility maximization theory it is possible to determine the impact of certain policies on car users for reduction congestion.

Data collection is very important in any study. In case of choice models, two types of data are used namely; revealed preference and stated preference. In both the data types, individual preference alternative data with available alternatives modes is collected. The only difference is the data source which in case of revealed preference is observed data of individual mode choice while for stated preference the data is collected through well-defined questionnaire with alternative attributes of time and cost are pre-defined and users is asked to select the mode which in his perspective is the most appropriate mode to travel conditional on his socio-economic characteristics such as income, age, etc. SP- data is well suited for studying the effect of new choices on demand which is not present in market. The individual characteristics data is also collected along with mode attributes data. Chapter 3 includes methodology of collecting data with description of SP & RP data types and their limitations. It also includes detail method of designing questionnaire for collection of SP-data.

Model estimation, analysis and results are given in chapter 4, which include defined model specifications and selected final model specification based on hypothesis tests, elasticities of choice variables, demand response analysis and value of travel time and. Conclusions are provided in chapter 5.

Chapter 2

LITERATURE REVIEW

2.1 General

In Planning of transportation in any context such as development of new facilities, introduction of new alternatives, implementation of pricing for congestion mitigation and all other projects related to transportation it is necessary to forecast the effect of such planning on users or own itself. For example, for planning a new transit service, it is necessary to forecast usage for a given pricing and operating schedules. How user will respond to pricing and service attributes such as time, frequency and cost; all these should be analyzed and predicted before implementation of such planning. In past, for planning in many metropolitan cities a four step process has been used for demand estimation which involves; 1) trip generation 2) trip distribution 3) mode choice and 4) traffic assignment. Now researchers are trying to find out new dimension for demand modeling such as job location, number of cars in household, time of day of travel, etc. Mode choice models are just the specific choice of demand model in which people faces discrete choices and they have to select one from which they get maximum satisfaction.

Within the context of mode choice models, the consider policies (introduction of BRT as new mode and congestion pricing) for mitigating congestion can be studied using stated preference approach. Many studies has been carried out in past related to modes and goods which are either present or not present in market for cases where it is needed to ascertain the effect of changes in certain attribute of mode or when new one is introduced in the market. Demand for traveling is analogous to the demands of goods in general economic theory and is dependent on individual income, price and other variables which in case of mode choice problems are time of travel, comfort, etc. Stubbs et al.(1980) describes the factors effecting choice of travel mode are; purpose of the trip, the distance traveled and income of traveler. The perceived changes related to present modes and attributes of the new mode are presented to the traveler in terms of hypothetically created experiments and asked to choose the alternative which is most appropriate for him within his budget constraints. All discrete modeling nowadays has approach to find willingness to pay to reduce travel time for which consumer behavior towards maximizing the utility function should be studied.

In general congestion pricing effects are studied under Dynamic flow models for highway demand, which can only be calibrated if pricing has been present in transportation infrastructure. Using choice models very few studies related congestion pricing are found in literature. Wangtu et al. (2008) studied the pricing effect on mode choice using SP data. He showed that the pricing has changed the proportion of modes considerably. Espino et al (2007) incorporated the pricing variables of parking costs in his study forming Multinomial Logit Model for analyzing suburban demand. In his study, he has showed that policies related to penalizing car users are more effective in reducing demand for cars than improvement in transit services. Chandra et al (2002) in his research studied the effects of congestion pricing showed that pricing has significant effect on reducing demand for cars with one passenger (drive alone). Brownstone et al (2003) studied willingness to pay to reduce travel time in the context of congestion pricing using Mode choice modeling. Other studies about the effects of congestion pricing reveal that pricing has reduced the congestion related problems quite significantly (Elaisson. J. at el, 2006, Schaller. B. 2010, and Litman, T. 2006). Kottenhoff et al. (2009) concluded the successful implementation of pricing needs contribution of improved transit modes. Congestion pricing induce more modal split than transit subsidies (Basso et al. 2011) but these have negative impact on consumer surplus. He also concluded that congestion pricing alone cannot be efficient, transit subsidies should also be increased. The later solution does not induce large changes as travel time, costs, frequency remains same in mixed traffic, dedicated lanes for transit system will do because attractiveness increases as travel time and other negative parameters are reduced. Acceptability dimension of congestion pricing is very complicated. Congestion pricing is not easily accepted by the public but after its implementation it has been concluded majority of public has supported it (Schuitema, G. at el. 2010: Odeck at el. 2002: and Tretvik, 2003). This is because public after being convinced by the positive effects of pricing implementation is now supports it.

Initially it was very difficult to analyze the impact of new modes on market demand but with improvement in data collection techniques it has become possible. Hensher and Louverie (1993) used Logit model with stated preference approach to study the effect of changes in ticket pricing on demand for travel through air. Yoo (1995) studied the flight choice for international travel using SP and RP data analysis of flights journey longer than 10 hours. Park et al (2006) studied the impact of newly introduced Korean Train Express on air demand using stated preference data. Philip Bly (2006) used stated preference technique to estimate demand for

Personal Rapid Transit (PRT) in London. Hensher and Bradley (1993) used stated preference data combined with Revealed Preference to model the demand for new alternative High Speed Rail in Australia.

2.2 Disaggregate Demand Model

Disaggregate travel demand modeling is made possible by individual decision making units; this approach explains directly the behavior at the level of person or household. Disaggregate models are based on microeconomic theory of demand and well explained the behavior of an individual in decision making among several alternatives. These models are also called discrete choice models.

For understanding the individual decision making process let use explain a hypothetical example. Suppose that a person has four choices of mode to complete his trip for work or studying; each mode is characterized by cost and travel time. Mode 1 is fastest but most expensive and mode 4 is cheaper but slowest. If an individual is observed to choose alternative 2, and nothing else matter, it means that he or she is not willing to pay extra amount C_1- C_2 to save t_2-t_1 time units. On the other hand, such choice implies a willing to pay of C_2-C_3 cost to save t_3-t_2 time units. For short, that person "values" travel time more than (C_2-C_3)/ (t_3-t_2) but less than (C_1-C_2)/(t_2-t_1).

In the above situation an individual is trying to maximize the utility that can be interpreted as the utility function values positively time Γ_i-t_i and available money I-$C_{i,}$ where Γ_i is the time under consideration and I is the personal income. In this way, by choosing among the alternatives individual is trading time with purchasing power. Consider a linear function which maximize the utility as shown in figure, $\alpha(\tau - t_i) + \beta(I - C_i)$ is equivalent to minimizing the time and cost as $\alpha t_i + \beta C_i$. The slope α / β, where fall in range of utility function of Figure 2.1 will represents the chosen alternative for the individual. Choices between fast and most expensive and slow but cheap modes are usual occurrence, example of which is daily work trip from home to office can have two alternative: scheduled city transport buses or van, private car or taxi, listed from cheapest to most expensive.

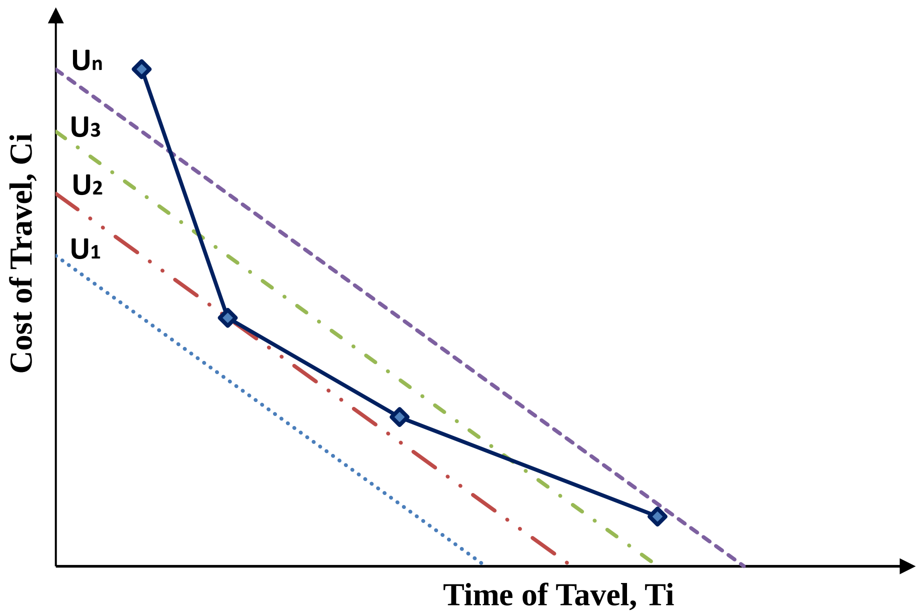


Figure 2.1 Mode choice by utility maximization (Transport Economic Theory book)

Discrete choice models are mathematical form of choice process in which individual chooses among several alternatives one alternative that will maximize the utility based on characteristics of the alternative, incorporating idiosyncrasies effects which are unobservable part of utility functions. The alternative specific utility function is represented as linear combination of cost, time and other characteristics of each alternative, also including socioeconomic variables of groups of individual. This constitutes the deterministic part of utility function to which random term is added representing idiosyncrasies effects. It is the probabilistic properties of random term which became the basis for discrete choice models.

2.2.1 Formulation of Model

Disaggregate demand model are based on utility maximization theory.The theory postulates that an individual chooses an alternative among several alternative that maximizes his utility. If an individual “n” has available alternative for transport mode j= 1,2,3…..J, he will choose the alternative which will maximize his utility given by

$$U_{jn} = V\left(Z_{jn}, S_n, \beta\right) + \varepsilon_{jn} \tag{2.1}$$

V(.) is function, known as systematic utility (deterministic part of utility function), z_{jn} are the attributes of modes experienced/ percept by the individual, s_n represents characteristics of an individual, β is the coefficient of attributes and ε_{jn} are the unobservable component of the utility function captures the idiosyncratic preference of the individual. U_{jn} and V are also known as conditional indirect utility functions, since they are conditional on choice j, depend on income and prices, and thus incorporate budget constraints.

The choice that individual will make is probabilistic because measured variables do not include everything relevant to individual decision making. This fact is represented by random error term in utility function. Once a functional form of V is specified, the model become complete by specifying the cumulative distribution function (cdf) for the random terms, $F(\varepsilon_{ji} + \varepsilon_{j2, \ldots\ldots,} \varepsilon_{jn})$. Denoting deterministic part of utility function as $V_{jn,}$ the choice probability for alternative i is then

$$P_{in} = \Pr(U_{in} > U_{jn}) \text{ for all } i \neq j \tag{2.2}$$

$$= \Pr(\varepsilon_{jn} - \varepsilon_{in} < V_{in} - V_{jn}) \text{ for all } j \neq k$$

$$= \int_{-\infty}^{+\infty} F_i(V_{1n} - V_{jn} + \varepsilon_{1n, \ldots,} V_{in} - V_{jn} + \varepsilon_{in}) d\varepsilon_{in}$$

This is the equation which is the basis for all discrete choice models in practice.

2.2.2 Multinomial Logit Model

The multinomial logit model arises when the random terms are identically and independently distributed (iid) with extreme value distribution, also known as weibull distribution. This distribution is defined as (McFadden, 1974).

$$\Pr(\varepsilon_{jn} < x) = \exp(-\exp(-\mu x)), x \in (-\infty, +\infty) \tag{2.3}$$

Assume that our distribution follows the Weibull distribution (Figure 2.2) with scale factor μ=1, the probability that individual n chooses alternative i from his choice set S_n can be written as (McFadden, 1984)

$$P_{jn} = \frac{\exp(V_{jn})}{\sum_{j=1}^{J}\exp(V_{jn})}, j \in S_n \tag{2.4}$$

Multinomial logit model has a property of Independence from irrelevant alternatives (also called **IIA** property); which means that the ratios of probability of two modes (P_{in}/P_{jn}) are independent of utility of other “irrelevant” modes. In other ways the change in utility of other modes will affect the utility of modes in consideration by same proportion. It also mean that the cross elasticities for the given mode k, the cross elasticities for all modes $j \neq k$ will be identical, mean if attractiveness of j is increased, the probabilities of all other alternatives will be decreased by identical percentages.

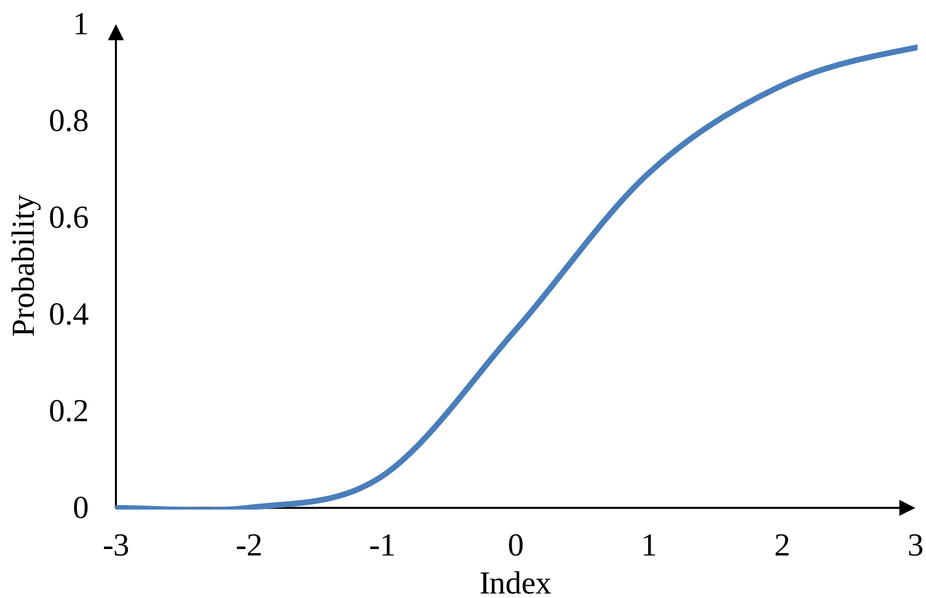


Figure 2.2 Cumulative probability distribution

a) Estimation of Model

Statistical tests are carried out to check whether the model specification (functional form and assumed error distribution) and parameter estimates from choice data are valid or not. Parameters are estimated by maximizing the log-likelihood functions defined as

$$L(\beta) = \sum_{n=1}^{N}\sum_{i=1}^{J} Y_{in} log P_{in}(\beta) \tag{2.5}$$

Where N is the sample size, Y_{in} is the choice variable, defined as 1 if individual n chooses alternative i and zero otherwise. $P_{in}(\beta)$ is the choice probability. Likelihood function is a function of the parameters of a statistical model. The likelihood of a set of parameter values, θ, given outcomes x, is equal to the probability of those observed outcomes given those parameter values. The values of these parameters that maximize the sample likelihood are known as the Maximum Likelihood Estimates or MLE's. Maximum likelihood estimation is a totally analytic maximization procedure. Maximum Log-likelihood estimated at mean of estimated parameters is used to check following:

- Assessing the significance of individual parameters
- Evaluating overall significance of the model
- Examining the transferability of results over space and time

The test is called "**likelihood ratio test**" and its statistic is given as

$$L^* = \frac{L(\beta_R)}{L(\beta_U)} \qquad (2.6)$$

Where $L(\beta_R)$the log-likelihood at convergence of restricted model and $L(\beta_U)$is the log-likelihood at convergence of unrestricted model. The restricted model means that all the parameters in the utility function are set to zero (Null Hypothesis that all parameters are zero). It also means that the probability P_i of an individual choosing an alternative *i* in independent of the values in MNL function. -2Ln (L*) is approximately Chi-Squared distribution if Null Hypothesis is true. Using this phenomenon, significance of parameters estimated can be check. One is needed to calculate value of $X^2 = -2[L(\beta_R) - L(\beta_U)]$and then compared it with the standard chi squared distribution against the critical value for 95% of the significance level. If value exceeds the critical value null hypothesis that parameters of the utility function are zero will be rejected. This statistic is chi-squared distribution with degrees of freedom equal to difference in the number of parameters between restricted and unrestricted model.

Parameters of the utility function can also be evaluated by using MLE, but that is only possible for large samples. The software output produces the asymptotic standard errors and t-stats of the parameters. The ratio of the mean parameter to standard error should not exceed 1.96 (95% confidence level). However, in practice, ratio as low as 1.6 is also accepted to stretch the usefulness of mean estimate. The parameters with small standard errors are sought out by researchers so that individual parameter influence in explaining relative utility can be represented well. There are many reasons for parameter to be insignificant, such as: presence of outlier in sample; normality assumption is violated; the way the individual ascertain about the hypothetical choice presented and parameter is not truly representing the utility.

Log likelihood test can also be used for comparison of models. For example, models with linear specification and model with nonlinear specification in which variables explaining utility function are interacted with each other. The other case may be the comparing the model with generic variables only with model in which alternative-specific variables are included. The test is same but little difference in that the restricted model will be one in which only generic variables are explaining the utility.

The other test is the measure of overall model fitness is McFadden's ρ^2(also known as Pseudo R^2)similar to R^2 used in regression analysis. Basis for this test is that if the explanatory power of the utility parameters is higher, $L(\beta_U)$ will be very large in comparison $L(\beta_R)$ of restricted mode. This test is defined as

$$\rho^2 = 1 - \frac{L(\beta_U)}{L(\beta_R)} \tag{2.7}$$

Where $L(\beta_U)$ and$L(\beta_R)$are same as explained before. The value of ρ^2 should be between zero and one and rises as variables are added to the model; if close to one, the statistic suggests that the model is predicting the outcomes with near certainty. Values of ρ^2 between 0.2 and 0.4 are considered to be indicative of good model fits.

b) IIA Property Test

Multinomial logit is based on the assumption that the disturbances are independent and homoscedastic, which means that the odd ratios of probabilities between two alternatives remain constant. Which may not be the case in real world? For example, a city having two modes of travel, a bus and an automobile, if third another transit mode of characteristics same as the bus is introduced will have more effect on the bus than on automobile. IIA property becomes invalid for such a situation. A theoretical test has been developed to test IIA property, called as Hauman's specification test. Hausman and McFadden (1984) suggest that if a subset of a choice is truly independent and irrelevant, than, omitting it from the model altogether will not change the parameter estimates systematically. But if the remaining odd ratios are not truly independent from these alternatives, then the parameter estimates obtained when these choices are excluded will be inconsistent. Hausman Statistics is:

$$\chi^2 = (\beta_s - \beta_f)'(V_s - V_f)(\beta_s - \beta_f) \tag{2.8}$$

Where s indicates the estimators based in restricted subset, f indicates the estimators based on full set of choices, and V_s and V_f are the respective estimates of the asymptotic covariance of matrices. The statistic has a limiting chi-squared distribution with K degrees of freedom.

2.2.3 Nested Logit Model

If IIA property is violated, then, model has been developed to relax the assumption that disturbances are independent and homoscedastic called as Nested Logit Model, first developed by Ben-Akiva (1974). In Nested Logit model, choices with same characteristics are group together in one nest. For example, a city having three mode choices: car, bus and train. The Nested model groups the bus and train in one nest of transit modes (Fig 2.3). This structure permits that the reduction in demand of any mode within the nest has greater will greatly affect the demand for other modes within the nest than a mode that does not belong to the same nest. MNL holds within the nest but not valid across the nests.

Nested Logit Models based on "*Generalized Extreme value distribution,"* the choice probabilities for nested Logit model (fig) are computed as:

$$P_i = P(B_{r(i)}) * P(i/B_{r(i)}) \tag{2.9}$$

$$P(B_r) = \frac{\exp(\rho.I_r)}{\sum_{x=1}^{2}\exp(\rho.I_r)} \tag{2.10}$$

$$P(i/B_r) = \frac{\exp(V_i/\rho)}{\sum_{x=1}^{2}\exp(V_j/\rho)} \tag{2.11}$$

$$I_r = log \sum_{J \in B_r} exp\,(\frac{V_j}{\rho}) \tag{2.12}$$

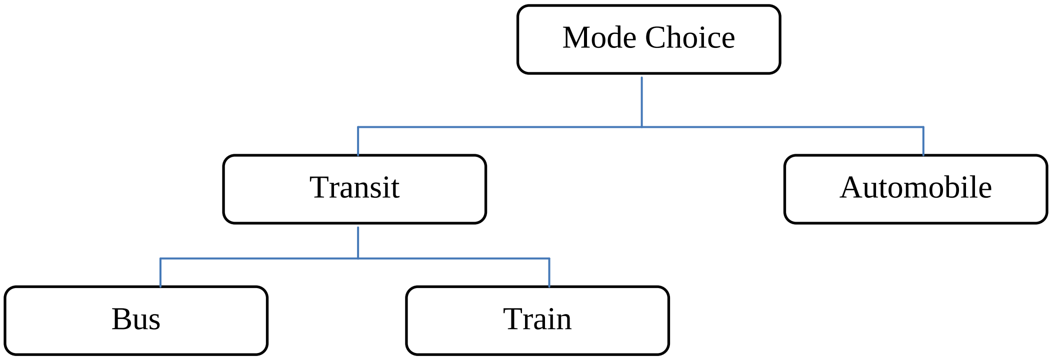


Figure 2.3 Nested logit tree structure

Where I_r is known as inclusive value of Nest $B_{r;}$ B_r are the choice set of nests; r(i) index of group of containing alternative I and ρ is the parameter of inclusive value has value between 0 and 1, indicator of dissimilarities between transit modes. If $\rho = 1$, model is multinomial Logit model and if $\rho = 0$, the transit utility is independent of the utilities of sub modes, which means that any change in the utilities of sub modes within the nest will not affect the utility of modes outside the nest and are perfect substitutes of each other. Value greater than 1 and below indicates inappropriate structure of the nest.

2.2.4 Functional Form of Utility Equation

Functional form of V(.) in Equation 2.1 is generally linear in specification with unknown parameter β, however, variables can be non-linear. Different types of non-linear specification for variables have been found in literature by specifying the new variables as a function of nonlinear once. Individual's income, being the most important variable, has been used in utility equation with different form of interactions to explain different effects. For example, travel cost divided by the traveler's income to reflect presumption that traveler with high income is less concerned about cost than traveler with low income (Train, 1980 and Jara-Diaz & Ortuzar, 1989). Travel time multiplied by income to reflect presumption that traveler with high income is more concerned about travel time compared to traveler with low income (McFadden 1974). Liu (2007) has included income in utility model as income by equivalent scale (income divided by square root of family size) and concluded as most preferred model explaining utility. In his study, he also included term travel cost divided by income to present that traveler with high income is less concerned about money. Other examples include interaction of dummy variables with other variables (variable characteristics of individual as they apply to mode choice, making it possible to affect utility in a different way. Hensher and Greene (2007) included income in utility function by interacting with mode specific alternative of air to reflect that the traveler with high income give more priority to fast modes of travel. This approach is actually interprets the differential effect of income on mode choice compared to other alternatives.

Utility equation may include the alternative-specific constant for one or more alternatives, also called dummy variables, represented as constant variable in a utility function. The utility equation with alternative-specific constant is of form

$$V_{in} = \alpha_i + \beta' z_{in} \tag{2.13}$$

Where α_i is the mode specific constant, has value when mode *i* is chosen otherwise 0. $z_{in}$is the vector of all such combination of original variables explaining utility. The constant α_i is the average unobserved utility of the *ith* alternative and is estimated by setting alternative specific constant of at least one alternative being zero as base alternative for estimation. If two alternatives have same utility calculated explained by variables in utility equation, then, the difference in probability is explained by mode specific constants. It also reflects the inadequacy of the variables z_{in} to explain choice but including all the objective characteristics of choices in utility equation is also impossible in practice. The use of alternative specific constants also makes it impossible to forecast the result of adding new alternative, unless there is some basis to guess what its alternative-specific constant will be.

2.2.5 Valuable Outcomes of Choice Models

The behavioural model has variety of useful outcomes that can help to develop effective policies for traffic management plans and urban transportation infrastructure. Policies effects individual travel mode choice in variety of ways, hence, it is important to be able to know how it will be. The policy can be any of the following: introduction of new travel modes; implementation of parking fee in CBD to reduce demand for autos; heavy tolls for diverting traffic to less congested routes and construction of new infrastructure. The most important behavioral outputs obtained from choice models are:

- Choice elasticities
- Marginal rates of substitution (VTTS)

- Marginal effects

a) Choice Elasticities

Elasticity is defined as “percentage change in probability of choosing an alternative mode due to changes in policy-relevant variables.” Elasticity measures the sensitivity of demand due to change in price or any other variable. Price elasticities of travel demand and user’s attitudes provide useful information on the responsiveness of travel behaviour to changes in transport policies that interferes with the travel costs (Odeck, J. at el, 2008).Elasticities are of two types: own-elasticities and cross elasticities. Own elasticities represents the responsiveness of the individual n’s choice probability of choosing alternative i, due to change in any attribute of alternative i, whereas change in probability of choosing alternative i due to change in attribute “k” of any other alternative j. If elasticity is responsiveness of individual it is called as disaggregate elasticity represents individual choice responsiveness. But planners and decision makers are more interested in aggregate elasticities representing the responsiveness of whole the population.

Elasticity of choice probability can be written as:

$$E_{X_{jkn}}^{P_{in}} = \beta_{jk} X_{jkn} \left(\delta_{ij} - P_{jn} \right) \qquad (2.14)$$

Where

δ_{ij} = 1 if i = j (Own- Elasticity)

δ_{ij} = o if $i \neq j$ (Cross- Elasticity)

β_{jk} = Coefficient of Attribute

X_{jkn} = Attributes of Alternative j.

The above equation gives the disaggregate elasticities. The aggregate elasticities can be computed using sample average but such practice can lead to errors in computation as MNL is non-linear in specification. A better way is to calculate elasticities by weighted average of disaggregate elasticity using choice probabilities as weights. The elasticities computed using sample averages are uniform across the alternatives because of IIA property but may not remain uniform when computed using weighted average technique.

b) Marginal Rates of Substitution

Interaction of coefficients of utility function provides very important meaningful quantities also known as marginal rate of substitution, that is, the rate at which the two alternatives can be traded against each other without affecting utility. The most important of which is "value of travel time saving." It is the value of time in monetary terms placed by the individual on time saving or amount of money that individual wants to pay to save his time for some sort of specific action. Time is assumed to be a valuable resource and viability of transport projects and service depend upon it. The value of time is paramount in transport modeling and certainly behind the demand function we use either explicitly or implicitly. It is simply the ratio of coefficients of travel time and travel cost in the utility equation. Mathematically, it can be written as

$$VTTS = \frac{\delta V_{jn}/\delta t_{ij}}{\delta V_{jn}/\delta c_{ij}} = \frac{\beta_t}{\beta_c} \tag{2.15}$$

Where, $\beta_t$is the coefficient of time variable and β_c is the coefficient of cost variable.

c) Marginal effects

Changes in probability of choosing alternative i for individual n's due to change in individual characteristic rather than attribute of alternative are defined as marginal effects. In general income is considered as the most important variable related to individual that affects individual choice process greatly by imposing restraints of expenditures on transport compared to other expenditures. Increase in income of an individual will tend to increase the demand of travel but that affects is mostly studied in trip making decision process rather than mode choice. Limiting this study to mode choice process it is generally ascertained as fact that increment in individual income will tend his choice to be more attracted to fast modes of travel, probably car.

2.3 Highway Demand Function Analogy with Choice Models Considering Pricing

Highway Demand function are the mathematical models representing demand for travel through highway with respect to cost of travel. Highway costs faced by the user are direct costs and indirect costs. Direct costs are those which are directly paid by the consumer in terms of money include; fuel cost, oil, tires and depreciation costs (out of pocket costs). Indirect costs are not directly faced by the consumer. The most important of which are the travel time and safety. Time spent on travel can be devoted to other activities such as working or recreational trip. Both safety and travel time are converted into monetary cost for economical evaluation. Value of safety and travel time are measured by determining the willingness to pay of individual to improve safety of traveling on highway and reducing travel time. Other indirect costs are comfort, convenience and reliability.

Demand for traveling is analogous to the demand of goods in general economic theory and is dependent on individual income, price and other relative variables. The choice for travel mode depends on several factors, such as the purpose of the trip, the distance traveled and income of the traveler (Stubbs et al., 1980 book). The demand for highway represents the value that the consumers place on traveling in a particular time, manner and place, as measured by the "willingness to Pay" for the trip (Congestion Primer). Different trips have different value, depends on the purpose of trip and individual preferences. The relationship between cost and demand Figure 2.3. This demand function represents aggregate demand curve for a group of travelers having particular level and distribution of income, population and socioeconomic characteristic. The demand function has always a negative slope, representing the situation if cost of travel increases results in decrease in demand of travel. Although, the case may not be true because of variables other than the perceived price such as income. Income directly affects the demand of travel. As the person income increases, his willingness to pay for the trips also increases so the demand. This can be represented by shifted demand curves as shown in Figure 2.4. The Figure 2.4 expresses that at the given price, different demand can be expected for different income level. As the income rises the quantity of trips will be shifted from D1 to D3.

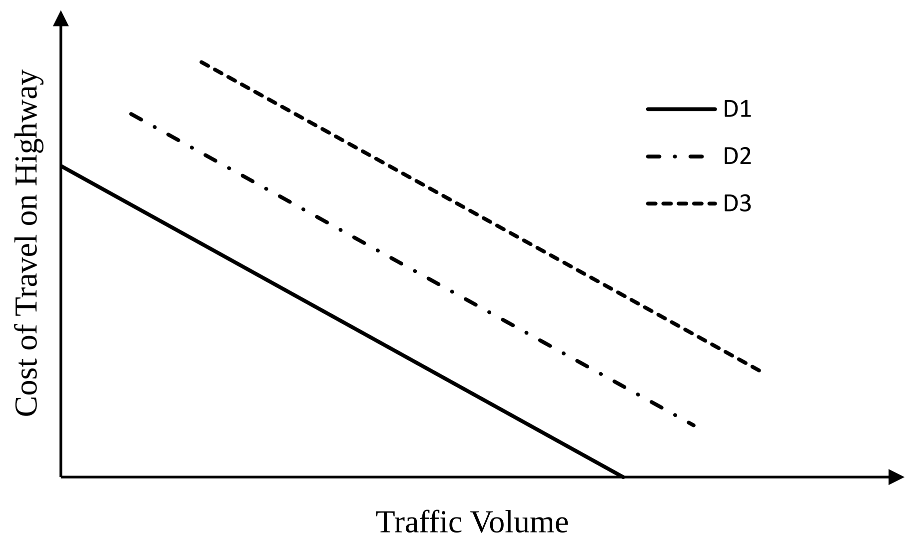


Figure 2.4 Demand function for different level of income groups

As the traffic volume increases the cost and time of travel increase, provides basis for mathematical relation between cost of travel for a particular highway to the traffic flow. A mathematical function expressing cost of travel with flow volume is called supply function. A general relationship is presented in Figure 2.5. Cost of travel remains constant for low traffic volume but increases exponentially as its approaches near to the capacity of the highway. Based upon above discussion the Demand and supply functions can be expressed as:

$$D = f(C) \tag{2.16}$$

$$C = f(V) \tag{2.17}$$

Consider Equation 2.13, the indirect utility equation defined is also a function of parameters of time and cost, in general known as the impedance associated with choosing a particular alternative mode same as the demand function represented as generalized cost (time is being converted to monetary units) of travel associated with highways. Increasing the cost of travel by implementation of toll if increased the willing to pay of traveler will either make traveler to shift mode of travel to less costly alternative, change route or do not travel, which indirectly reduce the congestion.

2.3.1 Pricing Evaluation

For efficient operation of the system the supply and the demand should be equal or demand should be less than supply. But when congestion occurs, user travel cost increases rapidly. Each additional user on highway imposes additional cost to the system, called as Marginal cost. These additional cost leads to excessive consumption of resources and economic inefficiency. In congested situation, the marginal cost faced by the highway user will be the addition of external cost and the average cost.

When average cost, marginal cost and demand function are interacted (Figure 2.5) with each other the difference FG is the optimal congestion pricing to accommodate the loss in benefit from trips that are not being taken. This will results in reducing inefficiency of use of transportation facility by diverting user to other modes/routes or by restricting the users whose trip are valued less than others to not use the facility and reducing congestion. If the elasticity of congestion pricing is very high, even with small toll cost, there will be very high reduction of demand or vice versa.

