Modeling the Influence of Traffic Information on Drivers' Route Choice Behavior

by

Amalia Polydoropoulou

Civil Engineer
National Technical University of Athens, Greece
(1990)

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Author ....
Department of Civil and Environmental Engineering
January 15, 1993

Certified by ....
Moshe Ben-Akiva
Professor of Civil and Environmental Engineering, Thesis Supervisor

Accepted by ....
Ole Madsen
Chairman, Departmental Committee on Graduate Students

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Abstract

This thesis presents the general framework of commuters' route choice behavior in an information-rich environment. A modeling framework for the acquisition and processing of pre-trip information and the drivers' route switching behavior is proposed. Revealed preference data is used for the estimation of the above models. Standard MLE procedures were used for the estimations (Ordered Probit and Logit models). It was found that travel characteristics and perceptions about the relevance and reliability of radio traffic reports are important factors affecting radio traffic information acquisition and its influence on drivers decisions. The key finding was that en-route diversion is primarily influenced by attitudinal factors and by information acquisition. Moreover, drivers' own observation is also a very important factor affecting route switching. It can be concluded that a reliable and frequently updated traffic information system will stimulate the acquisition of traffic information and affect route diversion.

Thesis Supervisor: Dr. Moshe Ben-Akiva
Title: Professor of Civil and Environmental Engineering

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Contents

List of Figures

List of Tables

Chapter 1

Introduction

1.1 Motivation

Traffic congestion is a daily phenomenon in most metropolitan areas. Congestion occurs especially during the morning and evening commute peak periods. The effects of congestion, such as excessive delay, instability of travel time, increased fuel consumption and incidents, can be translated into significant economic and social costs. Therefore, it is very important to minimize congestion in order to achieve safe, efficient and effective transportation systems for a better functioning of the society and the economy.

Congestion can be viewed as the outcome of the interaction between travel demand and capacity supply. When demand for road capacity, becomes larger than supply, congestion emerges. Therefore, congestion can be relieved either by increasing the capacity of the system or by reducing travel demand.

Capacity can be increased in three ways (OECD, 1987):

1. In the long run by changing the structure of the transportation system (new systems).

2. In the medium run by expanding the infrastructure (new constructions), and

3. In the short run by improving the operational efficiency of the existing traffic system (transportation system management).

On the other hand, demand can be reduced with the following strategies:

1. In the long run by changing the spatial distribution of demand (land use).

2. In the medium run by changing the demand volume (control of private car use and ownership and/or substitution of travel by telematics and/or other means of communication).

3. In the short run by spreading the demand peaks over time, space and mode (transportation system management).

However, the long run strategies can not offer the necessary immediate solution to the congestion problem that the society needs. Moreover, the expansion of the road network and high social, economic and environmental impacts and is not feasible in most urban cities with high road density.

Alternatively, the control of the demand volume generally meets with strong social and political opposition.

Therefore, transportation system management (TSM) is the most attractive option to address the traffic congestion problems.

Figure 1.1, illustrates the impact of the traffic management strategies (TMS) on the network demand and supply. TMS can be classified under two main categories; driver information services and direct traffic control systems (OECD, 1987).

1. Driver information services may include:

   a) Pre-trip information services, such as:

      - Media (radio, television);
      - Telephone pre-trip information services;
      - Route planning information services.

   b) En-route information services, such as:

      - Traffic information broadcasting services;
      - Telephone en-route information services;

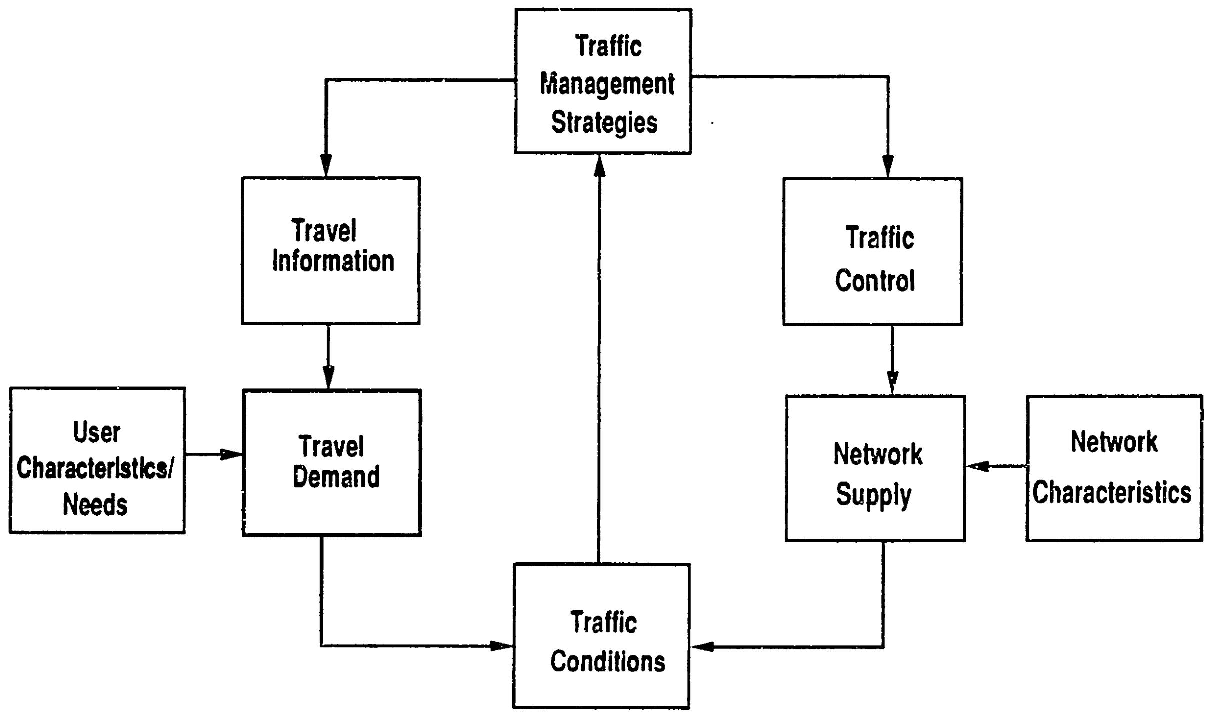

Figure 1-1: Traffic Management Strategies

- Variable message signs;
- In-vehicle route guidance systems.