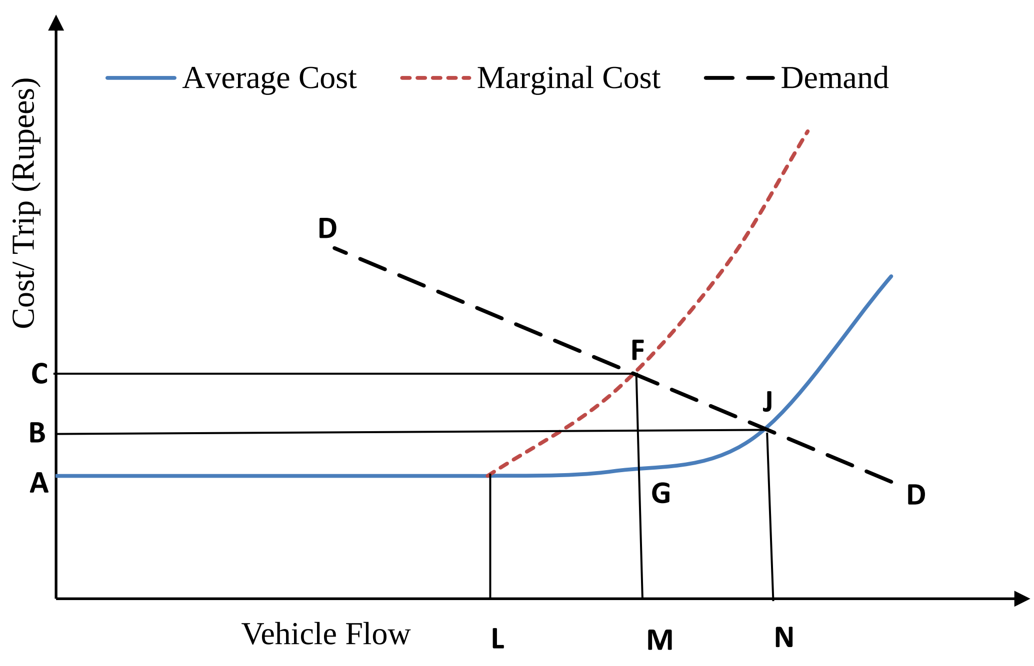


Figure 2.5 Congestion pricing evaluation

2.3.2 Pricing and Consumer Surplus

Consumer surplus is defined as "the benefit that individual gains in terms of money by choosing some facility or alternative." Consumer surplus is the difference between the amount that individual pay for facility or mode and maximum amounts that individual wants to pay or go without it. Consumer surplus is positive when the amount he wants to pay is greater than what he pays or vice versa. It is measured as area bounded by the demand and the supply curve. Effect of policy on users is normally measured in terms of change in consumer surplus. Now consider the pricing situation, the supply curve has been shifted to marginal cost curve after implementation of toll price, there is decrease in consumer surplus equal to the hatched area in Figure 2.7.

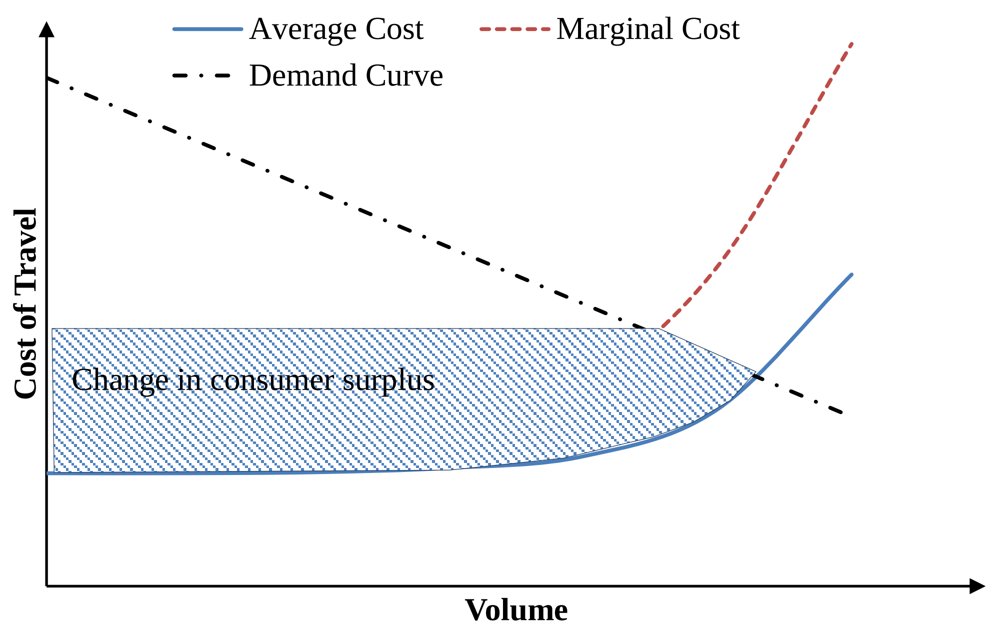


Figure 2.6 Pricing and consumer surplus

2.4 Summary

Disaggregate demand models are widely used for analyses of individual choice behaviour. These models are based on utility maximization theory. The theory postulates that individual choose among several alternatives the one which maximizes his income utility. The indirect utility function is the observable component of utility expressed in terms of combinations of attributes of choices. Based on the distribution of random unobservable component of utility choice models are defined. For mode choice analysis the most commonly used types of these models are Multinomial Logit model and Nested Logit model. Disaggregate demand models have some useful outputs which are very helpful for planners in decision making, which are: elasticities of mode choice and marginal rates of substitution.

In case mode choice model, utility function is expressed as function of individual characteristics and attributes of modes. Income has important role in decision making because it defines individual purchasing power. Therefore, specification of income variable in utility equation should be defined carefully.

Pricing is evaluated by interaction of demand, supply and marginal cost curves. Demand function is analogous to indirect utility function as both are function of cost and time. Pricing reduce consumer surplus thus reduce demand for car use.

Chapter 3

STUDY METHODOLOGY

3.1 General

The purpose of this study is to develop a travel mode choice model for work trip modes in Rawalpindi, and analyze the impact of congestion toll and new improved transit mode on mode choice. This can be done by using the similar cases studies from other countries but due to difference in user behavior to transport mode choice, socio-economic environment, and market framework and fare systems, there are limitations for using such studies. It is better to collect individual statements of respondents about their preferences for set of transport modes as they are more practicable and reliable in measuring the effects of changes in transport system. The framework of study is shown below:

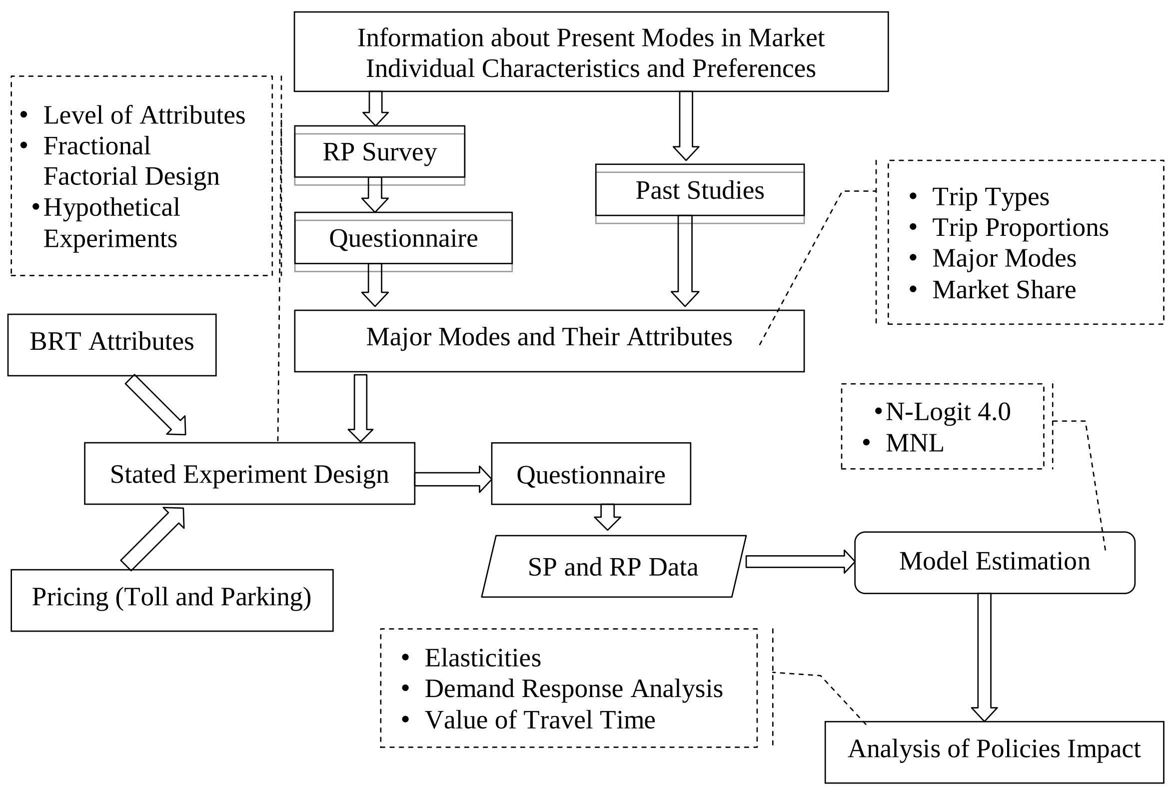


Figure 3.1 Framework of study

3.2 Data for Choice Models

In order to obtain information about the user transport modes, preferences and perception, a survey questionnaire was designed on common transport modes in Rawalpindi. There are two methodologies for collecting information from transport users as follows:

3.2.1 Revealed Preference Method

Revealed preference studies represent current market situations better than the stated preference techniques. RP data describe only the alternatives which are present in real market, which means the model estimated from this data will only include the attributes and correlation between the attributes of alternatives from real market. The choices made the respondents are known outcomes, although, they are dependent on the respondents perception of attribute levels which may or may not accurate (Hensher, 1994). Revealed preference data allows researchers to examine the actual choices of travelers and to characterize their travel choices. RP data has one favorable outcome is that it represents the real market along with individual constraints of job location, level of information about mode, etc. which makes it more reliable and valid but has limited capability to forecast and predict long term policies.

3.2.2 Stated Preference Method

Researchers have more interest in stated preference (SP) technique because of its ability to predict about modes not present in present transportation system and any transport related attribute that may be changes over time or induced by agency for demand management. Liu (2007) conducted a research for analyzing traveler's behavior towards mode choice in Shanghai and determined demand elasticities using revealed and stated preference approaches. Odeck et al. (2008) studied the user attitude towards toll, demand elasticities and relation between user attitudes and demand elasticities. Stated choice and stated preference methods have limits; however, they are limited by respondent ability to understand the hypothetical situations (Wang et al, 2000). If hypothetical situations are far removed from respondent daily experience, the stated preference studies will results in poor models and inaccurate results. Stated preference method should have some relation with real world. Stated Preference studies close to the real world situations are the best for pooling with revealed preference data (A.A. Ahern).

Stated preference studies are based on hypothetical situations, with selected attributes level by the designer. A respondent is given with options to select the best alternative based on his perceptions constraining his economic and social constraint. Under standard utility maximization theory, a person's choice changes only if the attributes of the chosen alternative become worse or attributes of non-chosen alternative improves. Stated preference techniques are designed along the same lines by changing attributes of competitive alternatives. Stated preference studies are less constrained than revealed preference studies and allow looking at potential changes (Swait et al, 1994). Stated preference studies allow us to examine how decision making varies as different types of attribute profiles and level changes (Hensher, 1994). SP methods are initially popularized by the work of Louverie and Hensher(1983) who demonstrated how researchers could examine trip maker answers to the hypothetical combinations of attribute for travel mode. In SP studies, outcomes are potential outcomes (Hensher, 1994). Suggesting different designs do not affect the variability or randomness of individual response (A.A. Ahern, 2008).Revealed preference studies allow researchers to examine actual choices made by travelers and to characterize how people really travel, while SP studies allow us to examine, how people choices might change if there are changes in alternatives available.

3.2.2.1 SP Data for Choice Models

How to measure the choice preferences and other dimensions that determine choice, such as measure of attributes, environment in which that choice is made and decision making units? The measures of choices and preferences fall in the "dominance measures." Many numerical methods have been found in the literature for such measures, here are the most commonly used methods for Random Utility modeling:

a) Discrete Choice**:** Most commonly used measuring method for modeling. Measure the response as the most preferred choice made by the consumer from the remaining alternatives. It just provides information about the preferred option but no information about the preferences among the remaining alternatives. Discrete choice measurements are simpler and easier to understand, a quick response can be implied by the respondent.

b) Ranking of Choices: A respondent has to order his preference from most preferred to least preferred. Quite complicated and demanding lot of attention from respondent to answer. The result of modeling is highly dependent on the respondent ability to analyze the options and give ranking preferences to each. It provides lot of information about preferences among the choice alternatives but no information about degree of preference.

c) Rating of Choices: Provide data about the relative degree of preference differences and magnitudes of differences among the choice alternatives. Require respondent to be able to order his choices and indicate how much he prefer one alternative than other. Respondent has to rate the choices on a scale.

3.2.3 Pooling SP and RP Data

The process of pooling two or more data is called data enrichment. For choice models, it was originally proposed by Ben-Akiva and Morikawa (1990) for overcoming the weaknesses of Revealed preference and Stated preference data. Further, literature about combining data sources is found in the work of Hensher and Bradley (1993), and Hensher (2001). Charzi and Ortuzar (2006) argue that combining revealed and stated preference studies permits the advantages of the both can be maximized while overcoming some limitations of each method. Stated and revealed reference studies together can improve the explanatory power of revealed preference studies. The goal of pooling the data is to produce a model to predict real future forecast model. Keeping this in mind, RP data is collected from real market representing real market situations along with real market trade off but real market trade-off has problems and low efficiency. Therefore, SP data is collected with SP equilibrium and trade-offs but in modeling only SP trade-offs information is used, which may be collected from same or different individuals. For pooling two data sources, it is assumed that two data sets have different scale factors but have same common attributes (Taste restriction). The relation between the two data sets is made on bases of variance which is inversely related to scale. The variance is expressed as:

$$\sigma^2 = \frac{\pi^2}{6\Lambda^2} \tag{3.1}$$

Where, Λ is the scale factor. Now, considering utility framework, the Equation 2.13 for two data sets can be written as:

$$V_{in}^{RP} = \Lambda^{RP}\alpha_i + \Lambda^{RP}\beta' z_{in} \tag{3.2}$$

$$V_{in}^{SP} = \Lambda^{SP}\alpha_i + \Lambda^{SP}\beta'^{z_{in}} \tag{3.3}$$

The model estimation process requires that one of the scale factors must be normalized to zero and others are to be estimated. Two methods are commonly used for estimating model using pooled data:

1. Manual method using general MNL software
2. Specified Nested Logit tree approach

In manual method technique, a range of scale factors is defined for SP-data while the scale factor for RP data is kept equal to one. Scale factor is multiplied by all data entities of SP data and then pooled with RP and log-likelihood of model using pooled data is computed. The estimates of ʎ are obtained for the model which maximizes the log-likelihood. Although, procedure is simple but can be used only for pooling of two data sets and yields inefficient estimates.

An alternative procedure proposed by Bradley and Daly (1997), needs to define a Nested logit structure with RP-alternatives pooled in one tree and SP-alternatives pooled in other. The IV-parameter thus obtained is inversely related to the scale factor of two data sets, that is *θ=1/ʎ* . This method needs the assumption of that two data sets are identically and independently distributed. The tree structure is shown in Figure 3.2. If scale factor is not significantly different from zero statistically the two data sets can be combined directly for estimation.

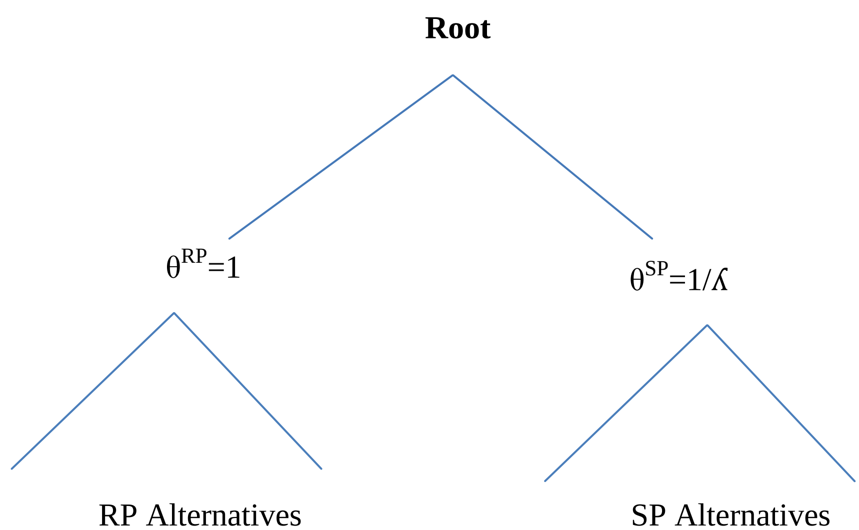


Figure 3.2 Nested Logit structure for combining two data sources

3.2.3.1 Tests for Pooling Two Data Sources

The data enrichment paradigm has assumption that the two data enrichment process must have same model parameters for common attributes. If the above assumption fails it will pose a problem to data enrichment process. Swait and Louverie (1993) proposed hypothetical method for checking that two data sets have same common parameters and different scale factors. The test procedure is as follows:

a. Estimate models for individual data sets with Log-likelihood as L^{RP} and L^{SP} having number of parameters N^{RP} and N^{SP}.

b. Estimate combined model with Log-likelihood L^{Joint} and Number of Parameters [N^{RP} + N^{SP}- │β│+1] where │β│ is the number of common parameters estimated in the model.

c. Calculate Chi-square statistic $-2[(L^{RP} + L^{SP}) - L^{Joint}]$ should be less than the critical value of Chi-squared statistic with degrees of freedom equal to │β│-1.

3.3 Data Collection

In this study, both SP and RP techniques are utilized for analyzing of choice preferences. Both techniques have been extensively and successively applied to the transport choice problems, such as mode choice between car and transit system, analyzing the effect of specific attributes of transport mode on demand and route choice problems. Revealed preference data is collected for existing modes while stated preference approach is used for new alternative BRT and congestion pricing effects analyses. Stated preference experiments are constructed using average attribute levels collected through Pilot survey and then comprehensive questionnaire is constructed which include questions related to both actual choices, stated choices and demographic variables of the individual. The details for data collection are as follows:

3.3.1 Attributes Selection

The attributes and levels of attributes are the dimensions along which the consumer evaluates the product, also known as variables determining the deterministic part of Utility functions, are determined through examining the all choice alternatives and understanding how transport user evaluate such choices. For example, in case of public transport, travel time, fare, walking time and distance, reliability, etc. are the attributes along which user evaluate the choices and choose one he presume to be best.

User perception about the transport mode is actually influence by the attributes of mode; therefore, all factors influencing transport mode choice should be included in the attribute set. However, it is very difficult to include all the variables explaining the mode choice as it is difficult for respondent to analyze the situation. Therefore, only important attributes for the hypothetical alternatives should be included and set their level considering simplicity and practicality. The major attributes selected for this study were cost of travel, in vehicle travel time, out of vehicle travel time and operational frequency of transit operations. Other than these pricing attributes; congestion toll and parking fee are included for analyzing impact of pricing strategies on private modes.

Trips and modes distribution data was collected by NESPAK for elevated multilane expressway study in Rawalpindi. The study indicates that work trip comprises 70% of the total trip types made by travelers a show in figure 3.3 and travel mode distribution in Figure 3.4. The major private transit mode in the city is car and motorcycle with car carries 75% of the total share indicating main reason for congestion of road in Rawalpindi and motorcycle has the second largest share. While the transit mode has only 10% share among which 7% is carried by Van and 3% by Bus.

A RP survey was carried out in Rawalpindi for determining attributes (cost, travel time, walking waiting time and frequency/headway in case of transit) related to the major travel modes available within city and their level experience by the users. Respondents were asked to provide details of recent trip, includes mode chosen and its attributes. Results of pilot survey indicate that the major travel modes within city are; car, motorcycle, bus and van, 98% of the total share. Only major modes were included in the study, because work trips are regular and most of time remains constant for longer period of time. This research only includes work trips as people tend to assign different level of importance to their attributes of choices to different purpose of trip making (Balcombe, 2004). For example, recreational trips are different than daily work trips. The average (Range in brackets) characteristics of modes for work trips are given in Table 3.1.

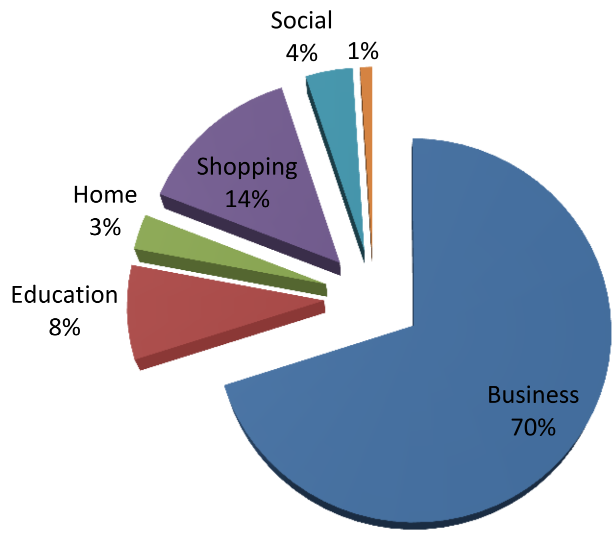


Figure 3.3. Trip types distribution in Rawalpindi (Source: Feasibility study of Murree road elevated Expressway, NESPAK, 2009)

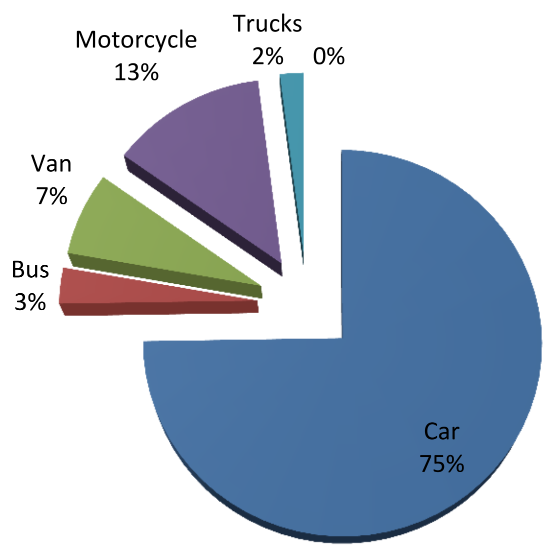


Figure 3.4. Travel modes distribution in Rawalpindi (Source: Feasibility study of Murree road elevated Expressway, NESPAK, 2009)

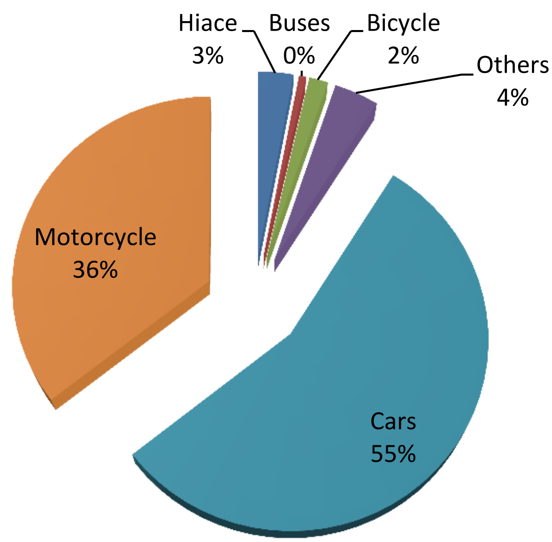


Figure 3.5. Modes type distribution on Murree road (Source: Feasibility study of Murree road elevated Expressway, NESPAK, 2009)

3.3.2 Setting of Attributes Levels

Individual response is directly influence by degree of variation and range of attributes. Lot of care is required for determining the attribute levels for composing hypothetical scenarios for SP response measurement. A reliable response can only be inducted from respondents if hypothetical scenarios created are not far removed from the real situation. SP scenarios created on assumptions may provide invalid result. It is better to construct stated preference experiments from observation of revealed preference data to enhance realism and better estimation. Constructing stated-preference (SP) experiments from a choice that a respondent made in a revealed-preference setting can enhance the realism of the SP task and efficacy of preference revelation (Train et al. 2008).

Table 3.1 Average values of attributes of modes perceived by the individuals in RP survey

Mode	In vehicle travel time	Out of vehicle travel time	Cost of travel	Headway/Frequency
Car	38 min. (15-55)	---	Rs. 142 (50-200)	---
Motorcycle	27 min. (12-45)	---	Rs. 34 (20-45)	---
Van	36 min. (15-60)	13 min. (5-15)	Rs.15 (10-25)	6 min. (2-20)

From revealed preference study in the RP survey, hypothetical scenarios were constructed, setting the attributes levels for SP experiments with attributes that were some amount above or below the those of the recent trip where base level being rounded to nearby multiple of 5 of mode characteristics in pilot survey. For two cases, namely: pricing impact on car share, includes congestion toll and parking fee; and introduction of new improved Bus Rapid Transit System in the city infrastructure for which infrastructure is under construction, reasonable values are assumed and included in SP choice experiment with different level of variations. Bus Rapid Transit system do not exist, so attributes level were derived from existing transport modes in the city so that the new transit mode should have characteristics level in a lot better than existing transit service (Van and Bus) in the Rawalpindi city. Values for level of attributes are given in table 3.2.

3.3.3 Stated Preference Experiments Design

All factors which influence the transport modal choice has been discussed in previous section will be used as attributes in SP experiment: in-vehicle travel time, out of vehicle travel time, cost of travel or fare and operational frequency including congestion toll and parking fee for impact analysis on reducing demand of private vehicles. Three levels are assigned to each attribute by variation above or below the average values of attributes in Pilot survey.

For composing the SP experiments researchers used experimental design techniques to create hypothetical choices. Effects of different variables are analyzed by making considerable variations (Level of attributes) in values of attributes for different alternatives separately and choice behavior is determined. A designed experiment is the way of manipulating attributes and their levels to permit rigorous testing of hypothesis of interest. In this study the terms in the utility model are the attributes.

Factorial design method is used to create experiment in which combinations of attributes levels were made and each combination is one experiment. Factorial design is only possible if attributes and level of attributes are small. But in real situation there may be the case involving too many attributes or attributes level, factorial designs are very large and impossible for practical application. For example, in case of transport mode, we have 4 modes, each being explained by four generic variables; cost, time, fare and operational frequency have four levels for factorial designs. The total combinations will be 4^{4x4}or 4^{16} so it will be necessary to reduce the number of experiments without affecting the particular effects of interest. For such cases a new design method is used called "**fractional factorial design**." Fractional factorial designs involve the selection of particular subset or sample of complete factorials, so that particular effects of interest can be estimated as efficiently as possible.

Table 3.2 Level of attributes selected for SP survey

Mode Type	Modes	Variables	Levels (values are for work trip only)		
			L (0)	L(1)	L(2)
Private	Car	In vehicle travel time	30 min	40 min	50 min
		Cost of travel	Rs. 100 per trip	Rs. 150 per trip	Rs. 200 per trip
		Parking toll	Free	Rs.10	Rs.20
		Congestion toll	Rs. 15	Rs. 25	Rs. 35
	Motorcycle	In vehicle travel time	25 min	35 min	45 min
		Cost of travel	Rs. 20 per trip	Rs. 30 per trip	Rs. 40 per trip
		Parking toll	Free	Rs. 5	Rs. 10
Transit	Vane	In vehicle time	30 min	40 min	50 min
		Cost of travel	Rs. 15 per trip	Rs. 20 per trip	Rs. 25 per trip
		Frequency	5 min	10 min	15 min
		Out of vehicle time	10 min	15 min	20 Min
	BRT	In vehicle travel time	20 min	30 min	40 min
		Cost of travel	Rs 25 per trip	Rs. 30 per trip	Rs. 35 per trip
		Frequency	5 min	10 min	15 min
		Out of vehicle time	10 min	15 min	20 min

JMP software was used to create stated preference choice sets (Appendix). For SP choice experiment, there are total 4 modes: car, motorcycle, van and BRT with total of 15 generic variables explaining mode choice. Using fractional factorial, minimum design possible has 27 choice sets. Conducting all 27 experiments on one individual is not possible, therefore, for practicality a choice sets are divided into blocks. Total 9 blocks are composed with each containing three choice sets. The design consists of main effects and some two way interactions. The design should include all main effects for reason that main effects typically count for 70-90 of the explained variance whereas two way interactions counts for 10-15 percent and rest is explained by high order interactions. The output given by the software may contain some unrealistic combination of variables. For such cases a minor adjustment has been made in variables to present realistic situation. For example, where car parking was free, motorcycle should also be free from parking charges. The output from software may results in combination presenting situation where motorcycle was charged for parking while car was not charged at all.

3.3.4 Structure of Questionnaire

As described in previous sections, generic attributes influences the modal choices are: cost of travel, in-vehicle travel time are common across all alternatives, whereas as pricing variables (parking fee and congestion toll) are specific to car and motorcycle and; headway an out of vehicle travel time are specific to transit modes are determined. Three levels were assigned to each attribute. Others variables specific to individual includes are: income, ownership of private modes, age, etc. were also determined.

Questionnaire was designed in three parts. In first part, questions related to individual characteristic are asked such as age, gender, education, occupation, income, family size, workers in family and auto ownership. **Part-2** contained the questions related to **revealed preference** modal choices. Individual was asked to provide information about his most preferred mode from a choice set of available modes in his locality. He was also asked to provide information about his 2nd choice if first is not available; and 3rd choice if both 1st and 2nd choices are not available. Stated choice sets are included in **Part3,** in which new transport mode BRT was included along with variables of congestion pricing; congestion toll and parking fee. In each questionnaire, three choice sets were included. The example of questionnaire is provided in appendix B.

3.4 Summary

Two types of data are used in mode choice modeling; revealed preference (RP) and stated preference (SP). RP data captures the real market, mode shares and attributes of modes. In SP data, hypothetical choices are presented to user with predefined attributes level and he is asked to choose one he will prefer within his socio-economic constraints. RP data represent idiosyncrasies effects better than SP data while SP data efficiently measures trade-offs. To overcome the disadvantages of both data a combined RP/SP data model estimation procedure is developed based on assumption that both data sets same taste weights but have different scales.

For this study, revealed preference data about work trip modes was collected through questionnaire in RP survey from individuals in Rawalpindi city along major corridors in the city. The major transport modes in city are; car, motorcycle and van, comprises 98% share of all travel modes available. Using attributes of mode in RP data collected, levels of attributes to be used in SP experiments are defined and SP experiments were created using fractional factorial design method. Stated choice experiments are included in questionnaire that was used in RP survey and distributed to individuals. The data collected is then used for model using N-Logit software.

Chapter 4

RESULTS AND ANALYSIS

4.1 General

The sets of questionnaire were prepared and issued to the users of Murree Road, Mall Road, I.J.P Road and Islamabad Expressway because these are the highly congested roads in Rawalpindi. A total of 270 questionnaires, which contains RP/SP experiments, are issued to the respondents and only 152 respondents have returned back the questionnaires. In RP survey, we have data of 296 individuals from which 264 individuals individual's observations are left after removing the individuals who have only one choice.

4.2 Overview of Respondent's

The respondent's routes distribution of combined (RP/SP) surveys is shown in Figure 4.1. 36% of the respondents use Murree road, 18% Islamabad expressway, 24% I.J. Principal road and 22% use Mall/G.T. road.

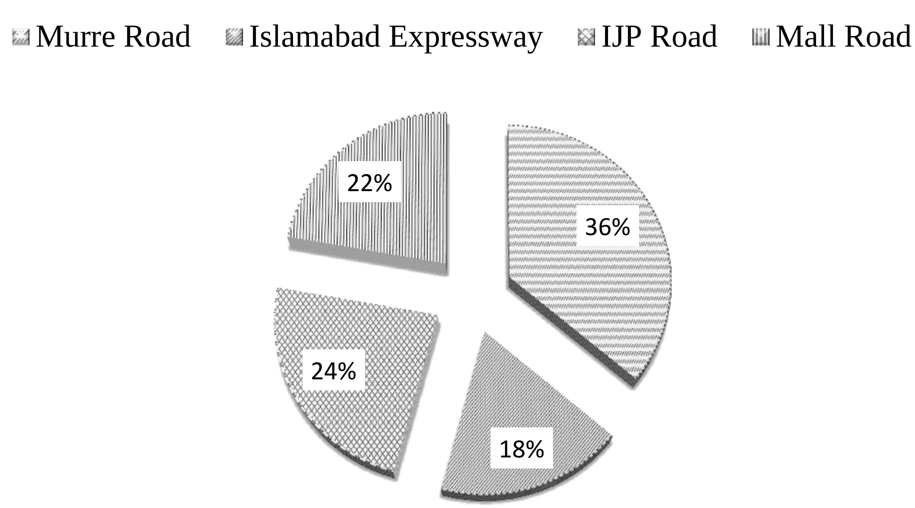


Figure 4.1 Routes distribution of respondents

Mode distribution of two data sets is shown in Figure 4.2 and income distribution of the respondents is shown in Figure 4.3. The auto-ownership of the sample is broken down to following groups: 25% owns no car, 43% has one car, 23.6% has two cars and 18.4% has more than two cars in household. Motorcycle ownership is broken down in following groups: 69.44%

owns no motorcycle, 27.77% has 1 motorcycle and 2.77% has two motorcycles in household. All trips data collected is about work trip mode or business trips. The trips for other reasons were not counted in this survey. Figure 4.4 and 4.5 presents individual mode choice for different ranges of income.

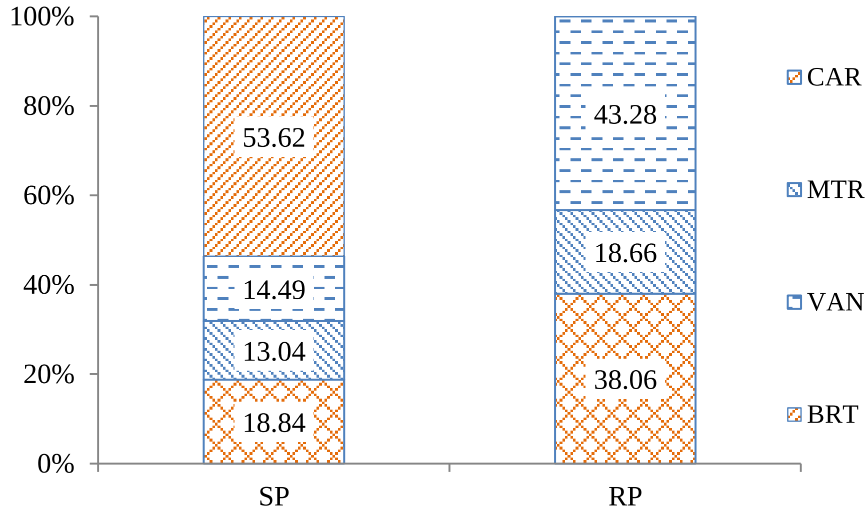
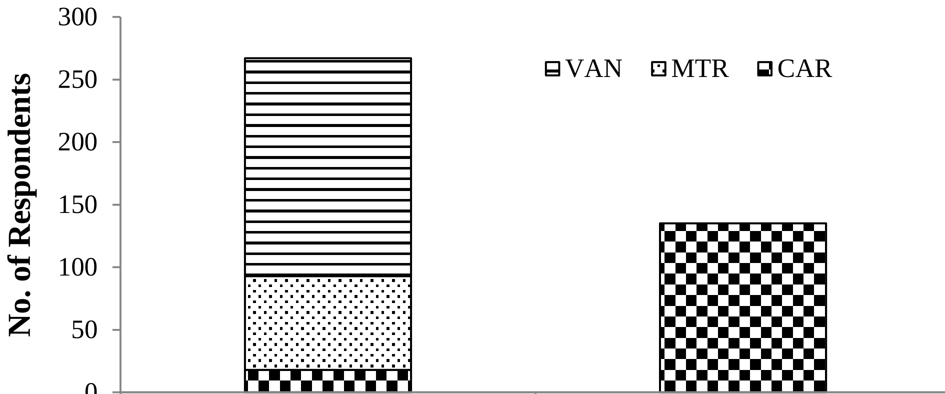


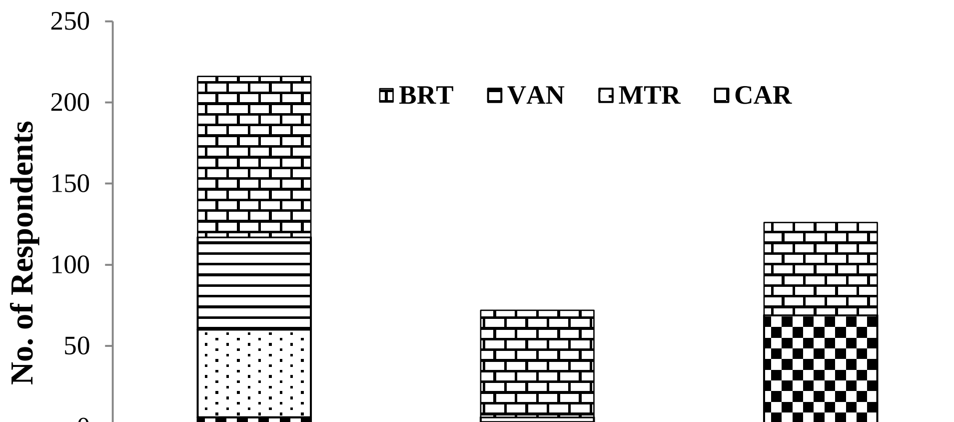
Figure 4.2 Mode shares of the respondents

Figure 4.3 Income distribution of the respondent



	0-40000	Greater than 40000
VAN	174	0
MTR	75	0
CAR	18	135

Figure 4.4 RP data mode distribution with respect to income



	PKR. 0-30000	PKR. 30000-60000	PKR. 60000->100000
BRT	99	66	57
VAN	57	3	0
MTR	54	0	0
CAR	6	3	69

Figure 4.5 SP data mode distribution with respect to income

Models were calibrated separately for RP,SP and combined RP-SP. In RP model only those modes were used for model calibration for which minimum number of observations was equal to or greater than 30.Models were calibrated using N-Logit 4.0 econometric software capable of analysis discrete choice models of any type and also for checking model validity.

Total 402 observations from different individuals were used for RP model with three major modes choices and for SP-model a total of 414 observations containing 4 choices each were used for Model Calibration. Others observations were rejected for following reasons: the individual did not considered options following attributes variation rather filled the questionnaire for the choice he usually used for travel and otherwise left blank or individual has shown lexicographic behavior.

4.3 Model Estimation

In mode choice, the prominent factors were always the cost and the travel time but the significance of these variables changes with the different modes available and attributes presented in stated choice questionnaire. Individual's income plays an important role in mode choice decision making. To determine, how to include income term in model, four specifications of models were defined in which income attribute was included in following ways.

a) Model 1: Income was multiplied by dummy variable of car to reflect high income individuals always tend towards faster and comfortable mode choices. This model incorporates the differential effect of income on car relative to other modes.

b) Model 2: Income was multiplied by in vehicle and out of vehicle travel times reflecting that time is major restraint for individual with high income and has greater disutility associated with time compared to individual with low income.

c) Model 3: Cost was divided by income defining budgetary constraints indicating that individual with high income has very small disutility associated with cost compared to individual with low income.

d) Model 4: No income attribute included so that we can statistically check which model form represents our data best.

The equations for above described model specification are:

$$V_{jn} = \alpha_{car}.I^{-\gamma} + \beta_1 t_{ij} + \beta_2 C_j + \beta_3 t_{oj} + \beta_4 C_{tj} + \beta_5 C_{pj} + \theta_{car}.O_{car} + \theta_{mtr}.O_{mtr} + \alpha_j \quad (4.1)$$

$$V_{jn} = I^{\gamma+1}\beta_1 t_{ij} + I^{\gamma}\beta_2 C_j + I^{\gamma+1}\beta_3 t_{oj} + I^{\gamma}\beta_4 C_{tj} + I^{\gamma}\beta_5 C_{pj} + \theta_{car}.O_{car} + \theta_{mtr}.O_{mtr} + \alpha_j \quad (4.2)$$

Equation 4.1 is general form for model specification 1 and 4 whereas Equation 4.2 represent generalized form for model specification 2 & 3.Where:

α_{car} = Alternative specific Dummy Variable for Mode car

I = Individual monthly income in thousands

t_{ij} = In-vehicle travel time

C_j = Cost associated in traveling with mode j.

t_{oj} = Out of Vehicle travel time.

C_{tj} = Toll cost

C_{pj} = Parking cost

O_{car} = Ownership Variables for car

O_{mtr} = Ownership Variables for motorcycle

α_j = Alternative Specific dummy for modes, and

$$\gamma = \begin{cases} -1, & If\ model\ spec.\ 1\ and\ 3 \\ 0, & otherwise \end{cases}$$

In all the models, income term was included as exogenous variable, not in term of wage rate because in our society mostly individual has fixed income and working hours respectively. Initially all variables were included in model whether statistically significant or not. The basic objective is to determine which model form actually represents our data.

For combined SP-RP model we assume the two data sets have different scale and same taste. Therefore to check our assumption we test the null hypothesis of taste equality and scale inequality using log-likelihood test for all model forms. The test statistic value for model 1 is 10.66, which is less than critical chi-squared value of 15.50 for 8 ($|\beta| = 9$) degrees of freedom. Similarly for model 2,3 and 4 test values are 1.78, 10.68 and 7.04 which are significantly less than the critical value of 14.07 for 7($|\beta| = 8$) degrees of freedom. Therefore we cannot reject the null hypothesis means the assumption of taste equality and scale inequality holds for all model forms.

Hausman test also carried out to check IIA property. The result of test was produced by NLogit 4.0 that "variance matrix is not positive definite," the case in which it is suggested not to reject Null Hypothesis and accept IIA property exist for the given data set (Econometric Analysis, William Greene). Therefore, we use multinomial logit model for analysis. A gradual decrease in log-likelihood from model form 1 to model form 4 clearly reflects the importance of income in explaining Mode choice. Model specification 4 with no income variable included has the lowest value of log-likelihood for all type of data sets used for estimation.

Considering the model specification based on income term specifications, model 1 is chosen as preferred model for following reasons as the log-likelihood for **model 1** is quite large than model 2 and 3 for all data types; and the coefficient estimates for **model 1** are significant for most of the variables compared to other models (Annex-A).For RP data, the log-likelihood for model 1 is -264.17 compared to model 2, 3 and 4 with values of -277.59, -270.40 and -284.4. In case of SP data, log-likelihood is -405.84 for model 1 compared to values of -428.22, -431.89 and -543.60 for model 2, 3 and 4. Similarly, for combined RP-SP data, model 1 has value of log-likelihood equal to -675.35 which is greater than -704.92, -696.95 and -734.48 of model 2, 3 and 4. Almost all the variables are significant for model form 1 and have expected signs for the coefficient values excluding parking cost. Frequency variable is removed initially as it has unexpected sign and poses statistical problems if included in model.

Initially, ownership variable was included in the model but removed as endogenous variable. This can be explained by the difference in loglikehood and pseudo R-Squared between the model with ownership included (0.31) and Excluded (0.13). Large differences between two models clearly indicate the effect of ownership in explaining choices rather than generic variables of cost and time. Variables of parking cost, No. of transfer , frequency, dummy constants for car and motorcycle are not significantly differ from zero at 95% significance level and are removed from the final model. Frequency variable also have inappropriate coefficient sign. The Equation 4.3 expressed general form of utility equation for best model form after removing all insignificant and endogenous variables.

$$V_{jn} = \alpha_{car}.I_n + \beta_1\, t_{ij} + \beta_2\, C_{ij} + \beta_3\, t_{oj} + \beta_2\, C_{tj} + \alpha_j \qquad (4.3)$$

Table 4.1 Model estimation results SP-data only

Attribute	Unit	Coefficient	t-value	Standard Error
In vehicle travel time (t_{ij})	min	-.04764046	-4.036	0.0118
Cost of travel/ Fare (C_{ij})	PKR.	-.01287938	-4.326	0.0029
Out of Vehicle Travel Time (t_{oj})	Min	-.08536609	-3.295	0.0259
Toll (C_{tj})	PKR.	-.06471298	-3.768	0.0171
Dummy Car x Interaction of Income (α_{car}xI_n)		0.05715177	10.12	0.0056
Dummy Van (α_{van})	----	1.78395471	4.125	0.4324
Dummy BRT (α_{BRT})		2.18576719	5.477	0.3990
Statistics				
Log Likelihood	-404.67			
Pseudo R^2	0.228			
Restricted Log Likelihood	-520.44			
No. of Observations	414			

4.4 Applications of Model

The finalized models estimated using SP and SP-RP data were used for computing elasticities, value of time and demand response analysis. The results of which are provided in sub-sections as follows.

4.4.1 Elasticities of Demand

Direct and cross Elasticities were computed for all choices using SP and SP-RP models. The values of elasticties are shown in table 4.3 & 4.4. The Elasticities given in table are probability weighted. Most of the elasticities values are lower than 1 means inelastic. A choice probability is called elastic when a percent change in value of choice determining variable leads to change in probability greater than 1%. In case of car, Elasticities for pricing variable is found elastic for both SP model and SP-RP model, while for public transport modes the values of elasticities of in vehicle and out of vehicle travel time are very near or greater than 1. For the rest of the cases, the figures are very lower than 1 that is the demand is inelastic.

Table 4.2 Model estimation results SP-RP data

Attribute	Unit	Coefficient	t-value	Standard Error
In vehicle travel time (t_{ij})	Min	-.03219157	-4.385	0.0073
Cost of travel/ Fare (C_{ij})	PKR.	-.00930499	-4.876	0.0019
Out of Vehicle Travel Time (t_{oj})	Min	-.06232309	-3.501	0.0178
Toll (C_{tj})	PKR.	-.05041153	-4.656	0.0108
Dummy Car x Interaction of Income (α_{car}xI_n)	PKR.	.04818290	8.570	0.0056
Dummy Van RP(α_{van})	----	1.85128361	6.131	0.3019
Dummy Van SP(α_{van})	----	1.43627796	4.413	0.3254
Dummy BRT SP(α_{BRT})		1.87214491	5.408	0.3461
Scale parameter (Λ)		0.8628	12.89 [2.37]*	0.0669
Statistics				
Log Likelihood	*-726.11*			
Pseudo R^2	0.209			
Restricted Log Likelihood	918.87			
No. of Observations	816			

*T-Statistic H_o μ=1 in square brackets (θ^{sp}=1.159)

In general, the demand for public transport is elastic for both in-vehicle and out of vehicle travel time, while the out of vehicle travel time is quite more elastic than in-vehicle travel time. Same is the case, the direct elasticities values for out of vehicle travel time for public transport modes are greater than 1 for both SP and RP-SP models. The values of elasticities related to out of vehicle time for van are -1.457 % and -1.224% while for BRT -1.949% and -1.661%. The direct demand elasticity relative to in-vehicle travel time is elastic for BRT with values of -1.09 % for SP-model and -0.856 % for RP-SP model. For alternative van, the direct elasticities for in-vehicle travel time are -0.813 % for SP and -0.658 % for SP-RP model, which are less than 1. Although BRT is high comfort mode of travel but is very sensitive to change in demand because of travel time. Reducing travel for BRT will increase demand extensively but more important is to reduce out of vehicle travel time by increasing frequency of buses, providing bus stop at close distance to residence and work places, improving pedestrian facilities by providing footpaths, etc., will induce more demand for BRT.

Table 4.3 Elasticities values (SP model)

	Actual Share	Predicted Share	Elasticities of Choice probability											
			Car			Motorcycle		Van			BRT			Income
			t_{ij}	C_j	C_{tj}	t_{ij}	C_j	t_{ij}	C_j	t_{oj}	t_{ij}	C_j	t_{oj}	
Car	0.22	0.21	-0.868	-0.235	-1.178	0.131	0.035	0.217	0.0587	0.389	0.519	0.056	0.931	1.041
Motorcycle	0.12	0.13	0.0745	0.020	0.101	-0.630	-0.170	0.153	0.042	0.274	0.339	0.403	0.723	-0.089
Van	0.19	0.20	0.106	0.029	0.144	0.135	0.036	-0.813	-0.220	-1.457	0.539	0.572	1.025	-0.127
BRT	0.47	0.46	0.210	0.057	0.285	0.338	0.091	0.539	0.145	0.965	-1.09	-0.294	-1.949	-0.292

Table 4.4 Elasticities values (SP-RP model)

	Actual Share	Predicted Share	Elasticities of Choice probability											
			Car			Motorcycle		Van			BRT			Income
			t_{ij}	C_j	C_{tj}	t_{ij}	C_j	t_{ij}	C_j	t_{oj}	t_{ij}	C_j	t_{oj}	
Car	0.2215	0.2140	-0.668	-0.194	-1.052	0.093	0.0266	0.169	0.050	0.331	0.410	0.117	0.794	1.01
Motorcycle	0.1697	0.1771	0.050	0.0150	0.0811	-0.441	-0.127	0.107	0.032	0.211	0.279	0.081	0.541	-0.079
Van	0.3727	0.3727	0.083	0.0254	0.1275	0.098	0.0283	-0.658	-0.181	-1.224	0.447	0.128	0.862	-0.128
BRT	0.2361	0.2362	0.177	0.0509	0.2804	0.245	0.0707	0.431	0.116	0.837	-0.856	-0.246	-1.661	-0.268

For private modes, Elasticities are very low with exception of congestion toll being greater than or nearly equal to one means demand for car is elastic to toll price and in-vehicle travel time being close to 1. Direct elasticity for toll price has value of -1.178% for SP model and -1.052% for SP-RP model, while the cross elasticity for BRT is 0.285% (SP) and 0.28% (SP-RP) which is comparatively greater than other competitive modes van and motorcycle. This clearly indicates that imposing pricing will significantly reduce demand for car and increase demand for BRT.

4.4.2 Value of Travel Time

The value of time of "in-vehicle travel time" and "out of vehicle travel time" can be calculated as follows:

$$\text{Value of In-Vehicle travel time} = \frac{\partial V_{jn} / \partial t_{ij}}{\partial V_{jn} / \partial C_j} = \frac{\beta_1}{\beta_2} \tag{4.4}$$

$$\text{Value of Out of Vehicle Travel Time} = \frac{\partial V_{jn} / \partial t_{oj}}{\partial V_{jn} / \partial C_j} = \frac{\beta_3}{\beta_2} \tag{4.5}$$

Our model contains two cost components; travel cost and toll cost. To compute value of travel time only one cost parameter should be included in model. Therefore for computing value of travel time a combined RP/SP model is calibrated in which all cost attributes are sum up to have single coefficient. Model estimation results are provided in Table 4.5. The value of in-vehicle travel time is computed PKR. 125.69/hr and out of vehicle travel time is PKR. 282.91/hr.

4.4.3 Demand Response to Policies:

Changes in demand with respect to change in policy attributes such as improvement of bus schedules, in-vehicle travel time, improvement of pedestrian facilities and implementation of tolls are analyzed using demand response scenarios. The equation can be written as:

$$\Delta P_j = \frac{P_j^1 - P_j^o}{P_j^o} \times 100$$

Where, ΔP_j is the percentage change in probability of choosing alternative j due to change in initial conditions, p_j^1 is probability of choosing alternative after policy is implemented and p_j^0 is probability before policy is implemented.

Table 4.5 Model estimation for computing value of travel time

Attribute	Unit	Coefficient	t-value	Standard Error
In vehicle travel time (t_{ij})	min	-0.0287	-3.998	0.0071
Cost of travel/ Fare (C_{ij})	PKR.	-0.0137	-8.004	0.0017
Out of Vehicle Travel Time (t_{oj})	Min	-0.0646	-3.615	0.0178
Dummy Car x Interaction of Income (α_{car}xI_n)	PKR.	0.0445	8.488	0.0052
Dummy Van RP(α_{van})	----	1.876	6.189	0.3032
Dummy Van SP(α_{van})	----	1.4376	4.428	0.3246
Dummy BRT SP(α_{BRT})		1.9538	5.449	0.3521
Scale parameter (Λ)		0.8620	6.953[1.0]*	0.1668
Statistics				
Log Likelihood	*-768.10*			
Pseudo R^2	0.164			
Restricted Log Likelihood	918.87			
No. of Observations	816			

Several policies were defined for analysis, with congestion pricing and Improvement of public transit services as major policies reflected in our case studies. The policies include implementation of toll alone, improvement in transit modes alone and combination of both. Toll policy was defined on basis of no toll and the maximum toll that can be possibly implemented whereas the values of variables determining choice for BRT were defined to decrease by relative percentage of value of SP data. All values of policy response changes were computed using sampling enumeration technique as average based techniques may provide misleading results. Demand response with respect to 23 different policies was computed for both SP and SP-RP model. The results of demand response analysis are provided in Table 4.6.

Table 4.6 Demand response to policy scenarios

S. #	Policy Description	SP		SP-RP	
		Car	BRT	Car	BRT
P-1	Toll Rs.25	-62.81	81.90	-49.88	45.96
P-2	Toll Rs. 50	-86.97	197.36	-76.19	98.80
P-3	BRT in-vehicle time reduced by 10%	-4.09	4.77	-1.72	3.47
P-4	BRT in-vehicle time reduced by 20%	-8.30	9.62	-3.53	7.06
P-5	BRT fare cost reduce by 10%	-1.78	2.03	-0.79	1.58
P-6	BRT fare cost reduce by 20%	-3.54	4.08	-1.58	3.18
P-7	BRT Out of Vehicle travel time reduced by 50 %	-25.24	32.79	-12.22	26.06
P-8	Toll Rs 25 and BRT time reduced by 10%	-64.04	91.86	-50.65	51.27
P-9	Toll Rs 50 and BRT time reduced by 10%	-87.44	211.22	-76.58	105.58
P-10	Toll Rs 25 and BRT time reduced by 20%	-65.27	102.10	-51.43	56.70
P-11	Toll Rs 50 and BRT time reduced by 20%	-87.91	225.18	-76.98	112.49
P-12	Toll Rs 25 and BRT fare reduced by 10%	-63.34	86.24	-50.23	48.41
P-13	Toll Rs 50 and BRT fare reduced by 10%	-87.18	203.68	-76.37	101.98
P-14	Toll Rs 25 and BRT fare reduced by 20%	-63.78	89.25	-50.50	50.25
P-15	Toll Rs 50 and BRT fare reduced by 20%	-87.38	210.04	-76.55	105.18
P-16	Toll RS. 25 and BRT out of vehicle travel time reduced by 50%	-78.65	231.57	-55.37	86.99
P-17	Toll RS. 50 and BRT out of vehicle travel time reduced by 50%	-89.97	303.13	-79.01	151.34
P-18	Toll Rs. 25; BRT fare and time reduced by 10%	-64.57	96.32	-51.00	53.77
P-19	Toll Rs. 25 ; BRT time reduced by 20% and fare 20%	-66.34	111.33	-52.15	61.84
P-20	BRT time reduced by 20%,fare 20% and OVT 50%	-30.32	69.55	-14.71	42.54
P-21	Toll Rs. 50 ; BRT time reduced by 20% and fare 20%	-88.32	238.10	-77.35	119.08
P-22	Toll Rs. 25 ; BRT time reduced by 20%,fare 20% and OVT 50%	-74.01	191.07	-57.80	105.28
P-23	Toll Rs. 50 ; BRT time reduced by by 20%,fare 20% and OVT 50%	-91.21	345.20	-80.24	173.81

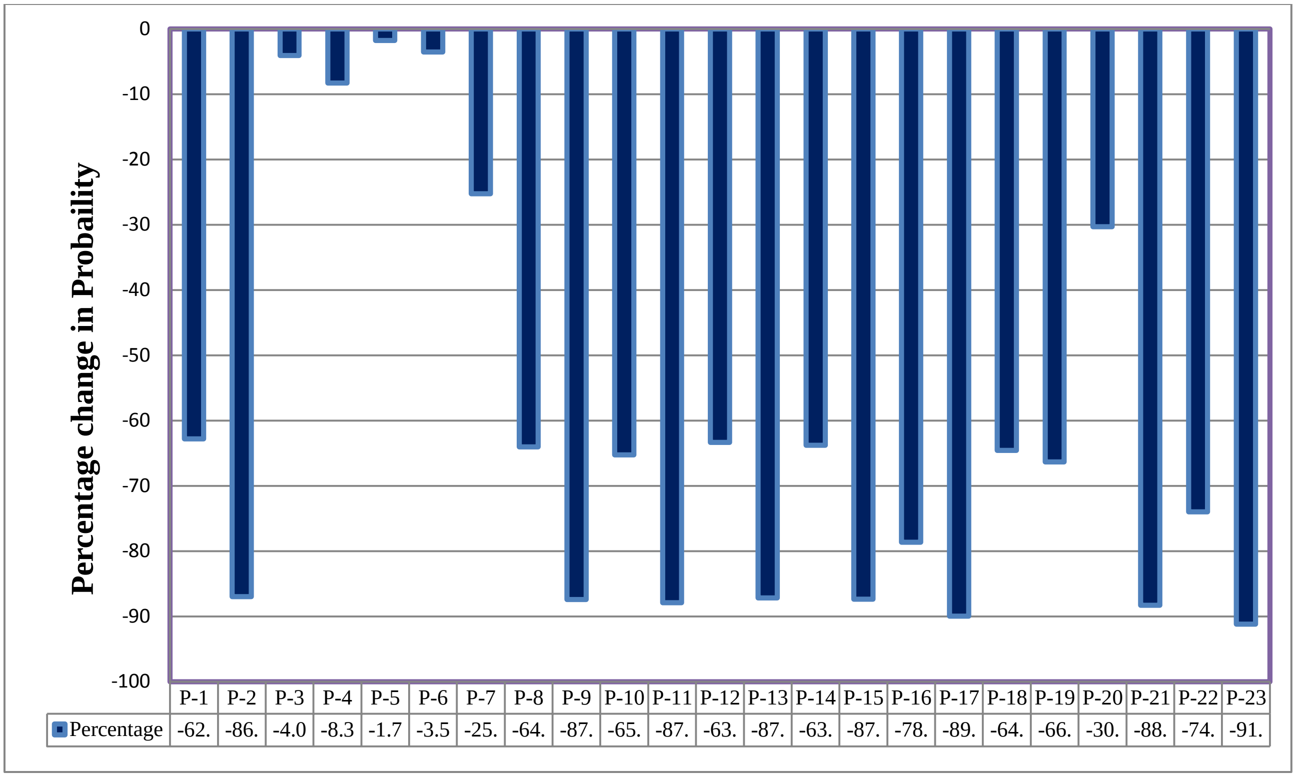


Figure 4.6 Demand response for policy scenarios (CAR) SP model

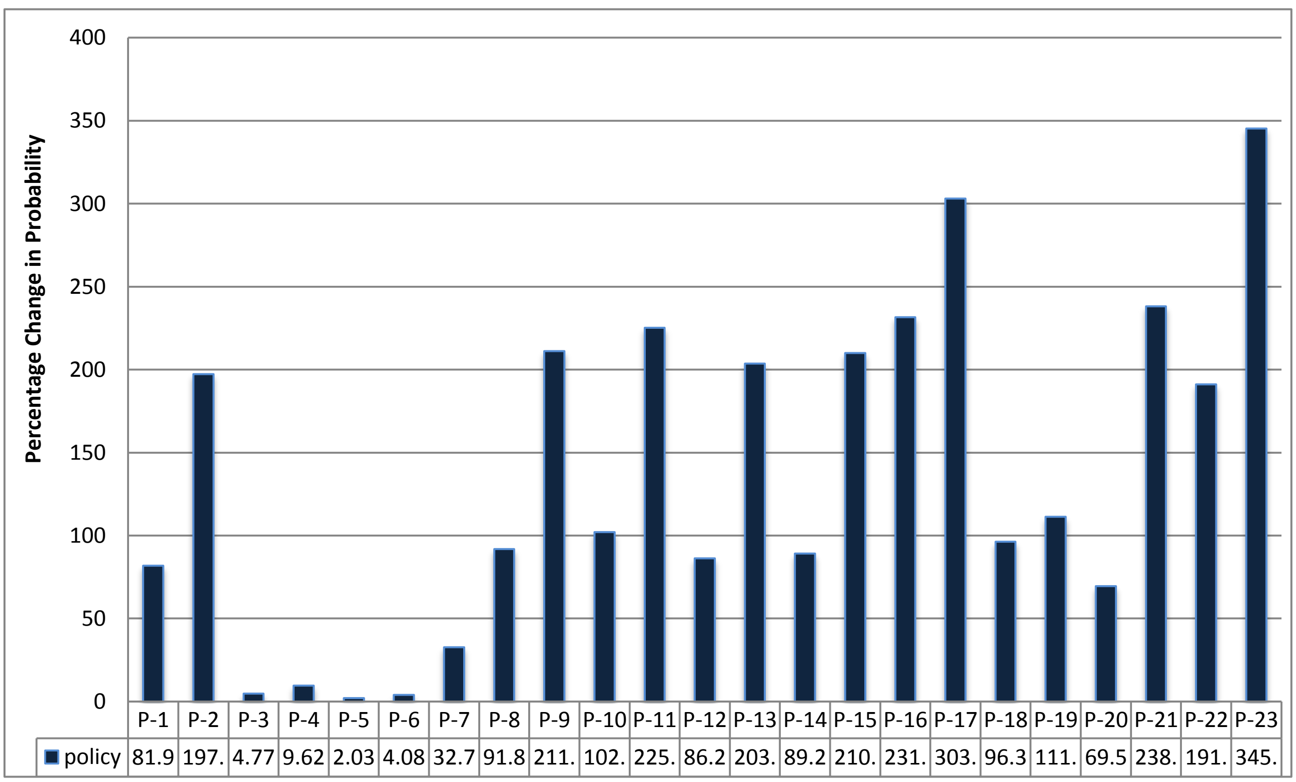


Figure 4.7 Demand response for policy scenarios (BRT) SP model

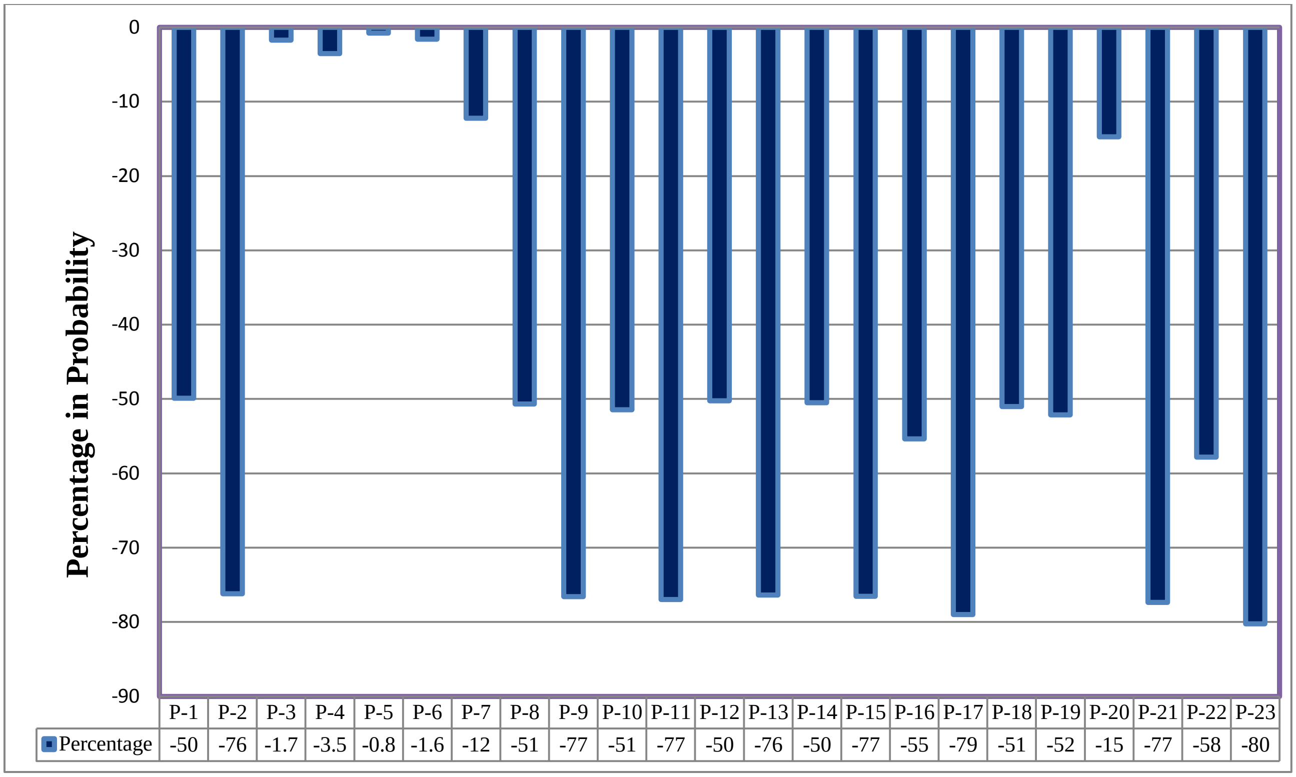


Figure 4.8 Demand response for policy scenarios (CAR) SP-RP model

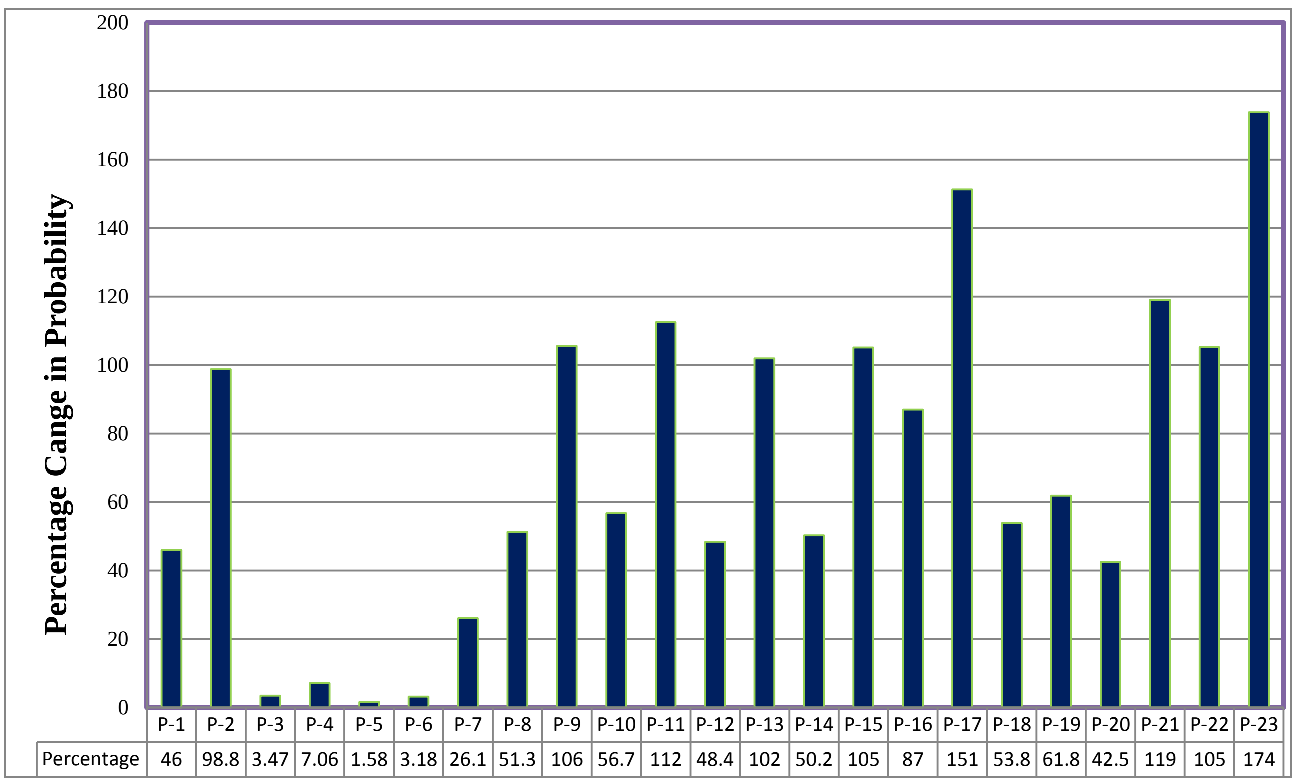


Figure 4.9 Demand response for policy scenarios (BRT) SP-RP model

Demand is found very sensitive to policy which includes implementation of toll pricing. The toll when implemented only Rs. 25, the demand for car has decreased by 62.81% (SP) and 49.88 % (RP-SP) whereas the demand for BRT has increased by 81.90% (SP) and 45.96% (SP-RP). When toll is increased to Rs. 50, the car demand is decreased by 86.97% (SP) and 76.19% (SP-RP) while demand for BRT has increased quite significantly by 197.36% (SP) and 98.80% (SP-RP).Compared to policies of toll pricing the policies which only consider the improvement in Bus Rapid Transit services are very insensitive, i-e, from policy P-3 to P-7 the values are very small. Considering travel in BRT when reduced by 20%, only increase the demand of BRT by 9.62% (SP) and 7.06 % (SP-RP) whereas car demand has only reduced by 8.30% (SP) and3.53 % (SP-RP). Out of vehicle travel time is moderately sensitive and seems to induce a great increase in demand of BRT if reduced significantly. The demand response analysis indicates that when OVT (Includes increase in frequencies of BRT and improvement of pedestrian facilities) is reduced by 50%, the demand for car is decreased by -25.24% and BRT demand increase by 32.79 % using SP-model; whereas by SP-RP model, change is -12.22% for car and 26.06 % for BRT.