2. Direct Traffic Control Systems, can be categorized as follows:

- Signal priority systems;
- Ramp metering systems;

The information provided to the users, together with their characteristics and needs, will affect their travel decisions. The direct control strategies, together with the network characteristics, will affect the network supply. The result of the interaction between the demand and supply is the actual traffic conditions of the network.

Increasing attention has been paid in recent years to the use of Advanced Traveller Information Systems (ATIS) for alleviating traffic congestion. ATIS is the application of advanced information systems and communications technology to a variety of components of our transportation systems. By collecting and transmitting information on traffic conditions and transit schedules, the system might improve the operational efficiency of the existing traffic system and spread the peak demand.

However, questions concerning the acquisition of traffic information, such as by whom, where and how traffic information will be used have been raised. These questions need to be answered for the efficient implementation of traffic information services.

The following section briefly analyses the impact of information technologies on people's travel decisions.

1.2 The Influence of Traffic Information on Travelers Decisions

One of the basic hypothesis underlying ATIS, is that better information can improve travel conditions and transport efficiency. This automatically implies that travelers decisions are not perfect, and in fact, are inferior than the ones made providing more and better information. This is true as choices are often made by habit, or on ignorance, or based on out-of-date information.

Travel information can be provided by two ways: by advertising and by using systems of Road Transport Informatics (RTI). Advertising aims at influencing the general disposition of the traveler towards modes or destinations. This is done by increasing the awareness of that opportunity or by changing its image or price. On the contrary, information provided by RTI systems aims at influencing particular decisions of the travelers.

Figure 1.2 shows the influence of the information on travelers pre-trip and enroute decisions. This influence is analyzed below.

Influence of Information on Pre-Trip Decisions

At the beginning of each trip, the traveler is faced with the decision to travel or not, choose his destination, departure time, mode to take and route to follow. Travellers' decisions will be influenced by two types of information: experience-based information and real-time information. Experience-based information is the information acquired by actual traveling and/or information gathered from the experiences of other commuters. However, the experience based data is inherently limited, imperfect and can not foreseen incident induced congestion.

On the contrary, real-time information provides reports on actual existing traffic congestion and gives the driver the ability to predict route travel times to his destination with accuracy.

Telecommunication options, such as telecommuting, teleshoping, telebanking and teleconsulting, give the travelers the opportunity to alter or postpone their trips. Dynamic traffic information, public transport information and parking information give them the ability to optimize their departure time and destination choice and therefore arrive earlier to their destination, or at least avoid unpleasant traffic conditions. the changing of destination is an easy adjustment for purpose like shopping and leisure activities.

The provision of travel time information both for transit and auto might influence the mode choice of the travelers (note that drivers always tend to underestimate travel time for auto and overestimate the ones for transit) and allow them to improve their choices. The provision of reliable time-tabled services, which increase the certainty of arrival time and save drivers from the "frustration" of driving during the peak hours, may cause a shift to the use of public transportation.

Finally, real-time information about traffic delays is likely to lead to route switching behavior. However a distinction should be made between pre-trip and enroute switching behavior. In the first case we are referring to the use of an alternative route while in the latter to a diversion from the existing route. In the second case the aim of the alternative route is not always to save time or distance but sometimes to "keep moving".

Influence of Information on En-route Decisions

Given that the driver have access to dynamic en-route information, he will be able to decide to acquire and process en-route information and therefore revise his pre-selected route by switching to another alternative, destination choice, and travel mode (see Figure 1.2).

For the next trip, the decisions to acquire pre-trip and en-route information, to process and review their choices, will be based on the utility derived from the previous travel choices and the utility expected from his new travel choices.

1.3 Objectives

The focus of this work is the investigation of the influence of traffic information on drivers' route choice behavior. The underlying hypothesis is that information acquisition, route choice and route switching are influenced by the following factors:

1. *Drivers socioeconomic characteristics* such as age, gender, income, education, working rules, as well as personality factors such as attitudes, preferences and perceptions.

2. *Travel characteristics* such as availability of alternative routes, traffic conditions on regular and alternative routes, as indicated by the provided information or observed by the commuters.

3. *Information characteristics*, such as accessibility, reliability and relevance of information provided.

The above factors are the basic inputs for the dynamic route choice behavior. However, the choice process is not a direct derivative of these exogenous variables. Bovy and Stern (1990) present the route choice process as a black box. This black box, is seen as a system of perception and evaluation filters, which the individual uses to make his final choices.

The objective of this thesis is to investigate the underlying mechanism of the route choice behavior under the impact of real- time traffic information. A modelling approach of pre-trip and en-route decisions is presented. The proposed framework is then tested by using revealed preference data.

1.4 Thesis Outline

The thesis is made of 6 chapters. Chapter 2 provides a literature review of the most recent research on route choice and route switching behavior and discusses major findings. Chapter 3 presents the general framework of route choice behavior under the influence of traffic information. The basic concepts underlying the dynamic driver behavior mechanism, such as perceptions, attitudes and learning are analyzed. It also presents the modeling framework for the pre-trip traffic information acquisition, its influence on route choice behavior and the en-route switching decisions of the drivers. Chapter 4 presents the data collection method and analysis of the survey results. Chapter 5 presents the estimation results of different modeling approaches used to model the acquisition of pre-trip information, the influence of pre-trip information and the route switching behavior of the drivers. Chapter 6 provides some concluding remarks and suggestions for further research.