Other than the scenarios with only one variable of choice was analyzed, a scenarios were also defined which includes combination of different policies. When considering combination of pricing individually with each reduction of in-vehicle travel time, fare and out-of-vehicle travel time car demand response ranges from -63.34 to 225.18 % in case of SP and -50.23 to 112.49 using SP-RP model. The lower value corresponds to the policy when toll Rs.25 and fare reduction by 10%, whereas highest values are for toll Rs. 50 and time reduced by 20%.

If all the policy maximum values except toll are considered the demand response for car has value of -30.32%(SP) and -14.71 % (RP-SP) which are comparatively very low compared to policy (P-1 & P-2) with only toll considered has values of -62.81%, 86.97 (SP) and -49.88%, -76.19% (SP-RP). This clearly indicates that demand is less sensitive to changes which include only changes in service attributes of BRT and transit modes compared to pricing methods to charge private mode users, a toll as penalty for causing congestion. Considering Scenarios which include combination of all policies (P-22 & P-23) of time, cost and toll, very large values of demand response are found for BRT. For policy 22, when toll Rs. 25 was implemented along with 20% reduction in In-vehicle travel time and fare; and 50% reduction in Out of vehicle travel time the demand for car has decreased by -74.01% (SP) and -57.80% (SP-RP) while the demand for BRT has Increased by 191.07% (SP) and 105.28% (SP-RP).

Demand Analysis results indicate that values computed using SP- model are quite large compared to SP-RP model. As SP-RP model has aspect of being more accurate predictions based on fact being encompasses real-world choice behavior with SP trade-offs, we will only consider SP-RP model results as being precise predictions

4.4.4 Toll Pricing vs. Probability of Choice

Using data enumeration method and SP-RP model with RP constants for calculations, the probability of Mode choice is computed on SP data, keeping all else constant for individual while increasing toll pricing rates. A graph in figure 4.10 shows the changes in probability of choice with respect to pricing rate. It is clear that with the increase in pricing the modal share proportion car decreases rapidly while the increase in other modes share is very small as indicated by the smooth curve for other modes. It also seems that BRT has highest probability of being chosen under increment of toll rates for car.

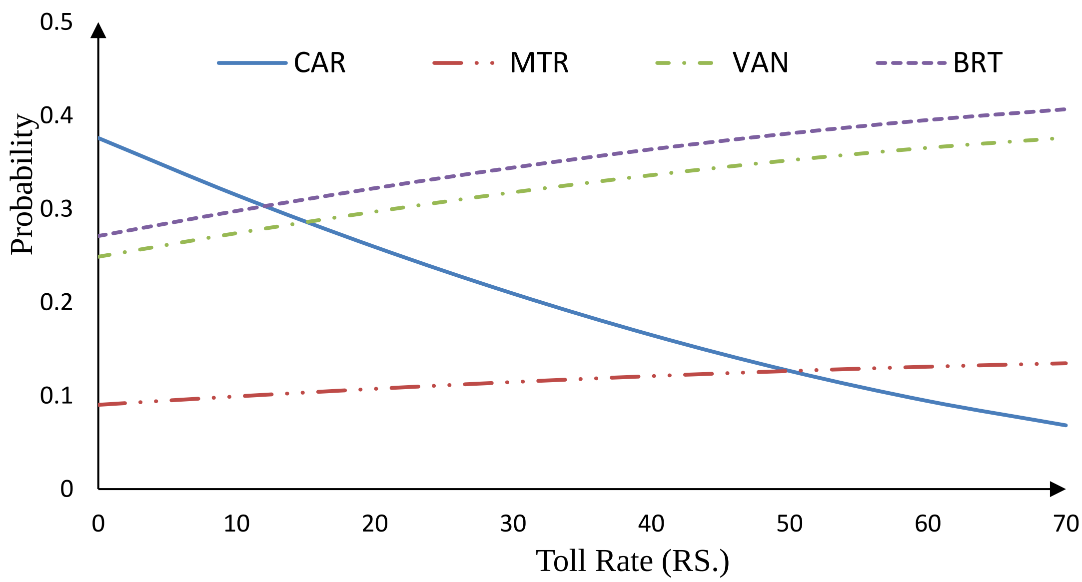


Figure 4.10 Probability vs. toll rate

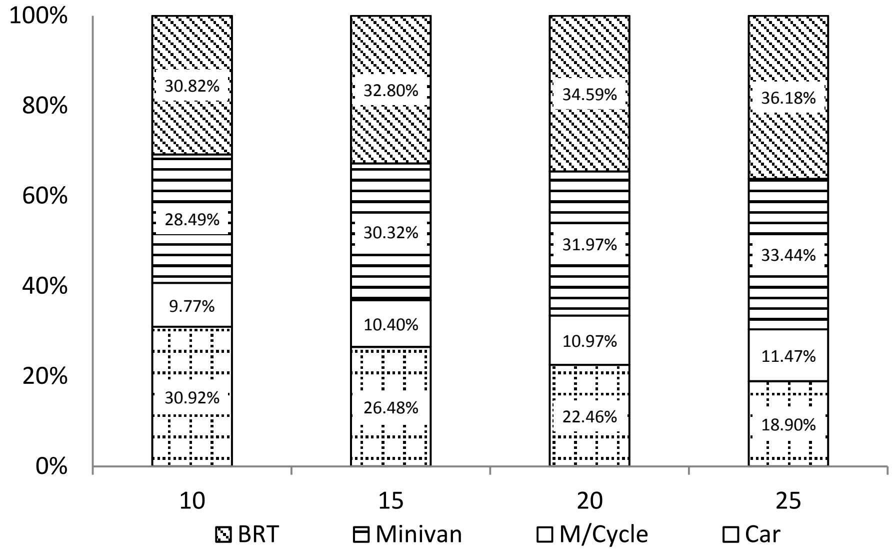


Figure 4.11 Mode share proportions with respect to toll cost

Modal share under different pricing condition was calculated using average aggregate values of mode and individuals characteristics in the data. Figure 4.11 represents the mode share proportion relative to toll price. Mode share of car decreases gradually with increment of toll rate. Car share is 30.92% when toll rate is PKR. 10 decreases to 26.5%, 22.5%, 18.9% and 15.85% with every 5 unit increase in toll rate from PKR. 15 to PKR.30. Van and BRT have approximately same modal proportions and increases with increase in toll rate.

4.5 Summary

In this chapter, data was analysed and then used for modeling. Four types of specifications are defined for utility equation base on income variable. After conducting statistical tests, most appropriate model specification was selected for further analysis. The statistical test concluded includes; goodness of fit test, parameters significance test, Hausman test and RP/SP data combination test. Models were estimated for RP, SP and SP/RP data for all specifications defined. Model specification in which income is interacted with alternative specific constant of car is choosen as appropriate model specification. The models estimated using SP and SP/RP data are then used for calculating probability weighted elasticities and analysis of demand response. Value of travel time is computed using model estimated using SP/RP data with only one cost variable.

Chapter 5

SUMMARY AND CONCLUSIONS

5.1 Summary

In this study we have used disaggregate demand models to determine the factors that characterize the travel mode choice decision and analyse the effect of two policies on modal split for reducing congestion. The analysis presented in this paper is based on the data collected along four major corridors in Rawalpindi city, Pakistan. The data collected was about work trips mode because they comprised about 70% of the total trips. The travel modes comprises of car, motorcycle and van which make 97% share of all modes available within city. Existing transit mode “van” has poor service facilities and in the recent times a Bus Rapid Transit (BRT) project has been started in the city which will be completed by end of year 2014. Pricing/ toll is not implemented within urban jurisdiction, however, it was considered as one of the attribute in SP survey. Stated preference experiments are constructed for new policies of pricing auto users and introduction of new alternative (BRT).Revealed preference data collected in RP survey was used to construct stated preference experiment. Appropriate levels of attributes were defined and included in stated choice experiments. Using fractional factorial method, choice sets are created. Each choice set represents one stated preference experiment. A questionnaire was designed including questions for demographic characteristics of travelers, revealed mode choice and stated mode choice experiments.

Using Revealed preference (RP) and stated preference (SP) data, MNL models are estimated using SP data alone and combined RP/SP data. Four specifications of utility equations are defined based on income and after conducting statistical tests it is concluded that model specification with differential income effect approach represents our data best. Parking cost, mode specific constants for car and motorcycle are found insignificant variables. Frequency although significant variable but also have inappropriate sign is excluded from the model.

Models estimated were used to obtain probability weighted elasticities, calculating value of travel time saving and demand response analysis. Elasticities were calculated for cost of travel, in-vehicle travel time, out of vehicle travel time, congestion toll and income. For most of cases elasticities values are very small meaning inelastic demand except own elasticities for out of vehicle travel time for both transit modes and pricing for mode car are greater than 1 means elastic demand. Value of travel time was computed using a separate RP/SP model with only one cost attribute included. Value of in-vehicle travel time is PKR. 125.69 /hr and out of vehicle travel time is PKR. 282.91 /hr. Using models demand response was analysed for 23 policies based on pricing and improvement in Transit services. Demand is found very sensitive to policies which include toll pricing compared to improvement in transit services.

5.2 Conclusions

This study has evaluated various congestion mitigation means in an urban environment through econometric modeling using SP and RP data. The mode choice model was estimated to analyze the factors characterizing demand for work trips in Rawalpindi city. Estimated model is then used for computing elasticities of mode choice and demand response analysis to several policies: combination of pricing strategies and improvement of transit services. It was concluded that own elasticity of car relative to pricing is greater than one means a little increase in pricing will reduce car demand significantly. With improvement in pedestrian facilities, buses frequencies and accessibility, BRT demand will increase as its demand is found elastic to out of vehicle travel time. Improvements of transit services are less effective in inducing modal split than pricing auto car. Pricing along with provision of improved transit services produces more modal split than pricing alone. BRT is more attractive to travelers and better substitute to car indicated by higher probability of being chosen than other contemporary modes of travel. The finding of this research can help decision makers to adopt effective policies for transportation supply and demand management.

5.3 Contribution to the State of Practice

The study highlights various aspect urban travel demand management in the context mode choice modeling and established a mode choice model which can be used for determining mode share in transportation planning projects. The study also highlights important parameters of mode choice which can help transportation planners in making appropriate decisions for mitigating travel demand. In this study value of travel time is also computed which is important in evaluating economics of Transportation projects.

REFERENCES

Ahern, A. A., & Tapley, N. (2008). "The use of stated preference techniques to model modal choices on interurban trips in Ireland." *Transportation Research Part A 42,* 15-27.

Basso, L.J., Guevara, C. A., Gschwender, A. and Fuster, M. (2011). "Congestion pricing, transit subsidies and dedicated bus lanes: Efficient and practical solutions to congestion." *Transport Policy, 18,* 676-684.

Ben-Akiva, M.E. and Morikawa, T. (1990)."Estimation of switching models from revealedreferences and stated intentions."*Transportation Research A,* 24, A(6): 485-495

Bradley, M.A., Daly, A.J., 1997. Estimation of logit choice models using mixed stated preference and revealed preference information. *In:Stopher, P.R., Lee-Gosselin, M. (Eds.), Understanding Travel Behaviour in an Era of Change*. Pergamon, Oxford.

Brownstone, D., Ghosh, A., Golob, T.F., Kazimi, C. and Amelsfort, D.V., 2003. "Driver's willingness-to-pay to reduce travel time: evidence from the San Diego I-15 congestion pricing project." *Tranportation Research part A, 37,* 373-387.

Burris, M.W. and Pendyala, R.M. (2002)."Discrete choice models of travelers participation in differential time of day pricing programs." *Transport Policy 9*, 241-251.

de Palma, A., Kilani, M. and Lindsey, R. (2005). "Congestion pricing on road network: A study using dynamic equilibrium simulator METROPOLIS." *Transportation Reasearch Part A*, 39, 558-611.

Elaisson, J. (2008). "Lessons from Stockholm congestion charging trial." *Transport Policy 15, 395-404.*

Elaisson, J. E., Hultkrantz, L., Nerhagen, L. and Rosqvist, L. S. (2009). "The Stockholm congestion – charging trial 2006: Overview of effects." *Transport Research Part A 43,* 240-250.

Eliasson J, Mattsson L G. 2001. "Transport and location effects of road pricing: a simulation approach."*Journal of Transport Economics and Policy,* 35(3): 417–456.

Espino, R., Ortuzar, J. D. and Roman, C., 2007. "Understanding suburban travel demand: Flexible modlling with revealed and stated preference approach." *Transportation Research Part A. 41*,899-912.

Greene, W. and Hensher, D. "Multinomial Logit and Discrete Choice Models." In W. Greene, NLOGIT Version 4.0 User's Manual, Revised, Plan view, NY: Econometric Software, Inc, 2007.

Greene, W. Limdep 9.0 Reference Guide. Plainview, New York: Econometric Software, Inc., 2007b.

Hensher, D. and Loverie, J., 1983. "Identifying individual preferences for international air fares: an application of functional measurement theory',." *Jounal of Transport Economics and Policy. 17*, 225-245.

Hensher, D., Louverie, J. and J. Swait. *Stated Choice Methods; Analysis and application*. Cambridge: Cambridge University Press, 2000.

Hensher, D.A. 1994. Stated preference analysis of travel choices: the state of practice. *Journal of transportation* 33 (2), 79-96.

Jara-Diaz, A.R. & Ortuzar, J. D. (1989). Introducing expenditure rate in the estimation of mode choice models. *Journal of transportation economics and Policy*, 23, 293-308.

Jara-Diaz, S. (2007). Transport Economic Theory, 1st Edition, Elsevier, Netherlands.

Kottenhoff, K. and Freij, K. B. (2009). "The role of public transport for feasibility and acceptability of congestion charging- The case of Stockholm." *Transportation Research Part A*, 43, 297-305.

Litman, T. (2006). "London Congestion Pricing." *Victoria Transport Policy Institute.*

LIU, G. (2007). "A behavioural model of work-trip mode choice in Shinghai." *China economic review* 18, 456-476.

Lo, H.K. and Szeto,W.Y.(2005). "Road pricing model for hyper congestion." *Tranportation Research part A*, 39, 705-722.

McFadden, D. (1974). The measurement of urban travel demand. *Journal of Public Economics,3, 303-328.*

McFadden, Daniel at el. (1977). “Demand model estimation and validation. Urban travel demand forecasting project phase I.” Report UCB-ITS-SR-77-9, Berkeley, CA: University of California, institute of transportation studies, 121-123.

Odeck, J. & Brathen, S. (2008). “Travel demand elasticities and user attitudes: A case study of Norwegian toll projects.” *Transportation Research Part A* 42, 77-94.

Odeck, J., Brathen, S., (2002). “Toll financing in Norway: the success, failures and perspective for the future.” *Transport Policy 9*, 253-260.

Park, Y. and Ha H., 2006. “Analysis of high rail-speed railroad service on air transport demand.” *Transportation Research Part E 42*, 95-104.

Schaller, B. (2010). “New York City’s congestion pricing experience and implications for pricing acceptance in United States.” *Transport Policy 17*, 266-273.

Schuitema, G., Steg, L. and Forward, S. (2010). “Explaining differences in acceptability before and acceptance after the implementation of a congestion charge in Stockholm.” *Transportation Research Part A 44*, 99-109.

Small, K. A. and Verhoef, E. T., (2007). The Economics of Urban Transportation, 1st Edition, Routledge, New York, NY.

Swait, J., Louviere, J.J, Williams, M., 1994. “A sequential approach to exploiting the combine approach of stated preference and revealed preference data: applications to freight shipper choice.” *Journal of Transportation*, 21, 135-152.

Train, K., & Wilson, W. W. (2008). “Estimation on stated preference experiments constructed from revealed preference choices.” *Transportation search Part B42*, 191-203.

Train, Keneth (1980). “A structural logit model of auto ownership and mode choice.” *Review of Economic Studies*, 47, 357-370.

Wang, D., Borgers, A., Oppewal, H. and Timmermans, H. (2000). “A sated choice approach to developing multifaced models of activity behaviour.” *Transportation research Part A: Policy and Practice,* 34, 625-643.

Wangtu, X., Shiwei, H., Rui, S., & Juan, L.(2008). “Disaggregate modal-split model considering congestion pricing.” *Journal of transportation system engineering and information technology,* 8(3), 92-102.

Yoo, K.E., 1995. A study of Korean passenger’s choice behavior utilizing stated preference and revealed preference methods.” Ph. D. Thesis, Lougborough University, England.

APPENDIX A

Model Estimation Results

Table A-1 Estimation results for RP data (All variables Included)

		Model 1	Model 2	Model 3	Model4
Attribute	**Unit**	**Coefficients**			
In vehicle travel time (T_{inv})	min	-0.0314 (-2.595)	-0.0089 (-3.719)	-0.03757 (-3.264)	-0.03378 (-3.011)
Cost of travel/ Fare (C_{ij})	Rs.	-.00569 (-1.871)	-0.0015 (-0.552)	-0.15728 (-2.701)	-0.002345 (-0.855)
Out of Vehicle Travel Time (T_{out})	Min	-0.0595 (-1.883)	-0.00054 (-1.609)	-0.06684 (-2.19)	-0.05306 (-1.80)
Toll (C_{toll})	Rs.	-0.0224 (-0.022)	0.00040 (0.026)	0.2677 (0.593)	-0.000182 (0.012)
Parking Cost (C_{park})	Rs.	-0.0334 (-1.030)	-0.0317 (-1.808)	-0.44383 (-1.026)	-0.03578 (-2.085)
Dummy Car x Interaction of Income (α_cx I_i)		0.0428 (6.707)	----	----	----
Onwership Car (O_{car})	----	1.115 (5.521)	1.3079 (7.092)	1.4852 (9.359)	1.4929 (8.368)
Onwership Motorcycle (O_{mtr})	----	2.962 (8.914)	2.7514 (8.963)	2.6870 (9.810)	2.733 (8.91)
Dummy Van (α_{van})		3.646 (6.151)	2.767 (8.766)	3.4323 (6.25)	3.370 (6.185)
Statistics					
Log Likelihood		-264.17	-277.59	-270.40	-284.4
Pseudo R^2		0.336	0.303	0.321	0.286
Restricted Log Likelihood		-398.43	-398.43	-398.43	-398.43

Table A-2 SP data Estimation Results

		Model 1	Model 2	Model 3	Model4
Attribute	**Unit**		**Coefficients**		
In vehicle travel time (T_{inv})	min	-0.05447 (-4.343)	-0.0018 (-6.760)	-0.0567 (-4.869)	-.0536 (-4.56)
Cost of travel/ Fare (C_{ij})	Rs.	-0.01099 (-3.554)	-0.0058 (-2.143)	-0.29486 (-3.294)	-.0053 (-2.055)
Out of Vehicle Travel Time (T_{out})	Min	-0.07780 (-3.016)	-0.0011 (-4.395)	-0.0745 (-2.981)	-.0778 (-3.142)
Toll (C_{toll})	Rs.	-0.05189 (-2.913)	-0.0118 (-0.806)	-0.3512 (-.402)	-.0107 (-0.769)
Parking Cost (C_{park})	Rs.	-0.0040 (-0.616)	-0.0071 (-1.20)	0.1748 (1.091)	-.0051 (-0.924)
Dummy Car x Interaction of Income (α_cx I_i)		0.0538 (8.178)	------	------	
Onwership Car (O_{car})	----	0.2361 (1.181)	0.80349 (5.082)	0.9682 (7.942)	1.1163 (7.810)
Onwership Motorcycle (O_{mtr})	----	1.3248 (5.498)	1.3221 (5.733)	1.098 (4.886)	1.2356 (5.341)
Dummy Van (α_{van})		2.3949 (5.199)	1.6371 (5.983)	2.020 (4.661)	2.256 (5.141)
Dummy BRT (α_{BRT})		2.7070 (3.369)	1.94178 (7.554)	2.374 (5.955)	2.528 (6.233)
Statistics					
Log Likelihood		-405.84	-428.22	-431.89	-453.60
Pseudo R^2		0.220	0.177	0.170	0.128
Restricted Log Likelihood		-520.44	-520.44	-520.44	-520.44

Table A-3 Combined data Estimation results

		Model 1	Model 2	Model 3	Model 4
Attribute	**Unit**	**Coefficient**			
In vehicle travel time (T_{inv})	Min	-0.0472 (-4.808)	-0.0013 (-6.264)	-0.0484 (-4.965)	-0.0508 (-5.170)
Cost of travel/ Fare (C_{ij})	Rs.	-0.00845 (-3.480)	-0.0033 (-1.439)	-0.2141 (-3.969)	-0.00433 (-1.863)
Out of Vehicle Travel Time (T_{out})	Min	-0.0854 (-3.613)	-0.00043 (-1.555)	-0.0965 (-3.981)	-0.0843 (-3.507)
Toll (C_{toll})	Rs.	-0.0439 (-3.189)	-0.01460 (-1.133)	0.195 (0.831)	-0.0141 (-1.097)
Parking Cost (C_{park})	Rs.	-0.0123 (-0.992)	-0.0204 (-2.531)	0.263 (3.816)	-0.0248 (-2.92)
Dummy Car x Interaction of Income (α_cx I_i)	----	0.05280 (9.413)	-----	-----	-----
Onwership Car (O_{car})	----	0.8986 (5.013)	1.1636 (6.882)	1.268 (8.103)	1.362 (8.076)
Onwership Motorcycle (O_{mtr})	----	2.4708 (8.868)	2.2420 (8.849)	2.540 (9.837)	2.513 (9.19)
Dummy Van RP (α_{van})	----	3.7436 (3.372)	2.400 (8.84)	3.807 (8.226)	3.595 (7.831)
Dummy Van SP (α_{van})		3.3726 (6.654)	2.587 (5.936)	4.857 (7.184)	3.953 (6.619)
Dummy BRT SP (α_{BRT})		4.0749 (7.686)	3.521 (6238)	5.768 (7.564)	4.814 (6.961)
Scale parameter (λ)		1.370 (8.276)	1.54 (6.471)	1.60 (6.905)	1.66 (6.439)
Statistics					
Log Likelihood		-675.35	-704.92	-696.95	-734.48
Pseudo R^2		0.265	0.232	0.244	0.222
Restricted Log Likelihood (Constant only)		-918.87	-918.87	-918.87	-918.87

Table A- 4 Model Estimation after removing insignificant and endogenous variables

Revealed Preference				
Attribute	Unit	Coefficient	t-value	Standard Error
In vehicle travel time (T_{inv})	min	-0.0214	-2.069	0.0103
Cost of travel/ Fare (C_{ij})	Rs.	-0.0080	-3.067	0.0026
Out of Vehicle Travel Time (T_{out})	Min	-0.0387	-1.403	0.0276
Dummy Car x Interaction of Income (α_cx I_i)	----	0.0509	8.830	0.0057
Toll (C_{toll})	Rs.	-0.0497	0.831	0.0598
Dummy Van (α_{van})	----	1.5335	1.553	0.4434
Statistics				
Log Likelihood	-321.89			
Pseudo R^2	0.192			
Restricted Log Lokelihood	-398.43			
No. of observation	402			
Stated Preference				
Attribute	Unit	Coefficient	t-value	Standard Error
In vehicle travel time (T_{inv})	Min	-.04764046	-4.036	0.0118
Cost of travel/ Fare (C_{ij})	Rs.	-.01287938	-4.326	0.0029
Out of Vehicle Travel Time (T_{out})	Min	-.08536609	-3.295	0.0259
Congestion Toll (C_{toll})	Rs.	-.06471298	-3.768	0.0171
Dummy Car x Interaction of Income (α_cx I_i)		0.05715177	10.12	0.0056
Dummy Van (α_{van})	----	1.78395471	4.125	0.4324
Dummy Van (α_{BRT})		2.18576719	5.477	0.3990
Statistics				
Log Likelihood	-401.67			
Pseudo R^2	0.228			
Restricted Log Lokelihood	-520.44			
No. of observation	414			
RP-SP				
Attribute	**Unit**	**Coefficient**	**t-value**	**Standard**

				Error
In vehicle travel time (T_{inv})	Min	-.03219157	-4.385	0.0073
Cost of travel/ Fare (C_{ij})	Rs.	-.00930499	-4.876	0.0019
Out of Vehicle Travel Time (T_{out})	Min	-.06232309	-3.501	0.0178
Congestion Toll (C_{toll})	Rs.	-.05041153	-4.656	0.0108
Parking Cost (C_{park})	Rs.	-------------------		
Dummy Car x Interaction of Income (α_cx I_i)		.04818290	8.570	0.0056
Dummy Van RP(α_{van})	----	1.85128361	6.131	0.3019
Dummy Van SP(α_{van})	----	1.43627796	4.413	0.3254
Dummy BRT SP(α_{BRT})		1.87214491	5.408	0.3461
Scale parameter (ʎ)		0.8628	12.896 [2.05]*	0.0669
Statistics				
Log Likelihood	*-726.11*			
Pseudo R^2	0.209			
Restricted Log Lokelihood	918.87			
No. of Observations	816			

***T-Statistic Ho ʎ =1 in square brackets**

APPENDIX B

Questionnaire & Stated Experiments Choice Sets

QUESTTIONAIRE ABOUT TRAVEL BEHAVIOUR FOR WORK TRIP MODE CHOICE

Questions in part are related to your personal information. These answers are just for statistical purpose only.

Part 1: Demographic Information

1. Name (Optional) ____
2. Occupation: ____
3. Age __________________

Average Monthly Income: (click the block given below for range of income you have)

	<Rs. 8000		Rs. 8000- Rs. 15000		Rs. 15000-Rs. 20000
	Rs. 20000- Rs. 25000		Rs. 25000 – Rs30000		Rs. 30000– Rs. 35000
	Rs. 35000 – Rs. 40000		Rs. 40000- Rs. 45000		Rs. 45000- Rs. 50000
	Rs. 50000- Rs. 60000		Rs. 60000- Rs. 70000		Rs. 70000- Rs. 80000
	Rs. 80000- RS. 90000		RS. 90000- Rs. 100,000		0ver Rs. 100,0000

4. Marital status: (Answer by Yes or No in blank) Single ________ Married _______
5. No. of persons in house: Below 5 Years____________ Above 5 years____________
6. No. of Automobiles in House: Car __________ Motorcycle __________ Other ________
7. How many numbers of students live in your household? ______
8. How many workers live in your household? ______
9. How many licensed drivers in your house: ______________________________________
10. Resident address: ____
11. Office Address: ____

____

12. If you are from Rawalpindi and working in Islamabad, which route or road you mostly follow during your journey from home to office using your own car among the followings:

	Murree Road		IJP road
	Islamabad Expressway		Mall Road/G.T. Road

Questions in part 2 belongs to the mode of travel (car, bus, vane, motorcycle) you use for going to work place.

Part 2: Information about present mode of travel for work trip (Revealed Preference Data)

What is your present mode of transport? (Tick the choice given below in the table)

	Private car		Walk +Van/Bus		Taxi+ Bus
	motorcycle		Carpool/ Car sharing		other
Please mention in the blank other mode of travel you use? _________________					

Fill in the cell the information about your mode of travel in the table below:

If you are private mode user (car , motorcycle, etc), fill the table below:

1.	In much time you reached your office from your home in your own car (In vehicle travel time)	In Minutes:
2.	What daily average cost incurred to you in traveling your own car? (Average cost of travel)	In Rupees:
3.	Parking fee	In Rupees:
4.	Congestion toll if applicable	In Rupees:

If you are public transport user (bus, vane, etc), fill the table below:

1.	How much time the vehicle takes from stop you ride on to stop you ride off? (In vehicle travel time)	In Minutes:
2.	The public vehicle fare? (cost of travel)	In Rupees:
3.	The vehicle is available at stop after how much time? (Frequency or headway)	In Minutes:
4.	How much time its take you to walk to bus stop from home to ride on and from bus stop to office after riding off? (Out of vehicle travel time)	In Minutes:

If your first choice mode is not available, what will be the alternative mode? Provide following attributes of your alternative mode.

Alternative Mode		
1.	In vehicle ravel time	In minutes:
2.	Cost of travel	In Rupees:
4.	Out of vehicle travel time	In minutes:

5.	Frequency or headway	In minutes:
7.	Parking fee	In Rupees:
8.	Toll is applicable	In Rupees:

Note: mention only those attributes which are related to your choice

Questions in part 3 are based on hypothetical scenario, in which you are provided with modes and some characterististics of mode which are not present or you have not experienced yet. Please go through all information provided in the table and choose the mode to travel which you will prefer the most with given cost and time restrictions.

Part 3: Hypothetical information (Stated Preference Data)

In this part a new transit mode is introduced with improved characteristics of comfort, safety and less travel times. Choose among the given alternatives the mode you prefer as your choice to travel given your income and budget constraint.

	Car	**Motorcycle**	**Van**	**Bus Rapid Transit**
Cost of travel	Rs. 200/trip	Rs. 30/trip	Rs. 15/trip	Rs. 30/trip
Congestion toll	Rs. 25			
Parking fee	Rs. 15	Rs.5		
In Vehicle travel time	30 min	45 min	40 min	30 min
Out of vehicle travel time			15 min	20 min
Headway/ Availability			every 10 min	Every 5 min
No. of transfer			0	1

If you are provided with above mentioned choices which mode you will prefer?

- Travel by Car ☐
- Travel by Motorcycle ☐
- Travel By Van ☐
- Travel By BRT ☐

	Car	Motorcycle	Van	Bus Rapid Transit
Cost of travel	Rs. 100/trip	Rs. 20/trip	Rs. 25/trip	Rs. 35 /trip
Congestion toll	Rs. 25			
Parking fee	Rs. 10	free		
In Vehicle travel time	40 min	45 min	40 min	30 min
Out of vehicle travel time			20 min	20 min
Headway/ Availability			every 15	Every 15 min
No. of transfer			0	0

If you are provided with above mentioned choices which mode you will prefer?

Travel by Car ☐
Travel by Motorcycle ☐
Travel By Van ☐
Travel By BRT ☐

	Car	Motorcycle	Van	Bus Rapid Transit
Cost of travel	Rs. 150/trip	Rs. 35/ trip	Rs. 20/ trip	Rs. 30/trip
Congestion toll	Rs.15			
Parking fee	free	free		
In Vehicle travel time	50 min	45 min	50 min	30 min
Out of vehicle travel time			10 min	15 min
Headway/ Availability			every 5 min	Every 15 min
No. of transfer			2	1

If you are provided with above mentioned choices which mode you will prefer?

Travel by Car ☐
Travel by Motorcycle ☐
Travel By Van ☐
Travel By BRT ☐

Thanks for your cooperation in this Survey

ATTRIBUTES OF MODES RELATED TO WORK TRIPS

Block	IVT Car	Cost Car	Park Car	Toll Car	IVT Mtr	Cost Mtr	Park Mtr	Cost Van	IVT Van	OVT Van	Freq Van	Cost BRT	IVT BRT	OVT BRT	Freq BRT
1	30 min	Rs. 200	Rs. 5	Rs. 25	35 min	Rs. 30	Rs.10	Rs. 15	40 min	15 min	10 min	Rs. 30	40 min	20 min	5 min
	40 min	Rs. 100	Rs. 10	Rs. 25	45 min	Rs. 20	Rs.10	Rs. 25	30 min	20 min	15 min	Rs. 35	30 min	20 min	15 min
	50 min	Rs. 150	free	Rs.15	45 min	Rs. 35	free	Rs. 20	50 min	10 min	5 min	Rs. 30	20 min	15 min	15 min
2	40 min	Rs. 100	Rs. 5	Rs.15	45 min	Rs. 35	Rs. 5	Rs. 15	50 min	15 min	15 min	Rs. 25	30 min	10 min	15 min
	30 min	Rs. 150	Rs. 10	Rs. 35	35 min	Rs. 20	Rs.10	Rs. 20	30 min	10 min	5 min	Rs. 35	40 min	15 min	5 min
	50 min	Rs. 200	Rs. 10	Rs. 25	25 min	Rs. 30	free	Rs. 25	40 min	20 min	10 min	Rs. 35	20 min	20 min	10 min
3	50 min	Rs. 200	Rs. 10	Rs.15	35 min	Rs. 20	Rs.10	Rs. 20	30 min	15 min	10 min	Rs. 35	20 min	10 min	10 min
	30 min	Rs. 150	free	Rs. 25	25 min	Rs. 35	Rs. 5	Rs. 25	30 min	20 min	15 min	Rs. 30	40 min	20 min	15 min
	40 min	Rs. 100	Rs. 5	Rs. 35	45 min	Rs. 30	free	Rs. 15	40 min	10 min	5 min	Rs. 25	30 min	20 min	5 min
4	30 min	Rs. 150	free	Rs. 25	35 min	Rs. 20	free	Rs. 15	40 min	20 min	15 min	Rs. 25	30 min	15 min	10 min
	40 min	Rs. 200	Rs. 10	Rs. 35	25 min	Rs. 35	Rs. 5	Rs. 25	50 min	15 min	5 min	Rs. 35	40 min	15 min	5 min
	30 min	Rs. 100	free	Rs.15	30 min	Rs. 30	Rs. 5	Rs. 25	30 min	10 min	10 min	Rs. 30	20 min	10 min	10 min
5	50 min	Rs. 100	Rs. 5	Rs. 35	45 min	Rs. 20	Rs. 5	Rs. 20	40 min	20 min	10 min	Rs. 30	40 min	15 min	10 min
	30 min	Rs. 200	free	Rs. 35	25 min	Rs. 35	free	Rs. 15	50 min	10 min	15 min	Rs. 35	20 min	15 min	10 min
	30 min	Rs.100	Rs. 10	Rs.15	35 min	Rs. 30	free	Rs. 25	30 min	20 min	5 min	Rs. 25	30 min	15 min	5 min

6	50 min	Rs. 100	Rs. 10	Rs. 25	35 min	Rs. 35	free	Rs. 15	30 min	15 min	10 min	Rs. 30	30 min	10 min	5 min
	40 min	Rs. 150	free	Rs. 35	25 min	Rs. 30	Rs.10	Rs. 20	50 min	20 min	5 min	Rs. 25	20 min	10 min	15 min
	40 min	Rs. 150	Rs. 5	Rs.15	25 min	Rs. 35	Rs. 5	Rs. 25	40 min	10 min	10 min	Rs. 35	30 min	20 min	10 min
7	50 min	Rs. 150	Rs. 10	Rs. 25	35 min	Rs. 30	Rs. 5	Rs. 20	50 min	15 min	15	Rs. 25	30 min	15 min	10 min
	40 min	Rs. 200	free	Rs.15	25 min	Rs. 20	free	Rs. 15	40 min	20 min	5 min	Rs. 30	40 min	10 min	5 min
	30 min	Rs. 100	free	Rs. 35	45 min	Rs. 20	Rs.10	Rs. 25	40 min	10 min	10 min	Rs. 35	20 min	15 min	5 min
8	40 min	Rs. 150	Rs. 5	Rs. 25	25 min	Rs. 30	Rs.10	Rs. 15	30 min	10 min	5 min	Rs. 30	20 min	10 min	10 min
	50 min	Rs. 200	free	Rs. 35	35 min	Rs. 20	Rs. 5	Rs. 25	50 min	20 min	15 min	Rs. 35	30 min	10 min	5 min
	30 min	Rs. 100	Rs. 10	Rs.15	25 min	Rs. 35	Rs.10	Rs. 20	40 min	15 min	10 min	Rs. 25	40 min	15 min	15 min
9	30 min	Rs. 150	Rs. 5	Rs. 25	45 min	Rs. 35	free	Rs. 20	50 min	20 min	10 min	Rs. 35	20 min	10 min	5 min
	40 min	Rs. 200	Rs. 5	Rs.15	25 min	Rs. 20	Rs.10	Rs. 20	30 min	10 min	15 min	Rs. 25	30 min	15 min	5 min
	50 min	Rs. 100	Rs. 10	Rs. 35	35 min	Rs. 20	Rs. 5	Rs. 15	50 min	10 min	5 min	Rs. 25	40 min	20 min	15 min

APPENDIX C

N-Logit Software Outputs

N-Logit Outputs

1. Finalized SP-RP Model with Elasticities

```
nlog; lhs=mode,NIJ,ALTIJ; choices=CARR,MTRR,VANR,CARS,MTRS,VANS,BRTS

;TREE=MODE[RP(CARR,MTRR,VANR),cars(CARS),mtrs(MTRS),vans(VANS),brts(BRTS)...
;IVSET :(RP)=[1]/(cars,mtrs,vans,brts)
;model: U(CARR)=CAR*INCCAR+IVT*IVT+COST*COST+CONG*CONG/
U(MTRR)=IVT*IVT+COST*COST/
U(VANR)=VANR*AVANR+IVT*IVT+COST*COST+OVT*OVT/
U(CARS)=CAR*INCCAR+IVT*IVT+COST*COST+CONG*CONG/
U(MTRS)=IVT*IVT+COST*COST/
U(VANS)=VANS*AVANS+IVT*IVT+COST*COST+OVT*OVT/
U(BRTS)=BRT*ABRTS+IVT*IVT+COST*COST+OVT*OVT$
+----------------------------------------------+
| Discrete choice and multinomial logit models|
+----------------------------------------------+

+-------------------------------------------------------+
|WARNING:   Bad observations were found in the sample. |
|Found   3 bad observations among     816 individuals. |
|You can use ;CheckData to get a list of these points. |
+-------------------------------------------------------+

Normal exit from iterations. Exit status=0.
+----------------------------------------------+
| FIML Nested Multinomial Logit Model          |
| Maximum Likelihood Estimates                 |
| Model estimated: Jul 14, 2014 at 05:49:51PM.|
| Dependent variable                MODE       |
| Weighting variable                None       |
| Number of observations             813       |
| Iterations completed                19       |
| Log likelihood function       -726.1111
| Number of parameters                 9       |
| Info. Criterion: AIC =         1.89410       |
|   Finite Sample: AIC =         1.89438       |
| Info. Criterion: BIC =         1.94614       |
| Info. Criterion:HQIC =         1.91408       |
| Restricted log likelihood     -1750.115      |
| McFadden Pseudo R-squared      .5851991      |
| Chi squared                   2047.188
| Degrees of freedom                   9       |
| Prob[ChiSqd > value] =         .0000000      |
| Constants only.  Must be computed directly. |
|                  Use NLOGIT ;...; RHS=ONE $ |
| At start values  -1011.4091  .24763 ******* |
| Response data are given as ind. choice.      |
+----------------------------------------------+
+----------------------------------------------+
| Notes No coefficients=>P(i,j)=1/J(i).       |
|       Constants only =>P(i,j) uses ASCs     |
|         only. N(j)/N if fixed choice set.    |
|         N(j) = total sample frequency for j |
|         N    = total sample frequency.       |
```

```
|       These 2 models are simple MNL models. |
|       R-sqrd = 1 - LogL(model)/logL(other)  |
|       RsqAdj=1-[nJ/(nJ-nparm)]*(1-R-sqrd)   |
|         nJ   = sum over i, choice set sizes |
+---------------------------------------------+

+---------------------------------------------+
| FIML Nested Multinomial Logit Model         |
| The model has 2 levels.                     |
| Nested Logit form:IV parms = taub|l,r,sl|r  |
| and fr. No normalizations imposed a priori. |
| p(alt=j|b=B,l=L,r=R)=exp[bX_j|BLR]/Sum      |
| p(b=B|l=L,r=R)=exp[aY_B|LR+tauB|LRIVB|LR)]/ |
| Sum. p(l=L|r=R)=exp[cZ_L|R+sL|RIVL|R)]/Sum  |
| p(r=R)=exp[qH_R+fRIVR]/Sum...               |
| Number of obs.=   816, skipped   3 bad obs. |
+---------------------------------------------+
+---------+--------------+----------------+--------+--------+
|Variable| Coefficient  | Standard Error |b/St.Er.|P[|Z|>z]|
+---------+--------------+----------------+--------+--------+
---------+Attributes in the Utility Functions (beta)
 CAR     |     .04818290       .00562205     8.570   .0000
 IVT     |    -.03219157       .00734140    -4.385   .0000
 COST    |    -.00930499       .00190850    -4.876   .0000
 CONG    |    -.05041153       .01082758    -4.656   .0000
 VANR    |    1.85128369       .30197649     6.131   .0000
 OVT     |    -.06232309       .01780267    -3.501   .0005
 VANS    |    1.43627784       .32547824     4.413   .0000
 BRT     |    1.87214480       .34619971     5.408   .0000
---------+IV parameters, tau(b|l,r),sigma(l|r),phi(r)
 RP      |    1.00000000    ......(Fixed Parameter).......
 CARS    |    1.15900822       .0669000112.89   .0000
 MTRS    |    1.15900822       .0669000112.89   .0000
 VANS    |    1.15900822       .0669000112.89   .0000
 BRTS    |    1.15900822       .0669000112.89   .0000

+------------------------------------------------------------+
| Partial effects = average over observations                |
|                                                            |
| dlnP[alt=j,br=b,lmb=l,tr=r]                                |
| ---------------------------- = D(k:J,B,L,R) = delta(k)*F   |
| dx(k):alt=J,br=B,lmb=L,tr=R]                               |
|                                                            |
| delta(k) = coefficient on x(k) in U(J|B,L,R)               |
| F = (r=R)  (l=L)  (b=B) [(j=J)-P(J|BLR)]                   |
|  +  (r=R)  (l=L) [(b=B) -P(B|LR)]P(J|BLR)t(B|LR)           |
|  +  (r=R) [(l=L)-P(L|R)] P(B|LR) P(J|BLR)t(B|LR)s(L|R)     |
|  + [(r=R) -P(R)] P(L|R)  P(B|IR) P(J|BIR)t(B|LR)s(L|R)f(R) |
|                                                            |
| P(J|BLR)=Prob[choice=J |branch=B,limb=L,trunk=R]           |
| P(B|LR), P(L|R), P(R) defined likewise.                    |
| (n=N) = 1 if n=N, 0 else, for n=j,b,l,r and N=J,B,L,R.     |
| Elasticity = x(k) * D(j|B,L,R)                             |
| Marginal effect = P(JBLR)*D = P(J|BLR)P(B|LR)P(L|R)P(R)D   |
| F is decomposed into the 4 parts in the tables.            |
+------------------------------------------------------------+
+-------------------------------------------------------------------------+
```

```
| Derivative (times 100) averaged over observations.                    |
| Attribute is IVT      in choice CARS                                  |
| Effects on probabilities of all choices in the model:                 |
| * indicates direct Derivative effect of the attribute.                |
|                        Decomposition of Effect if Nest    Total Effect|
|                        Trunk   Limb   Branch   Choice     Mean  St.Dev|
| Trunk=Trunk{1}                                                        |
| Limb=MODE                                                             |
|    Branch=RP                                                          |
|       Choice=CARR        .000   .000    .000    .000        .000   .000 |
|       Choice=MTRR        .000   .000    .000    .000        .000   .000 |
|       Choice=VANR        .000   .000    .000    .000        .000   .000 |
|    Branch=CARS                                                        |
| *     Choice=CARS        .000   .000   -.675    .000       -.675   .226 |
|    Branch=MTRS                                                        |
|       Choice=MTRS        .000   .000    .052    .000        .052   .055 |
|    Branch=VANS                                                        |
|       Choice=VANS        .000   .000    .085    .000        .085   .087 |
|    Branch=BRTS                                                        |
|       Choice=BRTS        .000   .000    .179    .000        .179   .169 |
+-----------------------------------------------------------------------+
+-----------------------------------------------------------------------+
| Derivative (times 100) averaged over observations.                    |
| Attribute is IVT      in choice VANS                                  |
| Effects on probabilities of all choices in the model:                 |
| * indicates direct Derivative effect of the attribute.                |
|                        Decomposition of Effect if Nest    Total Effect|
|                        Trunk   Limb   Branch   Choice     Mean  St.Dev|
| Trunk=Trunk{1}                                                        |
| Limb=MODE                                                             |
|    Branch=RP                                                          |
|       Choice=CARR        .000   .000    .000    .000        .000   .000 |
|       Choice=MTRR        .000   .000    .000    .000        .000   .000 |
|       Choice=VANR        .000   .000    .000    .000        .000   .000 |
|    Branch=CARS                                                        |
|       Choice=CARS        .000   .000    .171    .000        .171   .076 |
|    Branch=MTRS                                                        |
|       Choice=MTRS        .000   .000    .109    .000        .109   .051 |
|    Branch=VANS                                                        |
| *     Choice=VANS        .000   .000   -.633    .000       -.633   .153 |
|    Branch=BRTS                                                        |
|       Choice=BRTS        .000   .000    .432    .000        .432   .166 |
+-----------------------------------------------------------------------+
+-----------------------------------------------------------------------+
| Derivative (times 100) averaged over observations.                    |
| Attribute is IVT      in choice BRTS                                  |
| Effects on probabilities of all choices in the model:                 |
| * indicates direct Derivative effect of the attribute.                |
|                        Decomposition of Effect if Nest    Total Effect|
|                        Trunk   Limb   Branch   Choice     Mean  St.Dev|
| Trunk=Trunk{1}                                                        |
| Limb=MODE                                                             |
|    Branch=RP                                                          |
|       Choice=CARR        .000   .000    .000    .000        .000   .000 |
|       Choice=MTRR        .000   .000    .000    .000        .000   .000 |
|       Choice=VANR        .000   .000    .000    .000        .000   .000 |
|    Branch=CARS                                                        |
```

```
|       Choice=CARS        .000   .000    .410    .000        .410   .147 |
|    Branch=MTRS                                                          |
|       Choice=MTRS        .000   .000    .280    .000        .280   .126 |
|    Branch=VANS                                                          |
|       Choice=VANS        .000   .000    .448    .000        .448   .173 |
|    Branch=BRTS                                                          |
| *     Choice=BRTS        .000   .000   -.858    .000       -.858   .101 |
+-------------------------------------------------------------------------+
+-------------------------------------------------------------------------+
| Derivative (times 100) averaged over observations.                      |
| Attribute is IVT      in choice MTRS                                    |
| Effects on probabilities of all choices in the model:                   |
| * indicates direct Derivative effect of the attribute.                  |
|                        Decomposition of Effect if Nest    Total Effect|
|                        Trunk   Limb   Branch   Choice     Mean  St.Dev|
| Trunk=Trunk{1}                                                          |
| Limb=MODE                                                               |
|    Branch=RP                                                            |
|       Choice=CARR        .000   .000    .000    .000        .000   .000 |
|       Choice=MTRR        .000   .000    .000    .000        .000   .000 |
|       Choice=VANR        .000   .000    .000    .000        .000   .000 |
|    Branch=CARS                                                          |
|       Choice=CARS        .000   .000    .094    .000        .094   .053 |
|    Branch=MTRS                                                          |
| *     Choice=MTRS        .000   .000   -.442    .000       -.442   .155 |
|    Branch=VANS                                                          |
|       Choice=VANS        .000   .000    .099    .000        .099   .050 |
|    Branch=BRTS                                                          |
|       Choice=BRTS        .000   .000    .247    .000        .247   .120 |
+-------------------------------------------------------------------------+
+-------------------------------------------------------------------------+
| Derivative (times 100) averaged over observations.                      |
| Attribute is OVT      in choice BRTS                                    |
| Effects on probabilities of all choices in the model:                   |
| * indicates direct Derivative effect of the attribute.                  |
|                        Decomposition of Effect if Nest    Total Effect|
|                        Trunk   Limb   Branch   Choice     Mean  St.Dev|
| Trunk=Trunk{1}                                                          |
| Limb=MODE                                                               |
|    Branch=RP                                                            |
|       Choice=CARR        .000   .000    .000    .000        .000   .000 |
|       Choice=MTRR        .000   .000    .000    .000        .000   .000 |
|       Choice=VANR        .000   .000    .000    .000        .000   .000 |
|    Branch=CARS                                                          |
|       Choice=CARS        .000   .000    .794    .000        .794   .284 |
|    Branch=MTRS                                                          |
|       Choice=MTRS        .000   .000    .542    .000        .542   .244 |
|    Branch=VANS                                                          |
|       Choice=VANS        .000   .000    .867    .000        .867   .334 |
|    Branch=BRTS                                                          |
| *     Choice=BRTS        .000   .000  -1.662    .000      -1.662   .195 |
+-------------------------------------------------------------------------+
+-------------------------------------------------------------------------+
| Derivative (times 100) averaged over observations.                      |
| Attribute is OVT      in choice BRTS                                    |
| Effects on probabilities of all choices in the model:                   |
| * indicates direct Derivative effect of the attribute.                  |
```

```
|                        Decomposition of Effect if Nest    Total Effect|
|                        Trunk   Limb   Branch   Choice     Mean  St.Dev|
| Trunk=Trunk{1}                                                        |
| Limb=MODE                                                             |
|    Branch=RP                                                          |
|       Choice=CARR       .000   .000    .000    .000        .000   .000 |
|       Choice=MTRR       .000   .000    .000    .000        .000   .000 |
|       Choice=VANR       .000   .000    .000    .000        .000   .000 |
|    Branch=CARS                                                        |
|       Choice=CARS       .000   .000    .794    .000        .794   .284 |
|    Branch=MTRS                                                        |
|       Choice=MTRS       .000   .000    .542    .000        .542   .244 |
|    Branch=VANS                                                        |
|       Choice=VANS       .000   .000    .867    .000        .867   .334 |
|    Branch=BRTS                                                        |
| *     Choice=BRTS       .000   .000  -1.662    .000      -1.662   .195 |
+-----------------------------------------------------------------------+
+-----------------------------------------------------------------------+
| Derivative (times 100) averaged over observations.                    |
| Attribute is OVT      in choice VANS                                  |
| Effects on probabilities of all choices in the model:                 |
| * indicates direct Derivative effect of the attribute.                |
|                        Decomposition of Effect if Nest    Total Effect|
|                        Trunk   Limb   Branch   Choice     Mean  St.Dev|
| Trunk=Trunk{1}                                                        |
| Limb=MODE                                                             |
|    Branch=RP                                                          |
|       Choice=CARR       .000   .000    .000    .000        .000   .000 |
|       Choice=MTRR       .000   .000    .000    .000        .000   .000 |
|       Choice=VANR       .000   .000    .000    .000        .000   .000 |
|    Branch=CARS                                                        |
|       Choice=CARS       .000   .000    .332    .000        .332   .147 |
|    Branch=MTRS                                                        |
|       Choice=MTRS       .000   .000    .211    .000        .211   .098 |
|    Branch=VANS                                                        |
| *     Choice=VANS       .000   .000  -1.225    .000      -1.225   .297 |
|    Branch=BRTS                                                        |
|       Choice=BRTS       .000   .000    .837    .000        .837   .321 |
+-----------------------------------------------------------------------+
+-----------------------------------------------------------------------+
| Derivative (times 100) averaged over observations.                    |
| Attribute is OVT      in choice BRTS                                  |
| Effects on probabilities of all choices in the model:                 |
| * indicates direct Derivative effect of the attribute.                |
|                        Decomposition of Effect if Nest    Total Effect|
|                        Trunk   Limb   Branch   Choice     Mean  St.Dev|
| Trunk=Trunk{1}                                                        |
| Limb=MODE                                                             |
|    Branch=RP                                                          |
|       Choice=CARR       .000   .000    .000    .000        .000   .000 |
|       Choice=MTRR       .000   .000    .000    .000        .000   .000 |
|       Choice=VANR       .000   .000    .000    .000        .000   .000 |
|    Branch=CARS                                                        |
|       Choice=CARS       .000   .000    .794    .000        .794   .284 |
|    Branch=MTRS                                                        |
|       Choice=MTRS       .000   .000    .542    .000        .542   .244 |
|    Branch=VANS                                                        |
```

```
|       Choice=VANS       .000   .000    .867    .000        .867   .334 |
|    Branch=BRTS                                                         |
| *     Choice=BRTS       .000   .000  -1.662    .000      -1.662   .195 |
+------------------------------------------------------------------------+
+------------------------------------------------------------------------+
| Derivative (times 100) averaged over observations.                     |
| Attribute is OVT      in choice VANS                                   |
| Effects on probabilities of all choices in the model:                  |
| * indicates direct Derivative effect of the attribute.                 |
|                        Decomposition of Effect if Nest    Total Effect|
|                        Trunk   Limb   Branch   Choice     Mean  St.Dev|
| Trunk=Trunk{1}                                                         |
| Limb=MODE                                                              |
|    Branch=RP                                                           |
|       Choice=CARR       .000   .000    .000    .000        .000   .000 |
|       Choice=MTRR       .000   .000    .000    .000        .000   .000 |
|       Choice=VANR       .000   .000    .000    .000        .000   .000 |
|    Branch=CARS                                                         |
|       Choice=CARS       .000   .000    .332    .000        .332   .147 |
|    Branch=MTRS                                                         |
|       Choice=MTRS       .000   .000    .211    .000        .211   .098 |
|    Branch=VANS                                                         |
| *     Choice=VANS       .000   .000  -1.225    .000      -1.225   .297 |
|    Branch=BRTS                                                         |
|       Choice=BRTS       .000   .000    .837    .000        .837   .321 |
+------------------------------------------------------------------------+
+------------------------------------------------------------------------+
| Derivative (times 100) averaged over observations.                     |
| Attribute is COST     in choice CARS                                   |
| Effects on probabilities of all choices in the model:                  |
| * indicates direct Derivative effect of the attribute.                 |
|                        Decomposition of Effect if Nest    Total Effect|
|                        Trunk   Limb   Branch   Choice     Mean  St.Dev|
| Trunk=Trunk{1}                                                         |
| Limb=MODE                                                              |
|    Branch=RP                                                           |
|       Choice=CARR       .000   .000    .000    .000        .000   .000 |
|       Choice=MTRR       .000   .000    .000    .000        .000   .000 |
|       Choice=VANR       .000   .000    .000    .000        .000   .000 |
|    Branch=CARS                                                         |
| *     Choice=CARS       .000   .000   -.195    .000       -.195   .065 |
|    Branch=MTRS                                                         |
|       Choice=MTRS       .000   .000    .015    .000        .015   .016 |
|    Branch=VANS                                                         |
|       Choice=VANS       .000   .000    .025    .000        .025   .025 |
|    Branch=BRTS                                                         |
|       Choice=BRTS       .000   .000    .052    .000        .052   .049 |
+------------------------------------------------------------------------+
+------------------------------------------------------------------------+
| Derivative (times 100) averaged over observations.                     |
| Attribute is COST     in choice MTRS                                   |
| Effects on probabilities of all choices in the model:                  |
| * indicates direct Derivative effect of the attribute.                 |
|                        Decomposition of Effect if Nest    Total Effect|
|                        Trunk   Limb   Branch   Choice     Mean  St.Dev|
| Trunk=Trunk{1}                                                         |
| Limb=MODE                                                              |
```

```
|    Branch=RP                                                         |
|       Choice=CARR       .000   .000    .000    .000       .000   .000 |
|       Choice=MTRR       .000   .000    .000    .000       .000   .000 |
|       Choice=VANR       .000   .000    .000    .000       .000   .000 |
|    Branch=CARS                                                       |
|       Choice=CARS       .000   .000    .027    .000       .027   .015 |
|    Branch=MTRS                                                       |
| *     Choice=MTRS       .000   .000   -.128    .000      -.128   .045 |
|    Branch=VANS                                                       |
|       Choice=VANS       .000   .000    .029    .000       .029   .014 |
|    Branch=BRTS                                                       |
|       Choice=BRTS       .000   .000    .071    .000       .071   .035 |
+----------------------------------------------------------------------+
+----------------------------------------------------------------------+
| Derivative (times 100) averaged over observations.                   |
| Attribute is COST     in choice BRTS                                 |
| Effects on probabilities of all choices in the model:                |
| * indicates direct Derivative effect of the attribute.               |
|                       Decomposition of Effect if Nest    Total Effect|
|                       Trunk   Limb   Branch   Choice     Mean  St.Dev|
| Trunk=Trunk{1}                                                       |
| Limb=MODE                                                            |
|    Branch=RP                                                         |
|       Choice=CARR       .000   .000    .000    .000       .000   .000 |
|       Choice=MTRR       .000   .000    .000    .000       .000   .000 |
|       Choice=VANR       .000   .000    .000    .000       .000   .000 |
|    Branch=CARS                                                       |
|       Choice=CARS       .000   .000    .118    .000       .118   .042 |
|    Branch=MTRS                                                       |
|       Choice=MTRS       .000   .000    .081    .000       .081   .036 |
|    Branch=VANS                                                       |
|       Choice=VANS       .000   .000    .129    .000       .129   .050 |
|    Branch=BRTS                                                       |
| *     Choice=BRTS       .000   .000   -.248    .000      -.248   .029 |
+----------------------------------------------------------------------+
+----------------------------------------------------------------------+
| Derivative (times 100) averaged over observations.                   |
| Attribute is COST     in choice VANS                                 |
| Effects on probabilities of all choices in the model:                |
| * indicates direct Derivative effect of the attribute.               |
|                       Decomposition of Effect if Nest    Total Effect|
|                       Trunk   Limb   Branch   Choice     Mean  St.Dev|
| Trunk=Trunk{1}                                                       |
| Limb=MODE                                                            |
|    Branch=RP                                                         |
|       Choice=CARR       .000   .000    .000    .000       .000   .000 |
|       Choice=MTRR       .000   .000    .000    .000       .000   .000 |
|       Choice=VANR       .000   .000    .000    .000       .000   .000 |
|    Branch=CARS                                                       |
|       Choice=CARS       .000   .000    .050    .000       .050   .022 |
|    Branch=MTRS                                                       |
|       Choice=MTRS       .000   .000    .032    .000       .032   .015 |
|    Branch=VANS                                                       |
| *     Choice=VANS       .000   .000   -.183    .000      -.183   .044 |
|    Branch=BRTS                                                       |
|       Choice=BRTS       .000   .000    .125    .000       .125   .048 |
+----------------------------------------------------------------------+
```

```
+-------------------------------------------------------------------------+
| Derivative (times 100) averaged over observations.                      |
| Attribute is CONG     in choice CARS                                    |
| Effects on probabilities of all choices in the model:                   |
| * indicates direct Derivative effect of the attribute.                  |
|                       Decomposition of Effect if Nest    Total Effect|
|                       Trunk   Limb   Branch   Choice     Mean  St.Dev|
| Trunk=Trunk{1}                                                          |
| Limb=MODE                                                               |
|    Branch=RP                                                            |
|       Choice=CARR       .000   .000    .000    .000        .000   .000 |
|       Choice=MTRR       .000   .000    .000    .000        .000   .000 |
|       Choice=VANR       .000   .000    .000    .000        .000   .000 |
|    Branch=CARS                                                          |
| *     Choice=CARS       .000   .000  -1.057    .000      -1.057   .354 |
|    Branch=MTRS                                                          |
|       Choice=MTRS       .000   .000    .082    .000        .082   .086 |
|    Branch=VANS                                                          |
|       Choice=VANS       .000   .000    .134    .000        .134   .137 |
|    Branch=BRTS                                                          |
|       Choice=BRTS       .000   .000    .281    .000        .281   .265 |
+-------------------------------------------------------------------------+
+-------------------------------------------------------------------------+
| Derivative (times 100) averaged over observations.                      |
| Attribute is INCCAR   in choice CARS                                    |
| Effects on probabilities of all choices in the model:                   |
| * indicates direct Derivative effect of the attribute.                  |
|                       Decomposition of Effect if Nest    Total Effect|
|                       Trunk   Limb   Branch   Choice     Mean  St.Dev|
| Trunk=Trunk{1}                                                          |
| Limb=MODE                                                               |
|    Branch=RP                                                            |
|       Choice=CARR       .000   .000    .000    .000        .000   .000 |
|       Choice=MTRR       .000   .000    .000    .000        .000   .000 |
|       Choice=VANR       .000   .000    .000    .000        .000   .000 |
|    Branch=CARS                                                          |
| *     Choice=CARS       .000   .000   1.010    .000       1.010   .338 |
|    Branch=MTRS                                                          |
|       Choice=MTRS       .000   .000   -.079    .000       -.079   .083 |
|    Branch=VANS                                                          |
|       Choice=VANS       .000   .000   -.128    .000       -.128   .131 |
|    Branch=BRTS                                                          |
|       Choice=BRTS       .000   .000   -.268    .000       -.268   .253 |
+-------------------------------------------------------------------------+
+-------------------------------------------------------------------------+
| Derivative (times 100) averaged over observations.                      |
| Attribute is INCCAR   in choice CARS                                    |
| Effects on probabilities of all choices in the model:                   |
| * indicates direct Derivative effect of the attribute.                  |
|                       Decomposition of Effect if Nest    Total Effect|
|                       Trunk   Limb   Branch   Choice     Mean  St.Dev|
| Trunk=Trunk{1}                                                          |
| Limb=MODE                                                               |
|    Branch=RP                                                            |
|       Choice=CARR       .000   .000    .000    .000        .000   .000 |
|       Choice=MTRR       .000   .000    .000    .000        .000   .000 |
|       Choice=VANR       .000   .000    .000    .000        .000   .000 |
```

```
|    Branch=CARS                                                          |
| *     Choice=CARS        .000   .000    .294    .000       .294   .441 |
|    Branch=MTRS                                                          |
|       Choice=MTRS        .000   .000   -.042    .000      -.042   .070 |
|    Branch=VANS                                                          |
|       Choice=VANS        .000   .000   -.075    .000      -.075   .121 |
|    Branch=BRTS                                                          |
|       Choice=BRTS        .000   .000   -.177    .000      -.177   .267 |
+-------------------------------------------------------------------------+

+---------------------------------------------------------------------------+
|             Descriptive Statistics for Alternative CARR                   :
|     Utility Function            |                     |     87.0 observs.  |
|     Coefficient                 | All      402.0 obs.|that chose CARR     |
| Name           Value  Variable | Mean      Std. Dev.|Mean       Std. Dev. |
| -------------------  -------- | -------------------+------------------- |
| CAR            .0482  INCCAR   |   30.813     25.067|   56.966    30.101 |
| IVT           -.0322  IVT      |   14.664      3.973|   15.000     4.176 |
| COST          -.0093  COST     |  154.478     42.577|  150.000    41.763 |
| CONG          -.0504  CONG     |   23.619      8.054|   22.759     7.878 |
+---------------------------------------------------------------------------+
+---------------------------------------------------------------------------+
|             Descriptive Statistics for Alternative MTRR                   :
|     Utility Function            |                     |     90.0 observs.  |
|     Coefficient                 | All      402.0 obs.|that chose MTRR     |
| Name           Value  Variable | Mean      Std. Dev.|Mean       Std. Dev. |
| -------------------  -------- | -------------------+------------------- |
| IVT           -.0322  IVT      |   26.493      7.159|   25.333     7.220 |
| COST          -.0093  COST     |   30.000      8.206|   29.000     8.747 |
+---------------------------------------------------------------------------+
+---------------------------------------------------------------------------+
|             Descriptive Statistics for Alternative VANR                   :
|     Utility Function            |                     |    225.0 observs.  |
|     Coefficient                 | All      402.0 obs.|that chose VANR     |
| Name           Value  Variable | Mean      Std. Dev.|Mean       Std. Dev. |
| -------------------  -------- | -------------------+------------------- |
| IVT           -.0322  IVT      |   29.328      8.580|   28.400     8.510 |
| COST          -.0093  COST     |   19.776      4.187|   19.467     4.218 |
| VANR          1.8513  AVANR    |    1.000       .000|    1.000      .000 |
| OVT           -.0623  OVT      |   14.963      4.080|   14.800     3.962 |
+---------------------------------------------------------------------------+
+---------------------------------------------------------------------------+
|             Descriptive Statistics for Alternative CARS                   :
|     Utility Function            |                     |     87.0 observs.  |
|     Coefficient                 | All      411.0 obs.|that chose CARS     |
| Name           Value  Variable | Mean      Std. Dev.|Mean       Std. Dev. |
| -------------------  -------- | -------------------+------------------- |
| CAR            .0482  INCCAR   |   41.653     31.685|   80.414    29.421 |
| IVT           -.0322  IVT      |   14.635      4.086|   14.655     4.162 |
| COST          -.0093  COST     |  154.745     41.415|  146.552    37.193 |
| CONG          -.0504  CONG     |   24.416      8.273|   23.621     8.237 |
+---------------------------------------------------------------------------+
+---------------------------------------------------------------------------+
|             Descriptive Statistics for Alternative MTRS                   :
|     Utility Function            |                     |     54.0 observs.  |
|     Coefficient                 | All      411.0 obs.|that chose MTRS     |
| Name           Value  Variable | Mean      Std. Dev.|Mean       Std. Dev. |
```

```
| -------------------  -------- | ------------------+------------------- |
| IVT           -.0322  IVT     |   28.686      7.729|   26.667     6.729 |
| COST          -.0093  COST    |   28.285      6.414|   27.500     6.987 |
+------------------------------------------------------------------------+
+------------------------------------------------------------------------+
|             Descriptive Statistics for Alternative VANS                :
|     Utility Function          |                    |    78.0 observs.  |
|     Coefficient               | All     411.0 obs.|that chose VANS     |
| Name              Value  Variable | Mean      Std. Dev.|Mean      Std. Dev. |
| -------------------  -------- | ------------------+------------------- |
| IVT           -.0322  IVT     |   30.584      7.724|   27.692     8.046 |
| COST          -.0093  COST    |   19.927      4.057|   19.615     3.929 |
| OVT           -.0623  OVT     |   14.708      3.766|   14.231     4.115 |
| VANS          1.4363  AVANS   |    1.000       .000|    1.000      .000 |
+------------------------------------------------------------------------+
+------------------------------------------------------------------------+
|             Descriptive Statistics for Alternative BRTS                :
|     Utility Function          |                    |   192.0 observs.  |
|     Coefficient               | All     411.0 obs.|that chose BRTS     |
| Name              Value  Variable | Mean      Std. Dev.|Mean      Std. Dev. |
| -------------------  -------- | ------------------+------------------- |
| IVT           -.0322  IVT     |   18.759      4.181|   18.516     3.931 |
| COST          -.0093  COST    |   29.891      4.254|   30.078     4.108 |
| OVT           -.0623  OVT     |   13.577      3.726|   13.125     3.600 |
| BRT           1.8721  ABRTS   |    1.000       .000|    1.000      .000 |
+------------------------------------------------------------------------+
PREDICTED PROBABILITIES (* marks actual, + marks prediction.)
Indiv    CARR      MTRR      VANR      CARS      MTRS      VANS      BRTS
    1   .2615*    .3507     .3878 +   .0000     .0000     .0000     .0000
    2   .1077     .2549     .6374*+   .0000     .0000     .0000     .0000
    3   .0579     .1913     .7509*+   .0000     .0000     .0000     .0000
    4   .0530     .2616     .6854*+   .0000     .0000     .0000     .0000
    5   .0613     .1768     .7619*+   .0000     .0000     .0000     .0000
    6   .1170     .4501 +   .4329*    .0000     .0000     .0000     .0000
    7   .5385*+   .1084     .3532     .0000     .0000     .0000     .0000
    8   .8720*+   .0354     .0926     .0000     .0000     .0000     .0000
    9   .8886*+   .0347     .0766     .0000     .0000     .0000     .0000
   10   .0366*    .3506     .6128 +   .0000     .0000     .0000     .0000
   11   .0502*    .2368     .7131 +   .0000     .0000     .0000     .0000
   12   .1326     .2256     .6419*+   .0000     .0000     .0000     .0000
   13   .2334     .1544     .6123*+   .0000     .0000     .0000     .0000
   14   .0602     .3264*    .6134 +   .0000     .0000     .0000     .0000
   15   .0916     .2326     .6757*+   .0000     .0000     .0000     .0000
   16   .1315     .1749     .6936*+   .0000     .0000     .0000     .0000
   17   .0309     .3366     .6325*+   .0000     .0000     .0000     .0000
   18   .0897     .2688     .6415*+   .0000     .0000     .0000     .0000
   19   .0438     .1771     .7791*+   .0000     .0000     .0000     .0000
   20   .0424     .3226     .6350*+   .0000     .0000     .0000     .0000
   21   .3204     .1461     .5335*+   .0000     .0000     .0000     .0000
   22   .4633 +   .1852     .3516*    .0000     .0000     .0000     .0000
PREDICTED PROBABILITIES (* marks actual, + marks prediction.)
Indiv    CARR      MTRR      VANR      CARS      MTRS      VANS      BRTS
   23   .2562     .1455     .5983*+   .0000     .0000     .0000     .0000
   24   .2792     .1451     .5757*+   .0000     .0000     .0000     .0000
   25   .0754     .3212     .6035*+   .0000     .0000     .0000     .0000
   26   .1137     .2270     .6593*+   .0000     .0000     .0000     .0000
   27   .1009     .1679     .7312*+   .0000     .0000     .0000     .0000
```