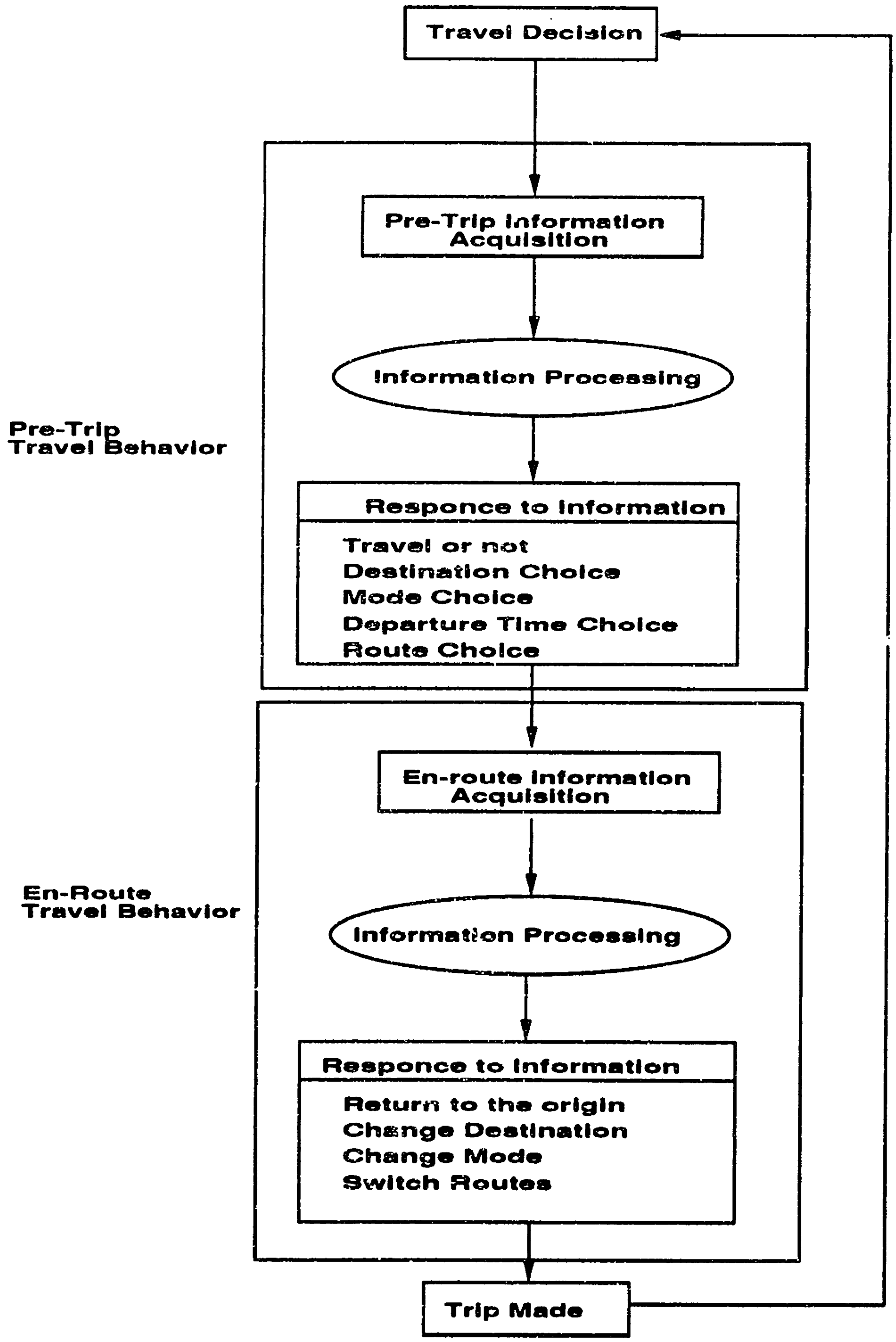

Figure 1-2: The Impact of Traffic Information on Travelers' Decisions

Chapter 2

Route Choice: A Literature Review

In this chapter a literature review of the route choice data collection approaches and analysis is provided. A discussion about the advantages and disadvantages of each type of approach is then presented.

2.1 Route Choice Behavior

An extensive review of the route choice state-of-the-art, is provided by Bovy and Stern (1990) and Kaysi (1992). Bovy and Stern, presented the behavioral theory that underlies route choice as a dynamic and multi-stage process. The various elements of route choice behavior, such as cognition, perception and evaluation of alternatives and their attributes were highlighted. Route choice was perceived to be influenced by two factors: the *traveler*, with his subjective needs, experiences, preferences and perceptions; and the *transport network*, with its objective opportunities and its characteristics. Therefore, the travellers' decision making problem consists of investigating his opportunities and of making a choice based on the available information. Bovy and Stern also provided a comprehensive review of various methods to observe route choice behavior, as well as modelling approaches to analyze and predict it. They finally concluded that the development of telematics would ease the operationalization of optimal routing.

Kaysi (1992) presented an overview of existing driver information systems and their most important characteristics, as well as a description of current demonstration projects. He also formulated a framework for dynamic driver behavior that describes the process of acquisition and processing of various types of information and adjustments to travel behavior. He also designed a data collection program which provides the data required by the models introduced in the framework.

The estimation of the models described in the literature review, requires data on drivers route choice behavior. Revealed preference data and stated preference data are the two basic approaches of data collection for modeling the dynamic interaction between the users decisions and the systems' performance in congested networks. Revealed preferences indicate how drivers behave in actual situations. On the contrary, stated preferences indicate how drivers say they will behave in hypothetical scenarios.

2.2 Revealed Preference Approach

The revealed preference approach analyses drivers' behavior in real-life situations on the basis of respondents reports about previous actions; usually it is based on detailed diaries of actual commuting trips or on field studies for demonstration projects that use navigation systems.

2.2.1 Diary approach

Cascetta *et al* (1992) estimated logit models for departure time and path choice for home to work trips, based on a revealed preferences survey carried out in the city of Turin. The survey was done on a sample of workers in a single industrial plant. Their experimental analysis consisted of two stages. In a first stage, the route choice model was specified and calibrated to define generalized route cost functions. In the second stage, the departure time and route choice models were specified and calibrated for different classes of employment qualification.