28	.0251	.3240	.6510*+	.0000	.0000	.0000	.0000
29	.1249	.2603	.6148*+	.0000	.0000	.0000	.0000
30	.1434	.1739	.6827*+	.0000	.0000	.0000	.0000
31	.1351	.3076	.5574*+	.0000	.0000	.0000	.0000
32	.1137	.2270	.6593*+	.0000	.0000	.0000	.0000
33	.2899	.2097	.5004*+	.0000	.0000	.0000	.0000
34	.1594	.1557	.6849*+	.0000	.0000	.0000	.0000
35	.1549	.2847	.5604*+	.0000	.0000	.0000	.0000
36	.0699	.3580	.5722*+	.0000	.0000	.0000	.0000
37	.0552*	.2610	.6838 +	.0000	.0000	.0000	.0000
38	.0231	.2629	.7140*+	.0000	.0000	.0000	.0000
39	.0901*	.3704	.5395 +	.0000	.0000	.0000	.0000
40	.0989	.3109	.5902*+	.0000	.0000	.0000	.0000
41	.0149	.2000	.7851*+	.0000	.0000	.0000	.0000
42	.5049 +	.1005	.3946*	.0000	.0000	.0000	.0000
43	.4875 +	.1823	.3303*	.0000	.0000	.0000	.0000
44	.4387 +	.1437	.4175*	.0000	.0000	.0000	.0000

PREDICTED PROBABILITIES (* marks actual, + marks prediction.)

Indiv	CARR	MTRR	VANR	CARS	MTRS	VANS	BRTS
45	.1615	.1688*	.6697 +	.0000	.0000	.0000	.0000
46	.0390	.3338*	.6272 +	.0000	.0000	.0000	.0000
47	.0600	.2407	.6993*+	.0000	.0000	.0000	.0000
48	.1440	.3485	.5075*+	.0000	.0000	.0000	.0000
49	.1571	.2908	.5521*+	.0000	.0000	.0000	.0000
50	.0251	.1979	.7770*+	.0000	.0000	.0000	.0000
51	.5931 +	.0819	.3250*	.0000	.0000	.0000	.0000
52	.2348	.2658	.4994*+	.0000	.0000	.0000	.0000
53	.3256*	.1727	.5017 +	.0000	.0000	.0000	.0000
54	.0393	.3497*	.6111 +	.0000	.0000	.0000	.0000
55	.0538	.2359*	.7104 +	.0000	.0000	.0000	.0000
56	.1411	.2234*	.6355 +	.0000	.0000	.0000	.0000
57	.2101	.3216*	.4683 +	.0000	.0000	.0000	.0000
58	.2276	.2665*	.5059 +	.0000	.0000	.0000	.0000
59	.0391	.1951*	.7658 +	.0000	.0000	.0000	.0000
60	.0494	.3460*	.6046 +	.0000	.0000	.0000	.0000
61	.0674	.2325*	.7001 +	.0000	.0000	.0000	.0000
62	.1729	.2151*	.6120 +	.0000	.0000	.0000	.0000
63	.1271	.3553	.5175*+	.0000	.0000	.0000	.0000
64	.1389	.2971	.5640*+	.0000	.0000	.0000	.0000
65	.0218	.1986	.7796*+	.0000	.0000	.0000	.0000
66	.8307*+	.0528	.1165	.0000	.0000	.0000	.0000

PREDICTED PROBABILITIES (* marks actual, + marks prediction.)

Indiv	CARR	MTRR	VANR	CARS	MTRS	VANS	BRTS
67	.6978*+	.0709	.2312	.0000	.0000	.0000	.0000
68	.8680*+	.0365	.0955	.0000	.0000	.0000	.0000
69	.0326	.2673	.7001*+	.0000	.0000	.0000	.0000
70	.0379	.1812	.7809*+	.0000	.0000	.0000	.0000
71	.0740	.4720 +	.4540*	.0000	.0000	.0000	.0000
72	.1315	.1749*	.6936 +	.0000	.0000	.0000	.0000
73	.0309	.3366*	.6325 +	.0000	.0000	.0000	.0000
74	.0478	.2439	.7084*+	.0000	.0000	.0000	.0000
75	.0770	.1739*	.7491 +	.0000	.0000	.0000	.0000
76	.1239	.4161*	.4601 +	.0000	.0000	.0000	.0000
77	.0286	.2775*	.6939 +	.0000	.0000	.0000	.0000
78	.1110	.1790	.7100*+	.0000	.0000	.0000	.0000
79	.0256	.3384*	.6359 +	.0000	.0000	.0000	.0000
80	.0397	.2459	.7144*+	.0000	.0000	.0000	.0000

81	.0911	.3498	.5591*+	.0000	.0000	.0000	.0000
82	.0723	.2563	.6714*+	.0000	.0000	.0000	.0000
83	.0306	.2609	.7085*+	.0000	.0000	.0000	.0000
84	.4592*+	.1010	.4398	.0000	.0000	.0000	.0000
85	.1629*	.2782	.5590 +	.0000	.0000	.0000	.0000
86	.5191*+	.1430	.3378	.0000	.0000	.0000	.0000
87	.5789 +	.0787	.3424*	.0000	.0000	.0000	.0000
88	.2395	.2527	.5078*+	.0000	.0000	.0000	.0000

PREDICTED PROBABILITIES (* marks actual, + marks prediction.)

Indiv	CARR	MTRR	VANR	CARS	MTRS	VANS	BRTS
89	.6361*+	.1082	.2557	.0000	.0000	.0000	.0000
90	.0825	.3735*	.5440 +	.0000	.0000	.0000	.0000
91	.0906	.3137*	.5956 +	.0000	.0000	.0000	.0000
92	.0136	.2002*	.7862 +	.0000	.0000	.0000	.0000
93	.2744	.1461	.5795*+	.0000	.0000	.0000	.0000
94	.0737	.3217	.6045*+	.0000	.0000	.0000	.0000
95	.1113	.2276	.6611*+	.0000	.0000	.0000	.0000
96	.0603	.2932	.6465*+	.0000	.0000	.0000	.0000
97	.0293	.2279	.7428*+	.0000	.0000	.0000	.0000
98	.0792	.2544	.6664*+	.0000	.0000	.0000	.0000
99	.0603	.2932*	.6465 +	.0000	.0000	.0000	.0000
100	.0293	.2279*	.7428 +	.0000	.0000	.0000	.0000
101	.0792	.2544	.6664*+	.0000	.0000	.0000	.0000
102	.6057 +	.1164*	.2779	.0000	.0000	.0000	.0000
103	.4164*	.1081	.4755 +	.0000	.0000	.0000	.0000
104	.4081 +	.1994	.3925*	.0000	.0000	.0000	.0000
105	.5402*+	.0969	.3630	.0000	.0000	.0000	.0000
106	.7746*+	.0686	.1568	.0000	.0000	.0000	.0000
107	.9184*+	.0360	.0456	.0000	.0000	.0000	.0000
108	.4952 +	.0943	.4105*	.0000	.0000	.0000	.0000
109	.1836	.2713	.5452*+	.0000	.0000	.0000	.0000
110	.5551 +	.1323	.3126*	.0000	.0000	.0000	.0000

PREDICTED PROBABILITIES (* marks actual, + marks prediction.)

Indiv	CARR	MTRR	VANR	CARS	MTRS	VANS	BRTS
111	.4433*+	.2143	.3425	.0000	.0000	.0000	.0000
112	.3823	.1707	.4471*+	.0000	.0000	.0000	.0000
113	.2006*	.2151	.5843 +	.0000	.0000	.0000	.0000
114	.1969	.1617	.6414*+	.0000	.0000	.0000	.0000
115	.0491	.3303	.6206*+	.0000	.0000	.0000	.0000
116	.0751*	.2369	.6880 +	.0000	.0000	.0000	.0000
117	.0435	.2015	.7551*+	.0000	.0000	.0000	.0000
118	.0363	.2932	.6705*+	.0000	.0000	.0000	.0000
119	.3033*	.3074	.3894 +	.0000	.0000	.0000	.0000
120	.5983*+	.1546	.2471	.0000	.0000	.0000	.0000
121	.5365*+	.1280	.3354	.0000	.0000	.0000	.0000
122	.3195*	.1831	.4974 +	.0000	.0000	.0000	.0000
123	.0837*	.1930	.7233 +	.0000	.0000	.0000	.0000
124	.0705	.2828	.6467*+	.0000	.0000	.0000	.0000
125	.4668*+	.2353	.2980	.0000	.0000	.0000	.0000
126	.0494	.3460*	.6046 +	.0000	.0000	.0000	.0000
127	.0674	.2325*	.7001 +	.0000	.0000	.0000	.0000
128	.1729	.2151*	.6120 +	.0000	.0000	.0000	.0000
129	.1984	.3264*	.4753 +	.0000	.0000	.0000	.0000
130	.2151	.2708*	.5141 +	.0000	.0000	.0000	.0000
131	.0365	.1956*	.7679 +	.0000	.0000	.0000	.0000
132	.2273	.1443	.6284*+	.0000	.0000	.0000	.0000

PREDICTED PROBABILITIES (* marks actual, + marks prediction.)

Indiv	CARR	MTRR	VANR	CARS	MTRS	VANS	BRTS
133	.0631	.3113	.6255*+	.0000	.0000	.0000	.0000
134	.2722	.2165	.5113*+	.0000	.0000	.0000	.0000
135	.0000	.0000	.0000	.7237 +	.0209	.0464	.2090*
136	.0000	.0000	.0000	.2859	.0646	.2407	.4089*+
137	.0000	.0000	.0000	.3645 +	.1491	.1350	.3515*
138	.0000	.0000	.0000	.4799 +	.0930	.1956	.2315*
139	.0000	.0000	.0000	.6735 +	.0411	.1022	.1833*
140	.0000	.0000	.0000	.5832*+	.0348	.1051	.2769
141	.0000	.0000	.0000	.5304*+	.0531	.1378	.2787
142	.0000	.0000	.0000	.6914*+	.0615	.0854	.1616
143	.0000	.0000	.0000	.5454*+	.0306	.1342	.2899
144	.0000	.0000	.0000	.0436	.1081	.2806*	.5677 +
145	.0000	.0000	.0000	.0828	.1829	.2539*	.4804 +
146	.0000	.0000	.0000	.0461	.0643	.2815	.6082*+
147	.0000	.0000	.0000	.1225*	.0664	.1474	.6637 +
148	.0000	.0000	.0000	.0209	.0886	.3300*	.5606 +
149	.0000	.0000	.0000	.0297	.2276	.2061	.5366*+
150	.0000	.0000	.0000	.0157	.1077	.3248*	.5518 +
152	.0000	.0000	.0000	.0990*	.1737	.2514	.4758 +
153	.0000	.0000	.0000	.0157*	.1077	.3248	.5518 +
154	.0000	.0000	.0000	.0072	.1405	.1142	.7381*+
155	.0000	.0000	.0000	.0990	.1737*	.2514	.4758 +

PREDICTED PROBABILITIES (* marks actual, + marks prediction.)

Indiv	CARR	MTRR	VANR	CARS	MTRS	VANS	BRTS
156	.0000	.0000	.0000	.0157	.1486	.2038	.6319*+
157	.0000	.0000	.0000	.1668	.2243	.1398	.4691*+
158	.0000	.0000	.0000	.0223	.1115	.2221*	.6441 +
159	.0000	.0000	.0000	.0132	.1446	.1687	.6734*+
160	.0000	.0000	.0000	.0276	.0735	.3218*	.5771 +
161	.0000	.0000	.0000	.0286	.1961	.2873*	.4880 +
162	.0000	.0000	.0000	.5621 +	.0761	.1044*	.2575
163	.0000	.0000	.0000	.0673	.1430	.2210	.5687*+
164	.0000	.0000	.0000	.1608	.0731	.1777	.5884*+
165	.0000	.0000	.0000	.0206	.1479	.2028	.6287*+
166	.0000	.0000	.0000	.2093	.2128	.1327	.4452*+
167	.0000	.0000	.0000	.0292	.1107	.2205	.6395*+
168	.0000	.0000	.0000	.0381	.0765	.3393*	.5461 +
169	.0000	.0000	.0000	.0484	.1857	.3281*	.4379 +
170	.0000	.0000	.0000	.0066	.0837	.2524	.6573*+
171	.0000	.0000	.0000	.1471	.1190	.1702	.5637*+
172	.0000	.0000	.0000	.2010	.0867	.1636	.5487*+
173	.0000	.0000	.0000	.0559	.0548	.2300	.6593*+
174	.0000	.0000	.0000	.0206	.1479	.2028	.6287*+
175	.0000	.0000	.0000	.2093	.2128	.1327	.4452*+
176	.0000	.0000	.0000	.0292	.1107	.2205*	.6395 +
177	.0000	.0000	.0000	.1358	.1359*	.2101	.5183 +

PREDICTED PROBABILITIES (* marks actual, + marks prediction.)

Indiv	CARR	MTRR	VANR	CARS	MTRS	VANS	BRTS
178	.0000	.0000	.0000	.0353	.2389*	.1919	.5338 +
179	.0000	.0000	.0000	.0304	.0693	.4178*	.4825 +
180	.0000	.0000	.0000	.0649	.1371	.1599	.6382*+
181	.0000	.0000	.0000	.1286	.0658	.2884*	.5171 +
182	.0000	.0000	.0000	.1325	.1751	.2565*	.4358 +
183	.0000	.0000	.0000	.8105*+	.0264	.0378	.1252
184	.0000	.0000	.0000	.8619*+	.0150	.0283	.0948
185	.0000	.0000	.0000	.5950*+	.0235	.0987	.2828

186	.0000	.0000	.0000	.1460	.1289	.1768	.5482*+
187	.0000	.0000	.0000	.6824 +	.0855	.0533	.1788*
188	.0000	.0000	.0000	.1965	.0916	.1825	.5294*+
189	.0000	.0000	.0000	.0891	.1375	.1886	.5848*+
190	.0000	.0000	.0000	.5514 +	.1207	.0753	.2526*
191	.0000	.0000	.0000	.1227	.1000	.1993	.5779*+
192	.0000	.0000	.0000	.6946*+	.0448	.0522	.2084
193	.0000	.0000	.0000	.8288*+	.0129	.0567	.1016
194	.0000	.0000	.0000	.8336*+	.0336	.0492	.0836
195	.0000	.0000	.0000	.6946*+	.0448	.0522	.2084
196	.0000	.0000	.0000	.8288*+	.0129	.0567	.1016
197	.0000	.0000	.0000	.8336*+	.0336	.0492	.0836
198	.0000	.0000	.0000	.0805	.1438*	.1892	.5865 +
199	.0000	.0000	.0000	.0270	.2210*	.2087	.5434 +

PREDICTED PROBABILITIES (* marks actual, + marks prediction.)

Indiv	CARR	MTRR	VANR	CARS	MTRS	VANS	BRTS
200	.0000	.0000	.0000	.1341	.0700*	.2752	.5207 +
201	.0000	.0000	.0000	.6946*+	.0448	.0522	.2084
202	.0000	.0000	.0000	.8288*+	.0129	.0567	.1016
203	.0000	.0000	.0000	.8336*+	.0336	.0492	.0836
204	.0000	.0000	.0000	.0224	.1069*	.3226	.5481 +
205	.0000	.0000	.0000	.0103	.1401*	.1139	.7358 +
206	.0000	.0000	.0000	.1364	.1665*	.2410	.4561 +
207	.0000	.0000	.0000	.0417	.1499	.1971	.6112*+
208	.0000	.0000	.0000	.0136	.2240	.2115	.5508*+
209	.0000	.0000	.0000	.0715	.0750	.2951*	.5584 +
210	.0000	.0000	.0000	.0396	.1502*	.1976	.6126 +
211	.0000	.0000	.0000	.0129	.2242*	.2117	.5512 +
212	.0000	.0000	.0000	.0679	.0753*	.2962	.5605 +
213	.0000	.0000	.0000	.7639*+	.0329	.0471	.1561
214	.0000	.0000	.0000	.8252*+	.0190	.0358	.1201
215	.0000	.0000	.0000	.5264*+	.0275	.1154	.3307
216	.0000	.0000	.0000	.7639*+	.0329	.0471	.1561
217	.0000	.0000	.0000	.8252*+	.0190	.0358	.1201
218	.0000	.0000	.0000	.5264*+	.0275	.1154	.3307
219	.0000	.0000	.0000	.0721	.0703	.1559	.7018*+
220	.0000	.0000	.0000	.0117	.0894	.3331	.5658*+
221	.0000	.0000	.0000	.0167	.2306	.2088	.5438*+

PREDICTED PROBABILITIES (* marks actual, + marks prediction.)

Indiv	CARR	MTRR	VANR	CARS	MTRS	VANS	BRTS
222	.0000	.0000	.0000	.0070	.1499	.2056	.6375*+
223	.0000	.0000	.0000	.0818	.2471	.1541	.5170*+
224	.0000	.0000	.0000	.0100	.1129*	.2249	.6522 +
225	.0000	.0000	.0000	.0394	.1287*	.2328	.5991 +
226	.0000	.0000	.0000	.0137	.1622	.2449*	.5793 +
227	.0000	.0000	.0000	.1283	.1170	.2234*	.5313 +
228	.0000	.0000	.0000	.0056	.1501	.2059	.6384*+
229	.0000	.0000	.0000	.0665	.2513	.1567*	.5256 +
230	.0000	.0000	.0000	.0080	.1131	.2253*	.6535 +
231	.0000	.0000	.0000	.0266	.1741	.3660*	.4333 +
232	.0000	.0000	.0000	.0576	.1185	.2950	.5289*+
233	.0000	.0000	.0000	.0398	.0802	.2421*	.6379 +
234	.0000	.0000	.0000	.4193 +	.0462	.2048	.3297*
235	.0000	.0000	.0000	.4811 +	.1013	.1789*	.2387
236	.0000	.0000	.0000	.1082	.0751	.2266	.5900*+
237	.0000	.0000	.0000	.0243	.1526*	.2007	.6223 +
238	.0000	.0000	.0000	.0078	.2253*	.2128	.5541 +

239	.0000	.0000	.0000	.0422	.0774	.3044	.5760*+
240	.0000	.0000	.0000	.0208	.1366	.1954	.6472*+
241	.0000	.0000	.0000	.0301	.1052	.1986	.6661*+
242	.0000	.0000	.0000	.0072	.0576	.2419	.6933*+
243	.0000	.0000	.0000	.0208	.1366	.1954	.6472*+

PREDICTED PROBABILITIES (* marks actual, + marks prediction.)

Indiv	CARR	MTRR	VANR	CARS	MTRS	VANS	BRTS
244	.0000	.0000	.0000	.0301	.1052*	.1986	.6661 +
245	.0000	.0000	.0000	.0072	.0576	.2419	.6933*+
246	.0000	.0000	.0000	.2437	.1109	.1293	.5161*+
247	.0000	.0000	.0000	.4068 +	.0448	.1964	.3521*
248	.0000	.0000	.0000	.4151 +	.1181	.1730*	.2939
249	.0000	.0000	.0000	.6062 +	.0570	.0781	.2587*
250	.0000	.0000	.0000	.6205 +	.0748	.0677	.2370*
251	.0000	.0000	.0000	.5840 +	.0303	.1070	.2787*
252	.0000	.0000	.0000	.3281*	.0535	.2370	.3814 +
253	.0000	.0000	.0000	.3854 +	.1199	.2119	.2828*
254	.0000	.0000	.0000	.0759	.0778	.2348	.6115*+
255	.0000	.0000	.0000	.1705	.0660	.2926	.4710*+
256	.0000	.0000	.0000	.2088*	.1544	.2728	.3640 +
257	.0000	.0000	.0000	.0334	.0814	.2456	.6396*+
258	.0000	.0000	.0000	.0122*	.1491	.2045	.6341 +
259	.0000	.0000	.0000	.1347	.2329*	.1452	.4872 +
260	.0000	.0000	.0000	.0174	.1121	.2232	.6473*+
261	.0000	.0000	.0000	.0343	.1397	.1916	.6344*+
262	.0000	.0000	.0000	.0363	.1899	.1720*	.6017 +
263	.0000	.0000	.0000	.0291	.1380	.2311	.6018*+
264	.0000	.0000	.0000	.3843*+	.1101	.2315	.2741
265	.0000	.0000	.0000	.5825 +	.0525	.1307	.2343*

PREDICTED PROBABILITIES (* marks actual, + marks prediction.)

Indiv	CARR	MTRR	VANR	CARS	MTRS	VANS	BRTS
266	.0000	.0000	.0000	.4862 +	.0429	.1295	.3413*
267	.0000	.0000	.0000	.0739	.1340	.1837	.6084*+
268	.0000	.0000	.0000	.0781	.1817	.1645	.5756*+
269	.0000	.0000	.0000	.0631	.1332	.2230*	.5807 +
270	.0000	.0000	.0000	.1079	.0710	.3147*	.5065 +
271	.0000	.0000	.0000	.1344	.1689	.2984	.3983*+
272	.0000	.0000	.0000	.0199	.0826	.2490	.6485*+
273	.2615*	.3507	.3878 +	.0000	.0000	.0000	.0000
274	.1077	.2549	.6374*+	.0000	.0000	.0000	.0000
275	.0579	.1913	.7509*+	.0000	.0000	.0000	.0000
276	.0530	.2616	.6854*+	.0000	.0000	.0000	.0000
277	.0613	.1768	.7619*+	.0000	.0000	.0000	.0000
278	.1170	.4501 +	.4329*	.0000	.0000	.0000	.0000
279	.5385*+	.1084	.3532	.0000	.0000	.0000	.0000
280	.8720*+	.0354	.0926	.0000	.0000	.0000	.0000
281	.8886*+	.0347	.0766	.0000	.0000	.0000	.0000
282	.0366*	.3506	.6128 +	.0000	.0000	.0000	.0000
283	.0502*	.2368	.7131 +	.0000	.0000	.0000	.0000
284	.1326	.2256	.6419*+	.0000	.0000	.0000	.0000
285	.2334	.1544	.6123*+	.0000	.0000	.0000	.0000
286	.0602	.3264*	.6134 +	.0000	.0000	.0000	.0000
287	.0916	.2326	.6757*+	.0000	.0000	.0000	.0000

PREDICTED PROBABILITIES (* marks actual, + marks prediction.)

Indiv	CARR	MTRR	VANR	CARS	MTRS	VANS	BRTS
288	.1315	.1749	.6936*+	.0000	.0000	.0000	.0000
289	.0309	.3366	.6325*+	.0000	.0000	.0000	.0000

290	.0897	.2688	.6415*+	.0000	.0000	.0000	.0000
291	.0438	.1771	.7791*+	.0000	.0000	.0000	.0000
292	.0424	.3226	.6350*+	.0000	.0000	.0000	.0000
293	.3204	.1461	.5335*+	.0000	.0000	.0000	.0000
294	.4633 +	.1852	.3516*	.0000	.0000	.0000	.0000
295	.2562	.1455	.5983*+	.0000	.0000	.0000	.0000
296	.2792	.1451	.5757*+	.0000	.0000	.0000	.0000
297	.0754	.3212	.6035*+	.0000	.0000	.0000	.0000
298	.1137	.2270	.6593*+	.0000	.0000	.0000	.0000
299	.1009	.1679	.7312*+	.0000	.0000	.0000	.0000
300	.0251	.3240	.6510*+	.0000	.0000	.0000	.0000
301	.1249	.2603	.6148*+	.0000	.0000	.0000	.0000
302	.1434	.1739	.6827*+	.0000	.0000	.0000	.0000
303	.1351	.3076	.5574*+	.0000	.0000	.0000	.0000
304	.1137	.2270	.6593*+	.0000	.0000	.0000	.0000
305	.2899	.2097	.5004*+	.0000	.0000	.0000	.0000
306	.1594	.1557	.6849*+	.0000	.0000	.0000	.0000
307	.1549	.2847	.5604*+	.0000	.0000	.0000	.0000
308	.0699	.3580	.5722*+	.0000	.0000	.0000	.0000
309	.0552*	.2610	.6838 +	.0000	.0000	.0000	.0000

PREDICTED PROBABILITIES (* marks actual, + marks prediction.)

Indiv	CARR	MTRR	VANR	CARS	MTRS	VANS	BRTS
310	.0231	.2629	.7140*+	.0000	.0000	.0000	.0000
311	.0901*	.3704	.5395 +	.0000	.0000	.0000	.0000
312	.0989	.3109	.5902*+	.0000	.0000	.0000	.0000
313	.0149	.2000	.7851*+	.0000	.0000	.0000	.0000
314	.5049 +	.1005	.3946*	.0000	.0000	.0000	.0000
315	.4875 +	.1823	.3303*	.0000	.0000	.0000	.0000
316	.4387 +	.1437	.4175*	.0000	.0000	.0000	.0000
317	.1615	.1688*	.6697 +	.0000	.0000	.0000	.0000
318	.0390	.3338*	.6272 +	.0000	.0000	.0000	.0000
319	.0600	.2407	.6993*+	.0000	.0000	.0000	.0000
320	.1440	.3485	.5075*+	.0000	.0000	.0000	.0000
321	.1571	.2908	.5521*+	.0000	.0000	.0000	.0000
322	.0251	.1979	.7770*+	.0000	.0000	.0000	.0000
323	.5931 +	.0819	.3250*	.0000	.0000	.0000	.0000
324	.2348	.2658	.4994*+	.0000	.0000	.0000	.0000
325	.3256*	.1727	.5017 +	.0000	.0000	.0000	.0000
326	.0393	.3497*	.6111 +	.0000	.0000	.0000	.0000
327	.0538	.2359*	.7104 +	.0000	.0000	.0000	.0000
328	.1411	.2234*	.6355 +	.0000	.0000	.0000	.0000
329	.2101	.3216*	.4683 +	.0000	.0000	.0000	.0000
330	.2276	.2665*	.5059 +	.0000	.0000	.0000	.0000
331	.0391	.1951*	.7658 +	.0000	.0000	.0000	.0000

PREDICTED PROBABILITIES (* marks actual, + marks prediction.)

Indiv	CARR	MTRR	VANR	CARS	MTRS	VANS	BRTS
332	.0494	.3460*	.6046 +	.0000	.0000	.0000	.0000
333	.0674	.2325*	.7001 +	.0000	.0000	.0000	.0000
334	.1729	.2151*	.6120 +	.0000	.0000	.0000	.0000
335	.1271	.3553	.5175*+	.0000	.0000	.0000	.0000
336	.1389	.2971	.5640*+	.0000	.0000	.0000	.0000
337	.0218	.1986	.7796*+	.0000	.0000	.0000	.0000
338	.8307*+	.0528	.1165	.0000	.0000	.0000	.0000
339	.6978*+	.0709	.2312	.0000	.0000	.0000	.0000
340	.8680*+	.0365	.0955	.0000	.0000	.0000	.0000
341	.0326	.2673	.7001*+	.0000	.0000	.0000	.0000
342	.0379	.1812	.7809*+	.0000	.0000	.0000	.0000

343	.0740	.4720 +	.4540*	.0000	.0000	.0000	.0000
344	.1315	.1749*	.6936 +	.0000	.0000	.0000	.0000
345	.0309	.3366*	.6325 +	.0000	.0000	.0000	.0000
346	.0478	.2439	.7084*+	.0000	.0000	.0000	.0000
347	.0770	.1739*	.7491 +	.0000	.0000	.0000	.0000
348	.1239	.4161*	.4601 +	.0000	.0000	.0000	.0000
349	.0286	.2775*	.6939 +	.0000	.0000	.0000	.0000
350	.1110	.1790	.7100*+	.0000	.0000	.0000	.0000
351	.0256	.3384*	.6359 +	.0000	.0000	.0000	.0000
352	.0397	.2459	.7144*+	.0000	.0000	.0000	.0000
353	.0911	.3498	.5591*+	.0000	.0000	.0000	.0000

PREDICTED PROBABILITIES (* marks actual, + marks prediction.)

Indiv	CARR	MTRR	VANR	CARS	MTRS	VANS	BRTS
354	.0723	.2563	.6714*+	.0000	.0000	.0000	.0000
355	.0306	.2609	.7085*+	.0000	.0000	.0000	.0000
356	.4592*+	.1010	.4398	.0000	.0000	.0000	.0000
357	.1629*	.2782	.5590 +	.0000	.0000	.0000	.0000
358	.5191*+	.1430	.3378	.0000	.0000	.0000	.0000
359	.5789 +	.0787	.3424*	.0000	.0000	.0000	.0000
360	.2395	.2527	.5078*+	.0000	.0000	.0000	.0000
361	.6361*+	.1082	.2557	.0000	.0000	.0000	.0000
362	.0825	.3735*	.5440 +	.0000	.0000	.0000	.0000
363	.0906	.3137*	.5956 +	.0000	.0000	.0000	.0000
364	.0136	.2002*	.7862 +	.0000	.0000	.0000	.0000
365	.2744	.1461	.5795*+	.0000	.0000	.0000	.0000
366	.0737	.3217	.6045*+	.0000	.0000	.0000	.0000
367	.1113	.2276	.6611*+	.0000	.0000	.0000	.0000
368	.0603	.2932	.6465*+	.0000	.0000	.0000	.0000
369	.0293	.2279	.7428*+	.0000	.0000	.0000	.0000
370	.0792	.2544	.6664*+	.0000	.0000	.0000	.0000
371	.0603	.2932*	.6465 +	.0000	.0000	.0000	.0000
372	.0293	.2279*	.7428 +	.0000	.0000	.0000	.0000
373	.0792	.2544	.6664*+	.0000	.0000	.0000	.0000
374	.6057 +	.1164*	.2779	.0000	.0000	.0000	.0000
375	.4164*	.1081	.4755 +	.0000	.0000	.0000	.0000

PREDICTED PROBABILITIES (* marks actual, + marks prediction.)

Indiv	CARR	MTRR	VANR	CARS	MTRS	VANS	BRTS
376	.4081 +	.1994	.3925*	.0000	.0000	.0000	.0000
377	.5402*+	.0969	.3630	.0000	.0000	.0000	.0000
378	.7746*+	.0686	.1568	.0000	.0000	.0000	.0000
379	.9184*+	.0360	.0456	.0000	.0000	.0000	.0000
380	.4952 +	.0943	.4105*	.0000	.0000	.0000	.0000
381	.1836	.2713	.5452*+	.0000	.0000	.0000	.0000
382	.5551 +	.1323	.3126*	.0000	.0000	.0000	.0000
383	.4433*+	.2143	.3425	.0000	.0000	.0000	.0000
384	.3823	.1707	.4471*+	.0000	.0000	.0000	.0000
385	.2006*	.2151	.5843 +	.0000	.0000	.0000	.0000
386	.1969	.1617	.6414*+	.0000	.0000	.0000	.0000
387	.0491	.3303	.6206*+	.0000	.0000	.0000	.0000
388	.0751*	.2369	.6880 +	.0000	.0000	.0000	.0000
389	.0435	.2015	.7551*+	.0000	.0000	.0000	.0000
390	.0363	.2932	.6705*+	.0000	.0000	.0000	.0000
391	.3033*	.3074	.3894 +	.0000	.0000	.0000	.0000
392	.5983*+	.1546	.2471	.0000	.0000	.0000	.0000
393	.5365*+	.1280	.3354	.0000	.0000	.0000	.0000
394	.3195*	.1831	.4974 +	.0000	.0000	.0000	.0000
395	.0837*	.1930	.7233 +	.0000	.0000	.0000	.0000

396	.0705	.2828	.6467*+	.0000	.0000	.0000	.0000
397	.4668*+	.2353	.2980	.0000	.0000	.0000	.0000

PREDICTED PROBABILITIES (* marks actual, + marks prediction.)

Indiv	CARR	MTRR	VANR	CARS	MTRS	VANS	BRTS
398	.0494	.3460*	.6046 +	.0000	.0000	.0000	.0000
399	.0674	.2325*	.7001 +	.0000	.0000	.0000	.0000
400	.1729	.2151*	.6120 +	.0000	.0000	.0000	.0000
401	.1984	.3264*	.4753 +	.0000	.0000	.0000	.0000
402	.2151	.2708*	.5141 +	.0000	.0000	.0000	.0000
403	.0365	.1956*	.7679 +	.0000	.0000	.0000	.0000
404	.2273	.1443	.6284*+	.0000	.0000	.0000	.0000
405	.0631	.3113	.6255*+	.0000	.0000	.0000	.0000
406	.2722	.2165	.5113*+	.0000	.0000	.0000	.0000
407	.0000	.0000	.0000	.7237 +	.0209	.0464	.2090*
408	.0000	.0000	.0000	.2859	.0646	.2407	.4089*+
409	.0000	.0000	.0000	.3645 +	.1491	.1350	.3515*
410	.0000	.0000	.0000	.4799 +	.0930	.1956	.2315*
411	.0000	.0000	.0000	.6735 +	.0411	.1022	.1833*
412	.0000	.0000	.0000	.5832*+	.0348	.1051	.2769
413	.0000	.0000	.0000	.5304*+	.0531	.1378	.2787
414	.0000	.0000	.0000	.6914*+	.0615	.0854	.1616
415	.0000	.0000	.0000	.5454*+	.0306	.1342	.2899
416	.0000	.0000	.0000	.0436	.1081	.2806*	.5677 +
417	.0000	.0000	.0000	.0828	.1829	.2539*	.4804 +
418	.0000	.0000	.0000	.0461	.0643	.2815	.6082*+
419	.0000	.0000	.0000	.1225*	.0664	.1474	.6637 +

PREDICTED PROBABILITIES (* marks actual, + marks prediction.)

Indiv	CARR	MTRR	VANR	CARS	MTRS	VANS	BRTS
420	.0000	.0000	.0000	.0209	.0886	.3300*	.5606 +
421	.0000	.0000	.0000	.0297	.2276	.2061	.5366*+
422	.0000	.0000	.0000	.0157	.1077	.3248*	.5518 +
424	.0000	.0000	.0000	.0990*	.1737	.2514	.4758 +
425	.0000	.0000	.0000	.0157*	.1077	.3248	.5518 +
426	.0000	.0000	.0000	.0072	.1405	.1142	.7381*+
427	.0000	.0000	.0000	.0990	.1737*	.2514	.4758 +
428	.0000	.0000	.0000	.0157	.1486	.2038	.6319*+
429	.0000	.0000	.0000	.1668	.2243	.1398	.4691*+
430	.0000	.0000	.0000	.0223	.1115	.2221*	.6441 +
431	.0000	.0000	.0000	.0132	.1446	.1687	.6734*+
432	.0000	.0000	.0000	.0276	.0735	.3218*	.5771 +
433	.0000	.0000	.0000	.0286	.1961	.2873*	.4880 +
434	.0000	.0000	.0000	.5621 +	.0761	.1044*	.2575
435	.0000	.0000	.0000	.0673	.1430	.2210	.5687*+
436	.0000	.0000	.0000	.1608	.0731	.1777	.5884*+
437	.0000	.0000	.0000	.0206	.1479	.2028	.6287*+
438	.0000	.0000	.0000	.2093	.2128	.1327	.4452*+
439	.0000	.0000	.0000	.0292	.1107	.2205	.6395*+
440	.0000	.0000	.0000	.0381	.0765	.3393*	.5461 +
441	.0000	.0000	.0000	.0484	.1857	.3281*	.4379 +
442	.0000	.0000	.0000	.0066	.0837	.2524	.6573*+

PREDICTED PROBABILITIES (* marks actual, + marks prediction.)

Indiv	CARR	MTRR	VANR	CARS	MTRS	VANS	BRTS
443	.0000	.0000	.0000	.1471	.1190	.1702	.5637*+
444	.0000	.0000	.0000	.2010	.0867	.1636	.5487*+
445	.0000	.0000	.0000	.0559	.0548	.2300	.6593*+
446	.0000	.0000	.0000	.0206	.1479	.2028	.6287*+
447	.0000	.0000	.0000	.2093	.2128	.1327	.4452*+

448	.0000	.0000	.0000	.0292	.1107	.2205*	.6395 +
449	.0000	.0000	.0000	.1358	.1359*	.2101	.5183 +
450	.0000	.0000	.0000	.0353	.2389*	.1919	.5338 +
451	.0000	.0000	.0000	.0304	.0693	.4178*	.4825 +
452	.0000	.0000	.0000	.0649	.1371	.1599	.6382*+
453	.0000	.0000	.0000	.1286	.0658	.2884*	.5171 +
454	.0000	.0000	.0000	.1325	.1751	.2565*	.4358 +
455	.0000	.0000	.0000	.8105*+	.0264	.0378	.1252
456	.0000	.0000	.0000	.8619*+	.0150	.0283	.0948
457	.0000	.0000	.0000	.5950*+	.0235	.0987	.2828
458	.0000	.0000	.0000	.1460	.1289	.1768	.5482*+
459	.0000	.0000	.0000	.6824 +	.0855	.0533	.1788*
460	.0000	.0000	.0000	.1965	.0916	.1825	.5294*+
461	.0000	.0000	.0000	.0891	.1375	.1886	.5848*+
462	.0000	.0000	.0000	.5514 +	.1207	.0753	.2526*
463	.0000	.0000	.0000	.1227	.1000	.1993	.5779*+
464	.0000	.0000	.0000	.6946*+	.0448	.0522	.2084

PREDICTED PROBABILITIES (* marks actual, + marks prediction.)

Indiv	CARR	MTRR	VANR	CARS	MTRS	VANS	BRTS
465	.0000	.0000	.0000	.8288*+	.0129	.0567	.1016
466	.0000	.0000	.0000	.8336*+	.0336	.0492	.0836
467	.0000	.0000	.0000	.6946*+	.0448	.0522	.2084
468	.0000	.0000	.0000	.8288*+	.0129	.0567	.1016
469	.0000	.0000	.0000	.8336*+	.0336	.0492	.0836
470	.0000	.0000	.0000	.0805	.1438*	.1892	.5865 +
471	.0000	.0000	.0000	.0270	.2210*	.2087	.5434 +
472	.0000	.0000	.0000	.1341	.0700*	.2752	.5207 +
473	.0000	.0000	.0000	.6946*+	.0448	.0522	.2084
474	.0000	.0000	.0000	.8288*+	.0129	.0567	.1016
475	.0000	.0000	.0000	.8336*+	.0336	.0492	.0836
476	.0000	.0000	.0000	.0224	.1069*	.3226	.5481 +
477	.0000	.0000	.0000	.0103	.1401*	.1139	.7358 +
478	.0000	.0000	.0000	.1364	.1665*	.2410	.4561 +
479	.0000	.0000	.0000	.0417	.1499	.1971	.6112*+
480	.0000	.0000	.0000	.0136	.2240	.2115	.5508*+
481	.0000	.0000	.0000	.0715	.0750	.2951*	.5584 +
482	.0000	.0000	.0000	.0396	.1502*	.1976	.6126 +
483	.0000	.0000	.0000	.0129	.2242*	.2117	.5512 +
484	.0000	.0000	.0000	.0679	.0753*	.2962	.5605 +
485	.0000	.0000	.0000	.7639*+	.0329	.0471	.1561
486	.0000	.0000	.0000	.8252*+	.0190	.0358	.1201

PREDICTED PROBABILITIES (* marks actual, + marks prediction.)

Indiv	CARR	MTRR	VANR	CARS	MTRS	VANS	BRTS
487	.0000	.0000	.0000	.5264*+	.0275	.1154	.3307
488	.0000	.0000	.0000	.7639*+	.0329	.0471	.1561
489	.0000	.0000	.0000	.8252*+	.0190	.0358	.1201
490	.0000	.0000	.0000	.5264*+	.0275	.1154	.3307
491	.0000	.0000	.0000	.0721	.0703	.1559	.7018*+
492	.0000	.0000	.0000	.0117	.0894	.3331	.5658*+
493	.0000	.0000	.0000	.0167	.2306	.2088	.5438*+
494	.0000	.0000	.0000	.0070	.1499	.2056	.6375*+
495	.0000	.0000	.0000	.0818	.2471	.1541	.5170*+
496	.0000	.0000	.0000	.0100	.1129*	.2249	.6522 +
497	.0000	.0000	.0000	.0394	.1287*	.2328	.5991 +
498	.0000	.0000	.0000	.0137	.1622	.2449*	.5793 +
499	.0000	.0000	.0000	.1283	.1170	.2234*	.5313 +
500	.0000	.0000	.0000	.0056	.1501	.2059	.6384*+

501	.0000	.0000	.0000	.0665	.2513	.1567*	.5256 +
502	.0000	.0000	.0000	.0080	.1131	.2253*	.6535 +
503	.0000	.0000	.0000	.0266	.1741	.3660*	.4333 +
504	.0000	.0000	.0000	.0576	.1185	.2950	.5289*+
505	.0000	.0000	.0000	.0398	.0802	.2421*	.6379 +
506	.0000	.0000	.0000	.4193 +	.0462	.2048	.3297*
507	.0000	.0000	.0000	.4811 +	.1013	.1789*	.2387
508	.0000	.0000	.0000	.1082	.0751	.2266	.5900*+

PREDICTED PROBABILITIES (* marks actual, + marks prediction.)

Indiv	CARR	MTRR	VANR	CARS	MTRS	VANS	BRTS
509	.0000	.0000	.0000	.0243	.1526*	.2007	.6223 +
510	.0000	.0000	.0000	.0078	.2253*	.2128	.5541 +
511	.0000	.0000	.0000	.0422	.0774	.3044	.5760*+
512	.0000	.0000	.0000	.0208	.1366	.1954	.6472*+
513	.0000	.0000	.0000	.0301	.1052	.1986	.6661*+
514	.0000	.0000	.0000	.0072	.0576	.2419	.6933*+
515	.0000	.0000	.0000	.0208	.1366	.1954	.6472*+
516	.0000	.0000	.0000	.0301	.1052*	.1986	.6661 +
517	.0000	.0000	.0000	.0072	.0576	.2419	.6933*+
518	.0000	.0000	.0000	.2437	.1109	.1293	.5161*+
519	.0000	.0000	.0000	.4068 +	.0448	.1964	.3521*
520	.0000	.0000	.0000	.4151 +	.1181	.1730*	.2939
521	.0000	.0000	.0000	.6062 +	.0570	.0781	.2587*
522	.0000	.0000	.0000	.6205 +	.0748	.0677	.2370*
523	.0000	.0000	.0000	.5840 +	.0303	.1070	.2787*
524	.0000	.0000	.0000	.3281*	.0535	.2370	.3814 +
525	.0000	.0000	.0000	.3854 +	.1199	.2119	.2828*
526	.0000	.0000	.0000	.0759	.0778	.2348	.6115*+
527	.0000	.0000	.0000	.1705	.0660	.2926	.4710*+
528	.0000	.0000	.0000	.2088*	.1544	.2728	.3640 +
529	.0000	.0000	.0000	.0334	.0814	.2456	.6396*+
530	.0000	.0000	.0000	.0122*	.1491	.2045	.6341 +

PREDICTED PROBABILITIES (* marks actual, + marks prediction.)

Indiv	CARR	MTRR	VANR	CARS	MTRS	VANS	BRTS
531	.0000	.0000	.0000	.1347	.2329*	.1452	.4872 +
532	.0000	.0000	.0000	.0174	.1121	.2232	.6473*+
533	.0000	.0000	.0000	.0343	.1397	.1916	.6344*+
534	.0000	.0000	.0000	.0363	.1899	.1720*	.6017 +
535	.0000	.0000	.0000	.0291	.1380	.2311	.6018*+
536	.0000	.0000	.0000	.3843*+	.1101	.2315	.2741
537	.0000	.0000	.0000	.5825 +	.0525	.1307	.2343*
538	.0000	.0000	.0000	.4862 +	.0429	.1295	.3413*
539	.0000	.0000	.0000	.0739	.1340	.1837	.6084*+
540	.0000	.0000	.0000	.0781	.1817	.1645	.5756*+
541	.0000	.0000	.0000	.0631	.1332	.2230*	.5807 +
542	.0000	.0000	.0000	.1079	.0710	.3147*	.5065 +
543	.0000	.0000	.0000	.1344	.1689	.2984	.3983*+
544	.0000	.0000	.0000	.0199	.0826	.2490	.6485*+
545	.2615*	.3507	.3878 +	.0000	.0000	.0000	.0000
546	.1077	.2549	.6374*+	.0000	.0000	.0000	.0000
547	.0579	.1913	.7509*+	.0000	.0000	.0000	.0000
548	.0530	.2616	.6854*+	.0000	.0000	.0000	.0000
549	.0613	.1768	.7619*+	.0000	.0000	.0000	.0000
550	.1170	.4501 +	.4329*	.0000	.0000	.0000	.0000
551	.5385*+	.1084	.3532	.0000	.0000	.0000	.0000
552	.8720*+	.0354	.0926	.0000	.0000	.0000	.0000

PREDICTED PROBABILITIES (* marks actual, + marks prediction.)

Indiv	CARR	MTRR	VANR	CARS	MTRS	VANS	BRTS
553	.8886*+	.0347	.0766	.0000	.0000	.0000	.0000
554	.0366*	.3506	.6128 +	.0000	.0000	.0000	.0000
555	.0502*	.2368	.7131 +	.0000	.0000	.0000	.0000
556	.1326	.2256	.6419*+	.0000	.0000	.0000	.0000
557	.2334	.1544	.6123*+	.0000	.0000	.0000	.0000
558	.0602	.3264*	.6134 +	.0000	.0000	.0000	.0000
559	.0916	.2326	.6757*+	.0000	.0000	.0000	.0000
560	.1315	.1749	.6936*+	.0000	.0000	.0000	.0000
561	.0309	.3366	.6325*+	.0000	.0000	.0000	.0000
562	.0897	.2688	.6415*+	.0000	.0000	.0000	.0000
563	.0438	.1771	.7791*+	.0000	.0000	.0000	.0000
564	.0424	.3226	.6350*+	.0000	.0000	.0000	.0000
565	.3204	.1461	.5335*+	.0000	.0000	.0000	.0000
566	.4633 +	.1852	.3516*	.0000	.0000	.0000	.0000
567	.2562	.1455	.5983*+	.0000	.0000	.0000	.0000
568	.2792	.1451	.5757*+	.0000	.0000	.0000	.0000
569	.0754	.3212	.6035*+	.0000	.0000	.0000	.0000
570	.1137	.2270	.6593*+	.0000	.0000	.0000	.0000
571	.1009	.1679	.7312*+	.0000	.0000	.0000	.0000
572	.0251	.3240	.6510*+	.0000	.0000	.0000	.0000
573	.1249	.2603	.6148*+	.0000	.0000	.0000	.0000
574	.1434	.1739	.6827*+	.0000	.0000	.0000	.0000

PREDICTED PROBABILITIES (* marks actual, + marks prediction.)

Indiv	CARR	MTRR	VANR	CARS	MTRS	VANS	BRTS
575	.1351	.3076	.5574*+	.0000	.0000	.0000	.0000
576	.1137	.2270	.6593*+	.0000	.0000	.0000	.0000
577	.2899	.2097	.5004*+	.0000	.0000	.0000	.0000
578	.1594	.1557	.6849*+	.0000	.0000	.0000	.0000
579	.1549	.2847	.5604*+	.0000	.0000	.0000	.0000
580	.0699	.3580	.5722*+	.0000	.0000	.0000	.0000
581	.0552*	.2610	.6838 +	.0000	.0000	.0000	.0000
582	.0231	.2629	.7140*+	.0000	.0000	.0000	.0000
583	.0901*	.3704	.5395 +	.0000	.0000	.0000	.0000
584	.0989	.3109	.5902*+	.0000	.0000	.0000	.0000
585	.0149	.2000	.7851*+	.0000	.0000	.0000	.0000
586	.5049 +	.1005	.3946*	.0000	.0000	.0000	.0000
587	.4875 +	.1823	.3303*	.0000	.0000	.0000	.0000
588	.4387 +	.1437	.4175*	.0000	.0000	.0000	.0000
589	.1615	.1688*	.6697 +	.0000	.0000	.0000	.0000
590	.0390	.3338*	.6272 +	.0000	.0000	.0000	.0000
591	.0600	.2407	.6993*+	.0000	.0000	.0000	.0000
592	.1440	.3485	.5075*+	.0000	.0000	.0000	.0000
593	.1571	.2908	.5521*+	.0000	.0000	.0000	.0000
594	.0251	.1979	.7770*+	.0000	.0000	.0000	.0000
595	.5931 +	.0819	.3250*	.0000	.0000	.0000	.0000
596	.2348	.2658	.4994*+	.0000	.0000	.0000	.0000

PREDICTED PROBABILITIES (* marks actual, + marks prediction.)

Indiv	CARR	MTRR	VANR	CARS	MTRS	VANS	BRTS
597	.3256*	.1727	.5017 +	.0000	.0000	.0000	.0000
598	.0393	.3497*	.6111 +	.0000	.0000	.0000	.0000
599	.0538	.2359*	.7104 +	.0000	.0000	.0000	.0000
600	.1411	.2234*	.6355 +	.0000	.0000	.0000	.0000
601	.2101	.3216*	.4683 +	.0000	.0000	.0000	.0000
602	.2276	.2665*	.5059 +	.0000	.0000	.0000	.0000
603	.0391	.1951*	.7658 +	.0000	.0000	.0000	.0000
604	.0494	.3460*	.6046 +	.0000	.0000	.0000	.0000

605	.0674	.2325*	.7001 +	.0000	.0000	.0000	.0000
606	.1729	.2151*	.6120 +	.0000	.0000	.0000	.0000
607	.1271	.3553	.5175*+	.0000	.0000	.0000	.0000
608	.1389	.2971	.5640*+	.0000	.0000	.0000	.0000
609	.0218	.1986	.7796*+	.0000	.0000	.0000	.0000
610	.8307*+	.0528	.1165	.0000	.0000	.0000	.0000
611	.6978*+	.0709	.2312	.0000	.0000	.0000	.0000
612	.8680*+	.0365	.0955	.0000	.0000	.0000	.0000
613	.0326	.2673	.7001*+	.0000	.0000	.0000	.0000
614	.0379	.1812	.7809*+	.0000	.0000	.0000	.0000
615	.0740	.4720 +	.4540*	.0000	.0000	.0000	.0000
616	.1315	.1749*	.6936 +	.0000	.0000	.0000	.0000
617	.0309	.3366*	.6325 +	.0000	.0000	.0000	.0000
618	.0478	.2439	.7084*+	.0000	.0000	.0000	.0000

PREDICTED PROBABILITIES (* marks actual, + marks prediction.)

Indiv	CARR	MTRR	VANR	CARS	MTRS	VANS	BRTS
619	.0770	.1739*	.7491 +	.0000	.0000	.0000	.0000
620	.1239	.4161*	.4601 +	.0000	.0000	.0000	.0000
621	.0286	.2775*	.6939 +	.0000	.0000	.0000	.0000
622	.1110	.1790	.7100*+	.0000	.0000	.0000	.0000
623	.0256	.3384*	.6359 +	.0000	.0000	.0000	.0000
624	.0397	.2459	.7144*+	.0000	.0000	.0000	.0000
625	.0911	.3498	.5591*+	.0000	.0000	.0000	.0000
626	.0723	.2563	.6714*+	.0000	.0000	.0000	.0000
627	.0306	.2609	.7085*+	.0000	.0000	.0000	.0000
628	.4592*+	.1010	.4398	.0000	.0000	.0000	.0000
629	.1629*	.2782	.5590 +	.0000	.0000	.0000	.0000
630	.5191*+	.1430	.3378	.0000	.0000	.0000	.0000
631	.5789 +	.0787	.3424*	.0000	.0000	.0000	.0000
632	.2395	.2527	.5078*+	.0000	.0000	.0000	.0000
633	.6361*+	.1082	.2557	.0000	.0000	.0000	.0000
634	.0825	.3735*	.5440 +	.0000	.0000	.0000	.0000
635	.0906	.3137*	.5956 +	.0000	.0000	.0000	.0000
636	.0136	.2002*	.7862 +	.0000	.0000	.0000	.0000
637	.2744	.1461	.5795*+	.0000	.0000	.0000	.0000
638	.0737	.3217	.6045*+	.0000	.0000	.0000	.0000
639	.1113	.2276	.6611*+	.0000	.0000	.0000	.0000
640	.0603	.2932	.6465*+	.0000	.0000	.0000	.0000

PREDICTED PROBABILITIES (* marks actual, + marks prediction.)

Indiv	CARR	MTRR	VANR	CARS	MTRS	VANS	BRTS
641	.0293	.2279	.7428*+	.0000	.0000	.0000	.0000
642	.0792	.2544	.6664*+	.0000	.0000	.0000	.0000
643	.0603	.2932*	.6465 +	.0000	.0000	.0000	.0000
644	.0293	.2279*	.7428 +	.0000	.0000	.0000	.0000
645	.0792	.2544	.6664*+	.0000	.0000	.0000	.0000
646	.6057 +	.1164*	.2779	.0000	.0000	.0000	.0000
647	.4164*	.1081	.4755 +	.0000	.0000	.0000	.0000
648	.4081 +	.1994	.3925*	.0000	.0000	.0000	.0000
649	.5402*+	.0969	.3630	.0000	.0000	.0000	.0000
650	.7746*+	.0686	.1568	.0000	.0000	.0000	.0000
651	.9184*+	.0360	.0456	.0000	.0000	.0000	.0000
652	.4952 +	.0943	.4105*	.0000	.0000	.0000	.0000
653	.1836	.2713	.5452*+	.0000	.0000	.0000	.0000
654	.5551 +	.1323	.3126*	.0000	.0000	.0000	.0000
655	.4433*+	.2143	.3425	.0000	.0000	.0000	.0000
656	.3823	.1707	.4471*+	.0000	.0000	.0000	.0000
657	.2006*	.2151	.5843 +	.0000	.0000	.0000	.0000

```
  658   .1969     .1617     .6414*+   .0000     .0000     .0000     .0000
  659   .0491     .3303     .6206*+   .0000     .0000     .0000     .0000
  660   .0751*    .2369     .6880 +   .0000     .0000     .0000     .0000
  661   .0435     .2015     .7551*+   .0000     .0000     .0000     .0000
  662   .0363     .2932     .6705*+   .0000     .0000     .0000     .0000
PREDICTED PROBABILITIES (* marks actual, + marks prediction.)
Indiv    CARR      MTRR      VANR      CARS      MTRS      VANS      BRTS
  663   .3033*    .3074     .3894 +   .0000     .0000     .0000     .0000
  664   .5983*+   .1546     .2471     .0000     .0000     .0000     .0000
  665   .5365*+   .1280     .3354     .0000     .0000     .0000     .0000
  666   .3195*    .1831     .4974 +   .0000     .0000     .0000     .0000
  667   .0837*    .1930     .7233 +   .0000     .0000     .0000     .0000
  668   .0705     .2828     .6467*+   .0000     .0000     .0000     .0000
  669   .4668*+   .2353     .2980     .0000     .0000     .0000     .0000
  670   .0494     .3460*    .6046 +   .0000     .0000     .0000     .0000
  671   .0674     .2325*    .7001 +   .0000     .0000     .0000     .0000
  672   .1729     .2151*    .6120 +   .0000     .0000     .0000     .0000
  673   .1984     .3264*    .4753 +   .0000     .0000     .0000     .0000
  674   .2151     .2708*    .5141 +   .0000     .0000     .0000     .0000
  675   .0365     .1956*    .7679 +   .0000     .0000     .0000     .0000
  676   .2273     .1443     .6284*+   .0000     .0000     .0000     .0000
  677   .0631     .3113     .6255*+   .0000     .0000     .0000     .0000
  678   .2722     .2165     .5113*+   .0000     .0000     .0000     .0000
  679   .0000     .0000     .0000     .7237 +   .0209     .0464     .2090*
  680   .0000     .0000     .0000     .2859     .0646     .2407     .4089*+
  681   .0000     .0000     .0000     .3645 +   .1491     .1350     .3515*
  682   .0000     .0000     .0000     .4799 +   .0930     .1956     .2315*
  683   .0000     .0000     .0000     .6735 +   .0411     .1022     .1833*
  684   .0000     .0000     .0000     .5832*+   .0348     .1051     .2769
PREDICTED PROBABILITIES (* marks actual, + marks prediction.)
Indiv    CARR      MTRR      VANR      CARS      MTRS      VANS      BRTS
  685   .0000     .0000     .0000     .5304*+   .0531     .1378     .2787
  686   .0000     .0000     .0000     .6914*+   .0615     .0854     .1616
  687   .0000     .0000     .0000     .5454*+   .0306     .1342     .2899
  688   .0000     .0000     .0000     .0436     .1081     .2806*    .5677 +
  689   .0000     .0000     .0000     .0828     .1829     .2539*    .4804 +
  690   .0000     .0000     .0000     .0461     .0643     .2815     .6082*+
  691   .0000     .0000     .0000     .1225*    .0664     .1474     .6637 +
  692   .0000     .0000     .0000     .0209     .0886     .3300*    .5606 +
  693   .0000     .0000     .0000     .0297     .2276     .2061     .5366*+
  694   .0000     .0000     .0000     .0157     .1077     .3248*    .5518 +
  696   .0000     .0000     .0000     .0990*    .1737     .2514     .4758 +
  697   .0000     .0000     .0000     .0157*    .1077     .3248     .5518 +
  698   .0000     .0000     .0000     .0072     .1405     .1142     .7381*+
  699   .0000     .0000     .0000     .0990     .1737*    .2514     .4758 +
  700   .0000     .0000     .0000     .0157     .1486     .2038     .6319*+
  701   .0000     .0000     .0000     .1668     .2243     .1398     .4691*+
  702   .0000     .0000     .0000     .0223     .1115     .2221*    .6441 +
  703   .0000     .0000     .0000     .0132     .1446     .1687     .6734*+
  704   .0000     .0000     .0000     .0276     .0735     .3218*    .5771 +
  705   .0000     .0000     .0000     .0286     .1961     .2873*    .4880 +
  706   .0000     .0000     .0000     .5621 +   .0761     .1044*    .2575
  707   .0000     .0000     .0000     .0673     .1430     .2210     .5687*+
PREDICTED PROBABILITIES (* marks actual, + marks prediction.)
Indiv    CARR      MTRR      VANR      CARS      MTRS      VANS      BRTS
  708   .0000     .0000     .0000     .1608     .0731     .1777     .5884*+
  709   .0000     .0000     .0000     .0206     .1479     .2028     .6287*+
```

710	.0000	.0000	.0000	.2093	.2128	.1327	.4452*+
711	.0000	.0000	.0000	.0292	.1107	.2205	.6395*+
712	.0000	.0000	.0000	.0381	.0765	.3393*	.5461 +
713	.0000	.0000	.0000	.0484	.1857	.3281*	.4379 +
714	.0000	.0000	.0000	.0066	.0837	.2524	.6573*+
715	.0000	.0000	.0000	.1471	.1190	.1702	.5637*+
716	.0000	.0000	.0000	.2010	.0867	.1636	.5487*+
717	.0000	.0000	.0000	.0559	.0548	.2300	.6593*+
718	.0000	.0000	.0000	.0206	.1479	.2028	.6287*+
719	.0000	.0000	.0000	.2093	.2128	.1327	.4452*+
720	.0000	.0000	.0000	.0292	.1107	.2205*	.6395 +
721	.0000	.0000	.0000	.1358	.1359*	.2101	.5183 +
722	.0000	.0000	.0000	.0353	.2389*	.1919	.5338 +
723	.0000	.0000	.0000	.0304	.0693	.4178*	.4825 +
724	.0000	.0000	.0000	.0649	.1371	.1599	.6382*+
725	.0000	.0000	.0000	.1286	.0658	.2884*	.5171 +
726	.0000	.0000	.0000	.1325	.1751	.2565*	.4358 +
727	.0000	.0000	.0000	.8105*+	.0264	.0378	.1252
728	.0000	.0000	.0000	.8619*+	.0150	.0283	.0948
729	.0000	.0000	.0000	.5950*+	.0235	.0987	.2828

PREDICTED PROBABILITIES (* marks actual, + marks prediction.)