The analysis yielded the following results: travel time spent on secondary roads played an important role in route choice. Therefore travel times spent on primary and secondary roads should be used separately. Safety and comfort variables were found to be significant. Finally, early/late arrival penalties were perceived differently by the subjects.

Khattak *et al* (1991) investigated the short-term commuter diversion response to incident-induced congestion and evaluated the ways in which drivers use real time information (the target population was automobile drivers who made repeated trips during which broadcast traffic information was available). Work trip drivers destined to Chicago central business district area were intercepted at downtown parking garages during the AM rush hours. Mail-back questionnaires were distributed in April 1990 and a total of 660 questionnaires were received (a response rate of 33%). His sample (in which the presence of self-selection bias should not be neglected) consisted of a stable, upper-income, well-educated and well-established group of drivers.

The survey indicated that 42% of the respondents had diverted to an alternate route in response to en-route delays. Moreover, 76% of those who diverted thought they gained some time, while 50% of those who did not divert thought that they would have gained some time by diverting but they did not do so. The cause of the above result might be that delay is conceived incremental and by the time that the driver realizes the delay, diversion is no longer possible. Personality factors were identified using factor analysis (e.g. the "Adventure and Discovery" factor showing the respondents propensity towards risk and exploration).

Multinomial logit models were used to estimate the diversion choice of the drivers. The effects of the following variables were explored: characteristics of the delay experience, attributes of the usual and alternative route, trip characteristics and socioeconomic attributes.

The results showed that there exists a preference for staying on the usual route and that drivers were more likely to divert having received delay information from radio than self-observation. Moreover, a Stated Preference Index which indicates the drivers' inherent tendency to divert and an "Adventure and Discovery" Index were found significant.

Mahmassani *et al* (1989) conducted a survey by mailing questionnaires to 3000 households randomly selected in Austin, Texas. A total of 638 completed surveys gave the following results: a.m. route switching appears to be motivated by network considerations rather than by sociodemographic characteristics (other than age) or rules at workplace. On the other hand, a.m. departure time switching is more influenced by factors such as lateness tolerance at the workplace, job position, and other individual characteristics. For the p.m. commute congestion is the main motivation for both route and departure time switching. The use of information, captured by radio traffic reports indicator, exerted a significant positive effect on the propensity for switching in all cases with the exception of p.m. departure time switching.

Hatcher and Mahmassani (1992) addressed the day-to-day variation of individual trip scheduling and route decisions for the evening commute. Their study was based on two-week diaries of actual commuting trips of a sample of auto commuters in Austin, Texas. Two ways of capturing departure time switching were discussed: 1) switching from commuter's median departure time (median switching), and 2) switching from a user's previous day's departure time (day- to-day switching). Median switching was indented to capture deviations from a usual daily routine. By the day-to-day definition, the current day was considered a switch from the previous day if the absolute difference between their respective departure times exceeded some minimum threshold. Two different definitions of route switch were also explored. 1) Route switch as a deviation from the "normal" (most frequently used) network route in which the commuter follows a "different than usual" set of nodes to arrive at work. 2) Day-to-day route switch as a route which is different from the previous day's route.

Poisson regression methodology was used to investigate the effect of the characteristics of the commuter and of the commuting environment on the observed departure time, route, and joint switching behavior. Some significant results were the following:

1. trip chaining significantly influenced route and joint switching behavior: trips with stops were much more likely to involve switching than trips without stops.

2. Commuters tend to change departure times more frequently than routes, pos-

sibly a reflection of a limited route choice set in comparison with a broader set of available departure times.

3. *Socioeconomic variables appeared insignificant.* As the authors argued: "some of these characteristics may be indirectly reflected through their effect on trip chaining patterns as well as commuter preference indicators". The factors affecting the route switching behavior in the evening commute were similar to the results acquired by using the same data set by Mahmassani *et al* (1991) for the home to work commute. About 25% of all reported commutes contained at least one non-work stop, underscoring the importance of trip-linking in commuting behavior. Furthermore trip chaining significantly impacted switching behavior. Trips with stops were much more likely to involve switching than trips without stops.

2.2.2 Field Study Approach

The field study approach, analyses drivers' behavior through field observation of drivers. for example observation of actual diversion behavior in response to information acquisition.

Apostolopoulou *al* (1990) and Polydoropoulou (1990) described a pilot route choice experiment on route choice conducted using an in-vehicle route-guidance system. The major objective of the experiment was to examine the dynamic aspects of route choice behavior, and the influence of electronic route guidance systems on the commuters' route choice decision making. Twenty subjects were involved in the experiment, that consisted of two parts. An out-of vehicle part where the personal characteristics and attitudes and preferences of each driver were asked; and an in-vehicle part which consisted of 3 trips that each driver had to make under the guidance of the route guidance system. Some main findings are:

1. The habitual route choice for the home to work trip is determined after the driver tried all the available alternative routes and decided to follow the one that best satisfied his route choice criteria. Thus habit, was the main route

choice criterion for the home to work trip.

2. The phenomenon of drivers choosing their route according to the traffic conditions they observed (also known as "myopic view") was frequent, especially in the cases that drivers were very familiar with the area and they used to divert frequently. Moreover, choice of route was often done according to the observed status of traffic control signals at intersections.

3. The expectation that *decision points* exist apriori was confirmed by the experiment. For each route the number of decision points was not the same for each driver as the habits and the perceptions of time and distances of each link differ.

4. Drivers can be separated into three major categories according to their attitudes towards route guidance systems: drivers who apriori decide to follow the route guidance advise; drivers who ignore the system instructions and drivers who are deciding at each decision point. In the last case, drivers followed the route guidance advise, only when it coincided with their judgement or their previous experience. However the more unfamiliar the drivers were with the network the more likely they were to follow the instructions given to them.

2.3 Stated Preferences Approach

There exist two different approaches of extracting stated preference data: by surveys and by simulation experiments.

2.3.1 Survey Type Approach

Polak *et al* (1992) studied the impact of in-home pre-trip traffic information. The study was carried out using a microcomputer based simulation. An in-home pre-trip information system, offered information on travel times from home to City Center, by bus and car at different times of day. The respondents had also the ability to generate their own choice set of alternatives through the process of information acquisition.

Surveys were undertaken in parallel, in Birmingham and Athens, allowing a comparison between the cities. The results showed that even amongst regular car users, there is a requirement for multi- modal pre-trip information. Moreover, the quantity and the type of pre-trip traffic information requested by travelers depends on a range of personal, journey related contextual and national factors. Finally, two important findings are that travelers are selective in the amount and type of information they request, and that the process of information acquisition is structured according to the travel preferences. Furthermore, as Apostopoulou *et al.* (1990) note, travelers in both Athens and Birmingham, would change their habits under the influence of information in order to avoid traffic congestion.

Khattak *et al* (1992) used stated preference data to evaluate the effects of real-time traffic information, along with driver attributes, roadway characteristics and situational factors on drivers' willingness to divert. The empirical aspects of the study focused on a survey of downtown Chicago automobile commuters. A five-point scale ranking from"definitely take usual route" to "definitely take alternate route" was used to access diversion propensity. Ordered probit models were used to model users diversion decisions. Drivers expressed a higher willingness to divert as expected delays on their usual route increased. Further, they were more willing to divert when the congestion was incident-induced, as opposed to recurring. Information for delay was received from radio traffic reports and compared with observed congestion. Trip direction was home-to-work rather than work-to-home. Respondents were less willing to divert if the alternate route was unfamiliar, unsafe or had several traffic stops. Drivers who normally experienced longer travel times were more likely to divert. Socioeconomic characteristics were also significant in predicting willingness to divert.

2.3.2 Simulation Approach

Most of the simulation studies examine the existing relationship between objective and subjective travel time, and propose various models to reflect the corrective mechanism of the travel time prediction, due to the learning acquired by repeated trips.

The perception of travel time is a topic that has been extensively studied not only by psychologists (see McGrath and Kelly, 1886, for a comprehensive synthesis), but also by transportation analysts (e.g. Horowitz, 1984) as well as geographers (e.g. Burnerr, 1978). According to the existing literature, the relationship between the objective time and the estimated duration is monotonically increasing. However, the psychological literature has vacillated between a linear function and an exponential function. For the latter function has much appeal, because, under the name "the Power of Law" (Stevens, 1967), it successfully captures the relationship between actual and perceived stimuli of the most various kinds.

Leiser and Stern (1988) used an urban driving simulator and found an exponent of .74, although the improvement of the exponential function over the linear was negligible (r-linear=.68; r-power=.70). Their data was divided in two different groups, according to overestimation or underestimation of travel time. It was found that the correlation between the objective and subjective travel time is quite high. The "average objective time" was however much smaller in the overestimation group compared to that in the underestimation group. This confirmed Vierordt's (cited in Woodrow, (1951)) early generalization: "short time are underestimated, while long ones are overestimated".

Leiser and Stern (1988) also proposed a general model that includes three different factors that play the role of a mediator between the objective and the subjective time estimation. These factors are: the physical distance, the various en route obstacles (e.g. traffic lights and turns) and the driving speed. The perception of driving speed for each individual is dynamic. Attributes related to the road (e.g. angularity, congestion, landmarks en route, various obstacles), to the traveling conditions (e.g. night, rain, fog, etc.), and to the driver's physical state (e.g. fatigue, alcohol, etc) are the main stimuli that contributes to the perception of travel speed. In en-route situations, the individuals' estimation of speed is based on their previous experiences. It is obvious that the dynamics of the their perceptions is continuously updated due to their daily driving experiences.

Iida *et al* (1988) tried to derive the corrective mechanism of the travel time prediction. The dynamics of the route choice behavior was analyzed by laboratory-like experiments that repeatedly asked participants to respond to hypothetical route choices. They found that if the actual travel time is longer than the predicted one, the next step's predicted travel time is corrected so that it becomes smaller and vice-versa. Linear relationship between the prediction error of travel time and the adjusted magnitude (correction value of the predicted travel time) was tested (correlation coefficient r=0.62). They also tried to construct a model which takes into account the repeated experiences in the past. It was found that the predicted time error in the last step is the most significant one. This coincides with the results of Chang and Mahmassani (1988) , who suggested that the more recent experience has a substantially greater effect on travel time.

An extension of the previous work is present by Iida *et al* (1992) . The following results were acquired: a) route switching behavior varies depending on the characteristics of the route, b) route switching rate increases as the actual time and the predicted travel time error increases and c) the relationship between an error in the predicted time and the adjustment from the actual travel time to the next predicted time is almost linear.

Two other simulation experiments were carried out. The first by Janssen *et al* (1991) using a driving simulator. The second, by Van der Mede and Van Berkum (1991) using a route-choice game on computer. Their work concerns simulation and modeling of individual route choice sequences in situations were RTI (road transport informatics), and particular a VMS (variable message sign) is or is not available. After developing a model which incorporates route choice, inertia and responses to VMS, their aim was to test its accuracy in simulating individual choice series and aggregate behavior obtained by laboratory experiments.

In this study, inertia in choice behavior was defined as an escape from the utility maximizing principle as assumed in random utility theory. Inert choices are based on the fact that the same choice has been made in the past and not on the fact that certain utility is expected from it. However, the last experience cannot be considered the same as the last choice. The latter is only a part of the tendency to become inert.

An increase of inertia means that the last choice increases the probability that the next choice will be the same. To model the impact of the information provided on route choice behavior it is assumed that the perception of reliability of the system depends on a history of experiences. Good experiences increase compliance and bad experience lead to a decrease. To model compliance with VMS, a so-called "buffer" is defined. The size of the buffer reflects the number of bad experiences with the VMS a person can handle before compliance decreases.