Indiv	CARR	MTRR	VANR	CARS	MTRS	VANS	BRTS
730	.0000	.0000	.0000	.1460	.1289	.1768	.5482*+
731	.0000	.0000	.0000	.6824 +	.0855	.0533	.1788*
732	.0000	.0000	.0000	.1965	.0916	.1825	.5294*+
733	.0000	.0000	.0000	.0891	.1375	.1886	.5848*+
734	.0000	.0000	.0000	.5514 +	.1207	.0753	.2526*
735	.0000	.0000	.0000	.1227	.1000	.1993	.5779*+
736	.0000	.0000	.0000	.6946*+	.0448	.0522	.2084
737	.0000	.0000	.0000	.8288*+	.0129	.0567	.1016
738	.0000	.0000	.0000	.8336*+	.0336	.0492	.0836
739	.0000	.0000	.0000	.6946*+	.0448	.0522	.2084
740	.0000	.0000	.0000	.8288*+	.0129	.0567	.1016
741	.0000	.0000	.0000	.8336*+	.0336	.0492	.0836
742	.0000	.0000	.0000	.0805	.1438*	.1892	.5865 +
743	.0000	.0000	.0000	.0270	.2210*	.2087	.5434 +
744	.0000	.0000	.0000	.1341	.0700*	.2752	.5207 +
745	.0000	.0000	.0000	.6946*+	.0448	.0522	.2084
746	.0000	.0000	.0000	.8288*+	.0129	.0567	.1016
747	.0000	.0000	.0000	.8336*+	.0336	.0492	.0836
748	.0000	.0000	.0000	.0224	.1069*	.3226	.5481 +
749	.0000	.0000	.0000	.0103	.1401*	.1139	.7358 +
750	.0000	.0000	.0000	.1364	.1665*	.2410	.4561 +
751	.0000	.0000	.0000	.0417	.1499	.1971	.6112*+

PREDICTED PROBABILITIES (* marks actual, + marks prediction.)

Indiv	CARR	MTRR	VANR	CARS	MTRS	VANS	BRTS
752	.0000	.0000	.0000	.0136	.2240	.2115	.5508*+
753	.0000	.0000	.0000	.0715	.0750	.2951*	.5584 +
754	.0000	.0000	.0000	.0396	.1502*	.1976	.6126 +
755	.0000	.0000	.0000	.0129	.2242*	.2117	.5512 +
756	.0000	.0000	.0000	.0679	.0753*	.2962	.5605 +
757	.0000	.0000	.0000	.7639*+	.0329	.0471	.1561
758	.0000	.0000	.0000	.8252*+	.0190	.0358	.1201
759	.0000	.0000	.0000	.5264*+	.0275	.1154	.3307
760	.0000	.0000	.0000	.7639*+	.0329	.0471	.1561
761	.0000	.0000	.0000	.8252*+	.0190	.0358	.1201
762	.0000	.0000	.0000	.5264*+	.0275	.1154	.3307

763	.0000	.0000	.0000	.0721	.0703	.1559	.7018*+
764	.0000	.0000	.0000	.0117	.0894	.3331	.5658*+
765	.0000	.0000	.0000	.0167	.2306	.2088	.5438*+
766	.0000	.0000	.0000	.0070	.1499	.2056	.6375*+
767	.0000	.0000	.0000	.0818	.2471	.1541	.5170*+
768	.0000	.0000	.0000	.0100	.1129*	.2249	.6522 +
769	.0000	.0000	.0000	.0394	.1287*	.2328	.5991 +
770	.0000	.0000	.0000	.0137	.1622	.2449*	.5793 +
771	.0000	.0000	.0000	.1283	.1170	.2234*	.5313 +
772	.0000	.0000	.0000	.0056	.1501	.2059	.6384*+
773	.0000	.0000	.0000	.0665	.2513	.1567*	.5256 +

PREDICTED PROBABILITIES (* marks actual, + marks prediction.)

Indiv	CARR	MTRR	VANR	CARS	MTRS	VANS	BRTS
774	.0000	.0000	.0000	.0080	.1131	.2253*	.6535 +
775	.0000	.0000	.0000	.0266	.1741	.3660*	.4333 +
776	.0000	.0000	.0000	.0576	.1185	.2950	.5289*+
777	.0000	.0000	.0000	.0398	.0802	.2421*	.6379 +
778	.0000	.0000	.0000	.4193 +	.0462	.2048	.3297*
779	.0000	.0000	.0000	.4811 +	.1013	.1789*	.2387
780	.0000	.0000	.0000	.1082	.0751	.2266	.5900*+
781	.0000	.0000	.0000	.0243	.1526*	.2007	.6223 +
782	.0000	.0000	.0000	.0078	.2253*	.2128	.5541 +
783	.0000	.0000	.0000	.0422	.0774	.3044	.5760*+
784	.0000	.0000	.0000	.0208	.1366	.1954	.6472*+
785	.0000	.0000	.0000	.0301	.1052	.1986	.6661*+
786	.0000	.0000	.0000	.0072	.0576	.2419	.6933*+
787	.0000	.0000	.0000	.0208	.1366	.1954	.6472*+
788	.0000	.0000	.0000	.0301	.1052*	.1986	.6661 +
789	.0000	.0000	.0000	.0072	.0576	.2419	.6933*+
790	.0000	.0000	.0000	.2437	.1109	.1293	.5161*+
791	.0000	.0000	.0000	.4068 +	.0448	.1964	.3521*
792	.0000	.0000	.0000	.4151 +	.1181	.1730*	.2939
793	.0000	.0000	.0000	.6062 +	.0570	.0781	.2587*
794	.0000	.0000	.0000	.6205 +	.0748	.0677	.2370*
795	.0000	.0000	.0000	.5840 +	.0303	.1070	.2787*

PREDICTED PROBABILITIES (* marks actual, + marks prediction.)

Indiv	CARR	MTRR	VANR	CARS	MTRS	VANS	BRTS
796	.0000	.0000	.0000	.3281*	.0535	.2370	.3814 +
797	.0000	.0000	.0000	.3854 +	.1199	.2119	.2828*
798	.0000	.0000	.0000	.0759	.0778	.2348	.6115*+
799	.0000	.0000	.0000	.1705	.0660	.2926	.4710*+
800	.0000	.0000	.0000	.2088*	.1544	.2728	.3640 +
801	.0000	.0000	.0000	.0334	.0814	.2456	.6396*+
802	.0000	.0000	.0000	.0122*	.1491	.2045	.6341 +
803	.0000	.0000	.0000	.1347	.2329*	.1452	.4872 +
804	.0000	.0000	.0000	.0174	.1121	.2232	.6473*+
805	.0000	.0000	.0000	.0343	.1397	.1916	.6344*+
806	.0000	.0000	.0000	.0363	.1899	.1720*	.6017 +
807	.0000	.0000	.0000	.0291	.1380	.2311	.6018*+
808	.0000	.0000	.0000	.3843*+	.1101	.2315	.2741
809	.0000	.0000	.0000	.5825 +	.0525	.1307	.2343*
810	.0000	.0000	.0000	.4862 +	.0429	.1295	.3413*
811	.0000	.0000	.0000	.0739	.1340	.1837	.6084*+
812	.0000	.0000	.0000	.0781	.1817	.1645	.5756*+
813	.0000	.0000	.0000	.0631	.1332	.2230*	.5807 +
814	.0000	.0000	.0000	.1079	.0710	.3147*	.5065 +
815	.0000	.0000	.0000	.1344	.1689	.2984	.3983*+

```
  816   .0000     .0000     .0000     .0199     .0826     .2490     .6485*+
```

2. Finalized SP-Model with Elasticities

```
nlog; lhs=mode; choices=CAR,MTR,VAN,BRT
;model: U(CAR)=CAR*INCCAR+IVT*IVT+COST*COST+CONG*CONG/
U(MTR)=IVT*IVT+COST*COST/
U(VAN)=VAN*AVAN+IVT*IVT+COST*COST+OVT*OVT/
U(BRT)=BRT*ABRT+IVT*IVT+COST*COST+OVT*OVT$
+----------------------------------------------+
| Discrete choice and multinomial logit models|
+----------------------------------------------+

+-------------------------------------------------------+
|WARNING:   Bad observations were found in the sample. |
|Found   3 bad observations among     414 individuals. |
|You can use ;CheckData to get a list of these points. |
+-------------------------------------------------------+

Normal exit from iterations. Exit status=0.
+----------------------------------------------+
| Discrete choice (multinomial logit) model   |
| Maximum Likelihood Estimates                 |
| Model estimated: Jul 16, 2014 at 09:50:58AM.|
| Dependent variable               Choice      |
| Weighting variable                 None      |
| Number of observations              411      |
| Iterations completed                  6      |
| Log likelihood function       -401.6789      |
| Number of parameters                  7      |
| Info. Criterion: AIC =          2.07734      |
|   Finite Sample: AIC =          2.07802      |
| Info. Criterion: BIC =          2.14578      |
| Info. Criterion:HQIC =          2.10442      |
| R2=1-LogL/LogL*  Log-L fncn  R-sqrd  RsqAdj |
| Constants only    -520.4403  .22821  .2416 |
| Response data are given as ind. choice.      |
| Number of obs.=   414, skipped   3 bad obs. |
+----------------------------------------------+

+----------------------------------------------+
| Notes No coefficients=>P(i,j)=1/J(i).       |
|       Constants only =>P(i,j) uses ASCs     |
|         only. N(j)/N if fixed choice set.   |
|         N(j) = total sample frequency for j |
|         N    = total sample frequency.      |
|       These 2 models are simple MNL models. |
|       R-sqrd = 1 - LogL(model)/logL(other)  |
|       RsqAdj=1-[nJ/(nJ-nparm)]*(1-R-sqrd)   |
|         nJ   = sum over i, choice set sizes |
+----------------------------------------------+
+--------+--------------+----------------+--------+--------+
```

```
|Variable| Coefficient  | Standard Error |b/St.Er.|P[|Z|>z]|
+--------+--------------+----------------+--------+--------+
 CAR     |     .05715177       .00564507    10.124   .0000
 IVT     |    -.04764046       .01180293    -4.036   .0001
 COST    |    -.01287938       .00297726    -4.326   .0000
 CONG    |    -.06471298       .01717515    -3.768   .0002
 VAN     |    1.78395471       .43246336     4.125   .0000
 OVT     |    -.08536609       .02590546    -3.295   .0010
 BRT     |    2.18576719       .39905977     5.477   .0000
+---------------------------------------------------+
| Derivative (times 100) averaged over observations.|
| Attribute is IVT      in choice CAR               |
| Effects on probabilities of all choices in model: |
| * = Direct Derivative effect of the attribute.    |
|                                  Mean    St.Dev   |
| *     Choice=CAR                -.8678     .2881   |
|       Choice=MTR                 .0745     .0857   |
|       Choice=VAN                 .1061     .1177   |
|       Choice=BRT                 .2103     .2198   |
+---------------------------------------------------+
+---------------------------------------------------+
| Derivative (times 100) averaged over observations.|
| Attribute is IVT      in choice MTR               |
| Effects on probabilities of all choices in model: |
| * = Direct Derivative effect of the attribute.    |
|                                  Mean    St.Dev   |
|       Choice=CAR                 .1313     .0832   |
| *     Choice=MTR                -.6305     .2350   |
|       Choice=VAN                 .1351     .0756   |
|       Choice=BRT                 .3387     .1797   |
+---------------------------------------------------+
+---------------------------------------------------+
| Derivative (times 100) averaged over observations.|
| Attribute is IVT      in choice VAN               |
| Effects on probabilities of all choices in model: |
| * = Direct Derivative effect of the attribute.    |
|                                  Mean    St.Dev   |
|       Choice=CAR                 .2171     .1029   |
|       Choice=MTR                 .1528     .0764   |
| *     Choice=VAN                -.8131     .2134   |
|       Choice=BRT                 .5385     .2211   |
+---------------------------------------------------+
+---------------------------------------------------+
| Derivative (times 100) averaged over observations.|
| Attribute is IVT      in choice BRT               |
| Effects on probabilities of all choices in model: |
| * = Direct Derivative effect of the attribute.    |
|                                  Mean    St.Dev   |
|       Choice=CAR                 .5194     .1952   |
|       Choice=MTR                 .4031     .1885   |
|       Choice=VAN                 .5719     .2325   |
| *     Choice=BRT               -1.0875     .1303   |
+---------------------------------------------------+
+---------------------------------------------------+
| Derivative (times 100) averaged over observations.|
| Attribute is OVT      in choice VAN               |
| Effects on probabilities of all choices in model: |
```

```
| * = Direct Derivative effect of the attribute.     |
|                                  Mean    St.Dev    |
|       Choice=CAR                 .3890     .1844   |
|       Choice=MTR                 .2738     .1369   |
| *     Choice=VAN              -1.4570     .3824   |
|       Choice=BRT                 .9648     .3961   |
+----------------------------------------------------+
+----------------------------------------------------+
| Derivative (times 100) averaged over observations.|
| Attribute is OVT      in choice BRT                |
| Effects on probabilities of all choices in model: |
| * = Direct Derivative effect of the attribute.     |
|                                  Mean    St.Dev    |
|       Choice=CAR                 .9308     .3498   |
|       Choice=MTR                 .7224     .3377   |
|       Choice=VAN               1.0248     .4165   |
| *     Choice=BRT              -1.9487     .2334   |
+----------------------------------------------------+
+----------------------------------------------------+
| Derivative (times 100) averaged over observations.|
| Attribute is COST     in choice CAR                |
| Effects on probabilities of all choices in model: |
| * = Direct Derivative effect of the attribute.     |
|                                  Mean    St.Dev    |
| *     Choice=CAR                -.2346     .0779   |
|       Choice=MTR                 .0202     .0232   |
|       Choice=VAN                 .0287     .0318   |
|       Choice=BRT                 .0569     .0594   |
+----------------------------------------------------+
+----------------------------------------------------+
| Derivative (times 100) averaged over observations.|
| Attribute is COST     in choice MTR                |
| Effects on probabilities of all choices in model: |
| * = Direct Derivative effect of the attribute.     |
|                                  Mean    St.Dev    |
|       Choice=CAR                 .0355     .0225   |
| *     Choice=MTR                -.1705     .0635   |
|       Choice=VAN                 .0365     .0204   |
|       Choice=BRT                 .0916     .0486   |
+----------------------------------------------------+
+----------------------------------------------------+
| Derivative (times 100) averaged over observations.|
| Attribute is COST     in choice VAN                |
| Effects on probabilities of all choices in model: |
| * = Direct Derivative effect of the attribute.     |
|                                  Mean    St.Dev    |
|       Choice=CAR                 .0587     .0278   |
|       Choice=MTR                 .0413     .0207   |
| *     Choice=VAN                -.2198     .0577   |
|       Choice=BRT                 .1456     .0598   |
+----------------------------------------------------+
+----------------------------------------------------+
| Derivative (times 100) averaged over observations.|
| Attribute is COST     in choice BRT                |
| Effects on probabilities of all choices in model: |
| * = Direct Derivative effect of the attribute.     |
|                                  Mean    St.Dev    |
```

```
|       Choice=CAR                 .1404     .0528   |
|       Choice=MTR                 .1090     .0510   |
|       Choice=VAN                 .1546     .0628   |
| *     Choice=BRT                -.2940     .0352   |
+----------------------------------------------------+

+----------------------------------------------------+
| Derivative (times 100) averaged over observations.|
| Attribute is CONG     in choice CAR               |
| Effects on probabilities of all choices in model: |
| * = Direct Derivative effect of the attribute.    |
|                                  Mean    St.Dev   |
| *     Choice=CAR               -1.1788     .3913   |
|       Choice=MTR                 .1013     .1164   |
|       Choice=VAN                 .1441     .1599   |
|       Choice=BRT                 .2857     .2986   |
+----------------------------------------------------+
+----------------------------------------------------+
| Derivative (times 100) averaged over observations.|
| Attribute is INCCAR   in choice CAR               |
| Effects on probabilities of all choices in model: |
| * = Direct Derivative effect of the attribute.    |
|                                  Mean    St.Dev   |
| *     Choice=CAR                1.0411     .3456   |
|       Choice=MTR                -.0894     .1028   |
|       Choice=VAN                -.1272     .1412   |
|       Choice=BRT                -.2523     .2637   |
+----------------------------------------------------+
;describe ;list $
+----------------------------------------------+
| Discrete choice and multinomial logit models|
+----------------------------------------------+


+---------------------------------------------------------------------------+
|            Descriptive Statistics for Alternative CAR                      :
|    Utility Function           |                    |     30.0 observs.   |
|    Coefficient                | All      138.0 obs.|that chose CAR       |
| Name           Value  Variable | Mean      Std. Dev.|Mean       Std. Dev. |
| ------------------- -------- | -------------------+-------------------- |
| CAR            .0572  INCCAR   |   41.435     31.750|   78.117    31.843 |
| IVT           -.0476  IVT      |   14.674      4.107|   14.833     4.251 |
| COST          -.0129  COST     |  155.072     41.544|  148.333    38.245 |
| CONG          -.0647  CONG     |   24.493      8.312|   24.000     8.449 |
+---------------------------------------------------------------------------+
+---------------------------------------------------------------------------+
|            Descriptive Statistics for Alternative MTR                      :
|    Utility Function           |                    |     18.0 observs.   |
|    Coefficient                | All      138.0 obs.|that chose MTR       |
| Name           Value  Variable | Mean      Std. Dev.|Mean       Std. Dev. |
| ------------------- -------- | -------------------+-------------------- |
| IVT           -.0476  IVT      |   28.696      7.720|   26.667     6.860 |
| COST          -.0129  COST     |   28.225      6.445|   27.500     7.123 |
+---------------------------------------------------------------------------+
+---------------------------------------------------------------------------+
|            Descriptive Statistics for Alternative VAN                      :
```

```
|     Utility Function         |                    |     26.0 observs.  |
|     Coefficient              | All      138.0 obs.|that chose VAN      |
| Name              Value  Variable | Mean      Std. Dev.|Mean       Std. Dev. |
| ------------------  -------- | ------------------+------------------- |
| IVT           -.0476  IVT      |   30.652      7.756|   27.692     8.152 |
| COST          -.0129  COST     |   19.964      4.075|   19.615     3.981 |
| VAN           1.7840  AVAN     |    1.000       .000|    1.000      .000 |
| OVT           -.0854  OVT      |   14.746      3.788|   14.231     4.169 |
+------------------------------------------------------------------------+
+------------------------------------------------------------------------+
|            Descriptive Statistics for Alternative BRT                  :
|     Utility Function         |                    |     65.0 observs.  |
|     Coefficient              | All      138.0 obs.|that chose BRT      |
| Name              Value  Variable | Mean      Std. Dev.|Mean       Std. Dev. |
| ------------------  -------- | ------------------+------------------- |
| IVT           -.0476  IVT      |   18.768      4.177|   18.538     3.925 |
| COST          -.0129  COST     |   29.928      4.271|   30.154     4.143 |
| OVT           -.0854  OVT      |   13.551      3.734|   13.077     3.611 |
| BRT           2.1858  ABRT     |    1.000       .000|    1.000      .000 |
+------------------------------------------------------------------------+
PREDICTED PROBABILITIES (* marks actual, + marks prediction.)
Indiv    CAR       MTR       VAN       BRT
    1   .7327 +   .0187     .0400     .2087*
    2   .2424     .0661     .2698     .4217*+
    3   .3076     .1905     .1362     .3657*+
    4   .4530 +   .1082     .2172     .2216*
    5   .6791 +   .0401     .1053     .1755*
    6   .5601*+   .0345     .1061     .2993
    7   .4707*+   .0609     .1622     .3062
    8   .6794*+   .0727     .0892     .1587
    9   .5208*+   .0292     .1444     .3056
   10   .0322     .1113     .2966*    .5599 +
   11   .0734     .2100     .2579*    .4586 +
   12   .0391     .0585     .2896     .6128*+
   13   .1200*    .0615     .1316     .6869 +
   14   .0157     .0859     .3505*    .5480 +
   15   .0216     .2692     .1925     .5167*+
   16   .0115     .1113     .3422*    .5350 +
   17   .0047*    .1495     .0940     .7518 +
   18   .1025*    .2011     .2507     .4457 +
   19   .0115*    .1113     .3422     .5350 +
   20   .0047     .1495     .0940     .7518*+
   21   .1025     .2011*    .2507     .4457 +
   22   .0112     .1660     .1940     .6288*+
PREDICTED PROBABILITIES (* marks actual, + marks prediction.)
Indiv    CAR       MTR       VAN       BRT
   23   .1691     .2724     .1210     .4375*+
   24   .0157     .1141     .2147*    .6555 +
   25   .0097     .1546     .1489     .6867*+
   26   .0228     .0688     .3406*    .5679 +
   27   .0256     .2236     .2929*    .4579 +
   28   .5877 +   .0807     .0943*    .2374
   29   .0460     .1599     .2234     .5707*+
   30   .1359     .0719     .1710     .6212*+
   31   .0149     .1653     .1932     .6265*+
   32   .2131     .2580     .1146     .4144*+
   33   .0208     .1135     .2135     .6521*+
```

34	.0308	.0701	.3646*	.5345 +
35	.0433	.2129	.3352*	.4087 +
36	.0043	.0807	.2483	.6667*+
37	.1304	.1339	.1588	.5769*+
38	.1859	.0890	.1570	.5680*+
39	.0421	.0478	.2330	.6772*+
40	.0149	.1653	.1932	.6265*+
41	.2131	.2580	.1146	.4144*+
42	.0208	.1135	.2135*	.6521 +
43	.1333	.1466*	.2047	.5154 +
44	.0268	.2864*	.1713	.5155 +

PREDICTED PROBABILITIES (* marks actual, + marks prediction.)

Indiv	CAR	MTR	VAN	BRT
45	.0218	.0620	.4638*+	.4523
46	.0504	.1482	.1428	.6585*+
47	.1116	.0625	.3096*	.5162 +
48	.1241	.2010	.2633*	.4116 +
49	.8004*+	.0307	.0364	.1324
50	.8593*+	.0154	.0271	.0982
51	.5402*+	.0229	.1118	.3250
52	.1143	.1487	.1737	.5633*+
53	.6978 +	.0991	.0440	.1591*
54	.1536	.0981	.1846	.5637*+
55	.0679	.1565	.1828	.5928*+
56	.5659 +	.1423	.0632	.2286*
57	.0929	.1051	.1978	.6041*+
58	.6540*+	.0540	.0520	.2400
59	.8173*+	.0129	.0637	.1062
60	.8345*+	.0380	.0498	.0778
61	.6540*+	.0540	.0520	.2400
62	.8173*+	.0129	.0637	.1062
63	.8345*+	.0380	.0498	.0778
64	.0731	.1575*	.1814	.5880 +
65	.0202	.2667*	.1935	.5196 +
66	.1278	.0666*	.2900	.5156 +

PREDICTED PROBABILITIES (* marks actual, + marks prediction.)

Indiv	CAR	MTR	VAN	BRT
67	.6540*+	.0540	.0520	.2400
68	.8173*+	.0129	.0637	.1062
69	.8345*+	.0380	.0498	.0778
70	.0166	.1107*	.3404	.5322 +
71	.0069	.1492*	.0938	.7502 +
72	.1420	.1923*	.2396	.4261 +
73	.0372	.1636	.1884	.6108*+
74	.0100	.2694	.1955	.5250*+
75	.0670	.0712	.3102*	.5516 +
76	.0352	.1640*	.1888	.6121 +
77	.0094	.2696*	.1957	.5253 +
78	.0635	.0715*	.3114	.5537 +
79	.7509*+	.0384	.0455	.1653
80	.8211*+	.0196	.0345	.1248
81	.4689*+	.0265	.1292	.3754
82	.7509*+	.0384	.0455	.1653
83	.8211*+	.0196	.0345	.1248
84	.4689*+	.0265	.1292	.3754
85	.0696	.0650	.1391	.7263*+
86	.0087	.0865	.3530	.5519*+

```
   87   .0120     .2718     .1944     .5218*+
   88   .0049     .1670     .1952     .6328*+
PREDICTED PROBABILITIES (* marks actual, + marks prediction.)
   89   .0816     .3011     .1337     .4836*+
   90   .0069     .1151*    .2166     .6614 +
   91   .0351     .1344*    .2336     .5969 +
   92   .0099     .1833     .2318*    .5750 +
   93   .1325     .1222     .2265*    .5188 +
   94   .0039     .1672     .1954     .6335*+
   95   .0660     .3062     .1360*    .4918 +
   96   .0055     .1153     .2169*    .6623 +
   97   .0221     .1935     .3883*    .3961 +
   98   .0546     .1181     .3101     .5171*+
   99   .0336     .0758     .2331*    .6576 +
  100   .3833 +   .0446     .2320     .3401*
  101   .4690 +   .1181     .1860*    .2268
  102   .0778     .0748     .2300     .6175*+
  103   .0213     .1663*    .1915     .6209 +
  104   .0057     .2706*    .1964     .5273 +
  105   .0389     .0734     .3195     .5682*+
  106   .0173     .1513     .1794     .6520*+
  107   .0261     .1065     .1879     .6796*+
  108   .0051     .0496     .2420     .7033*+
  109   .0173     .1513     .1794     .6520*+
  110   .0261     .1065*    .1879     .6796 +
PREDICTED PROBABILITIES (* marks actual, + marks prediction.)
Indiv    CAR       MTR       VAN       BRT
  111   .0051     .0496     .2420     .7033*+
  112   .2036     .1243     .1198     .5523*+
  113   .3770 +   .0438     .2171     .3621*
  114   .4055 +   .1364     .1787*    .2794
  115   .5774 +   .0659     .0770     .2797*
  116   .5840 +   .0958     .0685     .2516*
  117   .5688 +   .0285     .1093     .2934*
  118   .2941*    .0510     .2656     .3893 +
  119   .3719 +   .1398     .2200     .2683*
  120   .0535     .0767     .2360     .6337*+
  121   .1466     .0617     .3211     .4706*+
  122   .1962*    .1788     .2816     .3434 +
  123   .0228     .0792     .2437     .6543*+
  124   .0087*    .1664     .1945     .6304 +
  125   .1359     .2833*    .1258     .4550 +
  126   .0122     .1145     .2154     .6579*+
  127   .0280     .1515     .1771     .6434*+
  128   .0288     .2238     .1600*    .5874 +
  129   .0246     .1515     .2236     .6003*+
  130   .3570*+   .1272     .2553     .2605
  131   .5865 +   .0517     .1356     .2262*
  132   .4605 +   .0423     .1301     .3671*
PREDICTED PROBABILITIES (* marks actual, + marks prediction.)
Indiv    CAR       MTR       VAN       BRT
  133   .0620     .1462     .1709     .6209*+
  134   .0636     .2158     .1543     .5664*+
  135   .0546     .1468     .2167*    .5819 +
  136   .0908     .0657     .3421*    .5014 +
  137   .1242     .1949     .3068     .3741*+
  138   .0134     .0800     .2460     .6606*+
```

3. Finalized RP-Model

```
nlog; lhs=mode; choices=CAR,MTR,VAN
;model: U(CAR)=CAR*INCCAR+IVT*IVT+COST*COST+CONG*CONG/
U(MTR)=IVT*IVT+COST*COST/
U(VAN)=VAN*AVAN+IVT*IVT+COST*COST+OVT*OVT$
+---------------------------------------------+
| Discrete choice and multinomial logit models|
+---------------------------------------------+
Normal exit from iterations. Exit status=0.
+---------------------------------------------+
| Discrete choice (multinomial logit) model   |
| Maximum Likelihood Estimates                |
| Model estimated: Jul 16, 2014 at 10:19:08AM.|
| Dependent variable               Choice     |
| Weighting variable                 None     |
| Number of observations              402     |
| Iterations completed                  6     |
| Log likelihood function       -321.8926     |
| Number of parameters                  5     |
| Info. Criterion: AIC =          1.71399     |
|   Finite Sample: AIC =          1.71452     |
| Info. Criterion: BIC =          1.77364     |
| Info. Criterion:HQIC =          1.73761     |
| R2=1-LogL/LogL*  Log-L fncn  R-sqrd  RsqAdj |
| Constants only    -398.4343  .19210  .14401 |
| Response data are given as ind. choice.     |
| Number of obs.=   402, skipped   0 bad obs. |
+---------------------------------------------+

+---------------------------------------------+
| Notes No coefficients=>P(i,j)=1/J(i).      |
|       Constants only =>P(i,j) uses ASCs    |
|         only. N(j)/N if fixed choice set.   |
|         N(j) = total sample frequency for j |
|         N    = total sample frequency.      |
|       These 2 models are simple MNL models. |
|       R-sqrd = 1 - LogL(model)/logL(other)  |
|       RsqAdj=1-[nJ/(nJ-nparm)]*(1-R-sqrd)   |
|         nJ   = sum over i, choice set sizes |
+---------------------------------------------+
+--------+--------------+----------------+--------+--------+
|Variable| Coefficient  | Standard Error |b/St.Er.|P[|Z|>z]|
+--------+--------------+----------------+--------+--------+
 CAR     |     .05098695       .00577412     8.830   .0000
 IVT     |    -.02146710       .01037680    -2.069   .0386
 COST    |    -.00800524       .00261054    -3.067   .0022
 CONG    |    -.04975316       .05980746    -0.831   .4058
 VAN     |    1.53358466       .44345642     3.458   .0005
 OVT     |    -.03876072       .02762788    -1.403   .1606
```