Binary choice models of comply or not comply were estimated and the parameter values from the best fitted model and its corresponding knowledge update strategy and initial knowledge values vector were input in the simulation model. The results showed that the model that included only travel time, travel cost, variance in travel time and travel cost, as well as previous choice and VMS, had a satisfying fit on the data.

However, the differences in the laboratory settings for the two experiments causes problems on the comparison of the results. Therefore, the validity of the findings to actual tripmaking in real life is questionable.

Advanced Driving Simulators

Allen *et al* (1991) investigated the drivers use of in-vehicle navigation systems with a part task simulation. The simulation presented subjects with several traffic congestion scenarios in which they attempted to avoid congestion delays using prototype navigation system information. The objective of the experiment was to compare the effect of four navigation systems on driver diversion decisions when faced with traffic congestion. Three of the systems were developed on the basis of a heading-up map display. The systems varied from a basic map with vehicle position to a highly complex map with position, congestion, and route guidance information. The experiment simulated typical freeway trips using sequences of slides of real freeway scenes and auditory feedback controlled by a computer. Drivers were presented information on traffic congestion, vehicle speed and guide signs of off-ramps, and were motivated with monetary rewards and penalties to encourage diversion decisions that would minimize travel delays. The results showed that navigation system characteristics can have a significant effect on driver diversion behavior with better systems allowing more anticipation of traffic congestion. Driver age was also an important factor. Old drivers more reluctant to divert from the main freeway route. Route familiarity, commercial driving experience, and gender were not significant factors in driver diversion decision making.

Bonsall and Parry (1991) developed an interactive route-choice simulator (IGOR - interactive guidance on routes) to investigate drivers' compliance to route guidance advice. In this experiment, each user was invited to make a series of journeys through hypothetical networks from one junction to the next on the way to their destination. Conditions in the network varied from day to day and differed according to the time of the day at which the journey was made. At each junction, IGOR displayed a plan of the junction annotate with information about road sizes and alignments, signposts, current traffic conditions etc. For some journeys the user had access to a map and /or guidance advice. However, "wrong" exits were sometimes recommended in order to see the user responses to unreliable information. Regression curves were fitted to the data having as dependent variable the probability of acceptance the route guidance advice. The independent variables were an index of quality based on actual travel times or an index of quality based on free flow travel times. The results showed that the acceptance of an advice varies with the objective quality of the advice and with the quality of the previous received advice. The influence of the drivers' knowledge of the network and of the existence of corroborating or conflicting evidence is also demonstrated. The acceptance of an advice was depending on its credibility and this was a function of past experience, local conditions and psychological factors.

Lotan (1992) modeled the route choice process and the drivers perceptions in the presence of information by using concepts from fuzzy sets theory, approximate reasoning and fuzzy control. Empirical results were obtained by using a driving simulator developed at MIT. Ten subjects participated in the experiment, and each performed 20 trips under various traffic conditions (congestion levels, incidents, etc.). The data collected included prior perceptions (based on interviews), observed traffic conditions while driving, the available pre-trip and en-route information and the resulted choices made. In the case study presented, the underlying simplicity of the human reasoning concerning route choice was demonstrated. This agreed with the prior expectation that "a man, viewed as a behaving system, is quite simple. The apparent complexity of his behavior over time is largely a reflection of the complexity of the environment in which he finds himself" (Simon, 1969).

2.4 Combining Stated with Revealed Preference Data

Due to the fact that Stated Preferences indicate how drivers behave in hypothetical scenarios, the validity of the SP responses is a critical concern (Morikawa, 1989).

Biases in the SP data can be introduced by the indifference of the respondents to the experimental task and can be categorized as follows: prominence hypothesis, policy-responce bias, preference inertia or justification bias. Moroever, biases can be introduced by the imperfect description of the alternatives and by the omission of situational constraints.

For example, experience by using driving simulators (such as IGOR, see Polak 1992) showed that it is difficult for the subjects to perceive the differences in alternate driving scenarios, such as variable purposes of trips or weather conditions and therefore act accordingly. However, in real life commuters know through driving experience the differences in the signalization of the network in a rainy day. Moreover, the purpose of trip might strongly affect drivers' decisions; for example one might prefer to drive on a pleasant scenery route when the purpose of trip is recreation.

In addition, differences in the laboratory settings might cause significant changes in the results. For example, most of the stated preferences experiments offer to the volunteers certain incentives to participate and make the experiment more attractive. However, we notice that the participants' behavior varies according to these incentives. For example, it has been noticed, that when the experiment offers a winning price for the driver who arrives first at his destination, then people tend to switch more in order to win from their opponents. On the contrary, when there is a penalty delay, people tend to switch less and be more prone to reduce risk and loose less money (see, Van der Mede, 1991). Therefore the set-up of the experiment might change significantly the outcome of the experiment.

However, stated preferences can indicate some aspects of latent preferences and therefore could help in the identification and estimation of the latent preferences that determine actual behavior. For example the use of an advanced driving simulator with a complicated map display could give the opportunity to examine the spatial behavior of the drivers and the actual learning of the network, through the knowledge acquired from experience and information provision.

On the other hand, although revealed preference data represents the actual behavior, it might not contain significant information to identify the underlying preferences. It also contains measurement biases and the attributes of the alternatives can be highly correlated (for example it is very common for the drivers to confuse the shortest in distance and the quickest route). Moreover, survey data have the following drawbacks (see, Ben-Akiva *et al*, 1990):

1. High data collection costs and small budgets lead to small sample sizes and consequently large sampling errors; and
2. Nonsampling errors such as non-response may result biased statistics.

Moreover, RP data can not provide direct information about drivers' behavior on new-non existing alternatives, such as the construction of a new facility, the introduction of control measures on existing major highways or the introduction of dynamic route guidance systems with different levels of reliability, etc.

In order to be able to investigate how people will behave under the provision of traffic information through advanced traveller information systems such as route guidance devices a field experiment would be most appropriate.

However, field experiments that use real route guidance systems have several limitations:

1. An expensive and complicated infrastructure (route guidance devices, road-side

beacons, control center etc.) is needed.

2. Many subjects should participate, with different driving experiences, in order that the sample to appropriate for statistical analysis.

3. There exist time limits since drivers get tired when driving in traffic for a long time in one day. However in order to be able to observe how peoples' behavior change over time these people should be also observed for a period of time (this is almost impossible; except if you observe commuters for their trip to work). Note, that the researchers should allow a period of adjustment with the systems instructions.

4. The behavior of the drivers strongly depends on the specific network characteristics, the traffic problems they face every day and the time of the day the experiment was conducted. Therefore the validity of the findings for all the networks would be questionable.

5. The reaction of the drivers to the systems' instructions depends on the reliability of the system. Different levels of reliability should be provided in order to investigate drivers' decisions.

6. Drivers' behavior depends on the incentives of the experiments. As in the case of the driver simulator, here again the set-up of the experiment determines the validity of the responds.

Therefore, field experiments introduces many difficulties and are very expensive to conduct and get reliable and valuable results. From the above discussion, it is obvious that the alternative data sources have different levels of accuracy and contain various types of biases. The combination of different data sources is appropriate, in order to exploit their relative advantages and obtain more reliable parameter estimates than those of a single data source.

In the case of route choice behavior, the combination of laboratory experiments with selective field validation or the inclusion in weekly (or monthly) diaries of RP questions hold considerable promise for the scientific investigation of such complex dynamic phenomenon as drivers' behavior.

Chapter 3

General Framework for Route Choice Behavior and Model Structure

This chapter presents the general framework for route choice behavior. The nature of attitudes, preferences and perceptions of drivers is also explored, for a better understanding of the dynamic aspects of route choice behavior. Moreover, the potential impacts of both pre-trip and enroute information on drivers' decisions are analyzed. Finally, the structure of the models that capture s the impact of information on commuters' route choice behavior is described.

3.1 Route Choice Behavior For The Commuting Trip

Route choice is the result of a decision making process in which. each individual who makes a trip from an origin to a destination, decides which route to take.

In order to be able to understand and model the route choice behavior for the commuting trips to work, certain factors should be taken into account. As Ueberschaer (1971) stated, commuting trips have the following characteristics:

1. The origin and the destination of the trip are well determined.

2. When driving to their work, drivers move in a direct way, having a certain goal, and choose their routes in such a way so that they can reach their destination as soon as possible.

3. Drivers have an adequate knowledge of the area, and usually know many alternative routes.

4. The traffic conditions (travel time, waiting time), during the morning peak period are usually stable with small deviations, as compared with other times of the day. This holds, as long as no unusual events such as incidents, occur at these non-peak periods.

The key difference between the commuting trip in 1971 and that of today, is the availability of traffic information to the drivers. The provision of real time information is expected to have a significant impact on the behavior of travelers (Ben-Akiva *et al*, 1991). Travelers' responses to the provided information can vary. One might choose not to travel at all, change mode, destination, departure time, route or even choose a combination of these alternatives.

It is therefore very important to understand the underlying mechanism that triggers each traveler to acquire information, and then take it into account in their pre-trip and enroute decisions. The question raised is how the information is perceived, processed, and evaluated in the travelers' mind in order to make his final choices.

The following section introduces some general concepts related to human behavior as they appear in the psychological literature. These concepts provide the basis for modelling human decisions (such as route choice), data requirements and estimation methods.

3.2 Basic Definitions

The knowledge of the psychological basis of behavior is necessary, in order to efficiently support, control and model the decision making of the drivers when planning their trips, choosing modes and routes while driving.

Behavior, signifies the relation and/or movement of a system (in our case the organism, the human body, the person) because of its possibilities of reaction, towards conditions in its environment (Uexkull, 1934). This definition also determines *perception* as behavior, because perception is the sensual activity of the whole organism (Gibson, 1950 , 1973).

Action is a behavior which is reflected by a person in his environment (Lewin 1963 , 1969) and/or which has an aspired objection or intention (Cranach, 1980). Action is behavior with human consciousness. "Action includes behavior plus planning" (Schurian, 1986)

3.2.1 Learning

Learning can be defined as an experiential process resulting in a relatively permanent change in behavior, that can not be explained by temporary states, maturation, or innate response tendencies (Klein, 1991). This definition of learning has three important components:

1. Learning reflects a change in the potential for a behavior, it does not automatically lead to a change in behavior. Individuals must be sufficiently motivated in order to translate learning into behavior. For example, although a person might know that information about traffic conditions is helpful for his route choice, he will not be motivated to receive information until he is going to travel or during his trip. Also, an individual might be unable to exhibit a particular behavior even though he has learned it and is sufficiently motivated to exhibit it. For example, the individual might want to acquire traffic information, but he does not have a radio.

2. Behavior changes caused by learning are not always permanent. As a result of new experiences, previously learned behavior is no longer exhibited. For example, a driver may learn a new and faster route to work and no longer take the old route. Also, there are times in which people forget a previously learned

behavior and they are no longer able to exhibit it.

3. Changes in behavior can be originated from processes other than learning. The behavior can change as a result of motivation rather than learning.

Knowledge

What is called learning is really recollection, and every human soul has a vision of reality and needs, not to have knowledge put to it but to recollect. The states of mind (knowledge and perception) differ in that knowledge is infallible, whereas perception may be true or false. The objects of knowledge must be completely real and unchanging, while the objects of perception are not wholly real and are mutable. While knowledge comes to us from the external world, perception is the outcome of a wide range of meanings, including sensation, awareness of outer objects or of facts, feelings and emotions. For example, each traveler has only limited knowledge of all available routes. The traveler's cognition is associated with his travel experiences (feedback from previously chosen routes) and the way of acquiring information. The perception of the attributes of these alternarive routes, will be the outcome of the interelationship of many factors such as his personal characteristics, the encountered travel characteristics on each alternative and the information characteristics.

3.2.2 Attitudes

Many psychologists think of attitudes as "predispositions" or "tendencies" to engage in a variety of behaviors linked to the attitude, which is seen as a hypothetical construct. A hypothesized attitude towards traffic information acquisition, for example, would affect route switching behavior, choice of radio station, and so on.

To better understand route choice behavior, it is important to measure drivers' attitudes, preferences and perceptions. Attitude measurement is one of the oldest topics in social psychology. Psychologists have been measuring attitudes since the 1920's. Attitudes can be considered to have three aspects (Lewin, 1967):

1. A cognitive or belief component: the content of the attitude.

2. An valuative or feeling component: the "like-dislike" or "good and bad" dimension.

3. A behavior component: the action which expresses the attitude.

As an illustration, let us consider the attitudes of commuters towards information for their home to work trip:

1. The belief: a well informed driver can choose his/her route to work with efficiency.

2. The evaluation of the belief: this is a desirable outcome.

3. Behavior based on the belief: the driver seeks traffic information from the sources available to him (e.g., radio and/or television), to become a well informed driver.

Considerable research has been done on the degree of congruence among the three components of the attitude, and especially the relationship between the action and the first two components. Several times, behavior is inconsistent with the beliefs and evaluations. This inconsistency probably occurs because an action is never influenced only by a given attitude. The action is also a result of other aspects of the situation and of the characteristics of the person. "Not everything we do is consistent with everything we think and feel", a fact that complicates the task of attitude measurement.

The nature of attitude measurement

In order to provide satisfactory measures of the underlying attitudes under consideration, the following factors should be taken into account:

1. Anything can be measured, so long as magnitude (amount, more or less, greater or smaller) or direction (position, close-distant, nearer-further), or both, can be detected.

2. Most measurement of attitudes involves "ordinal" scales which tell the relative order of two or more levels of an attitude, but not the precise distance between them.

3. The reliability and the validity of an attitude measure are two very important factors. Will the attitude measure give consistent results upon repeated use and similar conditions; and, does it measure what we wanted to measure?

Various methods of ordering scale items have been used (See, for example Lewin, 1987). The Likert Scale appeared in 1932 and has been widely used ever since. Although it is called a scale, it is really a response format. Each item consists of a statement followed by five or seven response categories such as:

1. Strongly agree

2. Agree

3. I neither agree nor disagree

4. Disagree

5. Strongly disagree

The use of an odd number of categories permits a neutral middle answer such as "I don't know" or "I don't care one way or another".

Personality Questionnaires

Adorno *et al* (1950) , introduced the "F" scale, a personality-test questionnaire. The format of this questionnaire is the following:

+3 means: I agree strongly

+2 means: I agree moderately

+1 means: I agree somewhat

-1 means: I disagree somewhat

-2 means: I disagree moderately

-3 means: I disagree strongly

The F-scale is remarkable in the history of social and personality psychology for its endurance and popularity, because it "discriminated" in a great number of variables. People that scored high on the "F" scale differed significantly from people low on the F scale, on almost everything psychologists tried to study.

It is very important also to incorporate in the questionnaire the "not applicable" category. If this category is not provided there cannot be a distinction between the people who overlooked the question and the people who did not check the answer for a good reason. In the worse case such people may select to answer another category, thus introducing bias in the results.

The discussion about peoples' behavior and attitudes measurement presented above, describes the basic psychological tools that are needed to model dynamic route choice behavior. This is because, the modeling of dynamic route choice behavior requires the detection of mechanisms and rules of behavioral adaptation. This modelling is done across different user segments and through the evolution of time, so that phenomena such as habits, learning process, inertia[1] and even cohort effects[2], can be accounted for.

3.3 Framework for Route choice behavior

The general framework of route choice behavior is presented in Figure 3-1. The ultimate choice, that is the route taken, is the result of the following factors: 1) the driver characteristics, 2) the travel characteristics and 3) the information characteristics.

The route choice of the travelers depends on their socioeconomic characteristics such as age, genre, income, as well as their personality, habits, preferences, driving experiences and familiarity with the transportation network.

[1] Inertia is an indisposition in changing behavior

[2] A cohort is a group of people with same characteristics in common

Travel characteristics, such as purpose of trip, flexibility in arrival time, availability of alternatives and traffic conditions on alternatives, affect strongly the route choice behavior. The purpose of trips is a very important factor, due to the constraints it imposes. Moreover, each traveler has only limited knowledge of all available routes. The traveler's cognition is associated with his travel experiences (feedback from previously chosen routes) and the way of acquiring information. The characteristics of each known alternative route have not the same importance for his final decisions; they will counter-balance one another and a relevant value will be attributed to them high or low, positive or negative. Therefore, based on a factor-importance hierarchy (Bovy and Stern, 1990) the traveler formulates a choice-set of sufficiently attractive alternatives. From this set the traveller makes his choices; the chosen route will be the one that best satisfies his needs and is consistent with his personal restrictions and preferences.

The attributes of information play an important role on the attitude of travelers towards it. Reliability of information is very important. Discrepancies between the acquired information and the observed traffic conditions, will lead travelers to reject further information acquisition. Moreover, the accuracy and precision of traffic information play a significant role, as provision of misinformation or negligence to provide information about congestion, incidents or other hazardous situations, will result in a negative attitude towards the acquisition of information. Only information submitted in a timely manner, adapted to changing situations and relevant to the travelers trip, will positively affect travelers' decisions and general attitude towards its acquisition.

Figure 3-1, illustrates the decisions making process. The three ovals enclosed in a box in this figure, can be viewed as a system of perception and evaluation filters through which information is processed. The decision making process has a dynamic character due to the feedback from each trip made, acquiring new experiences on each trip. Therefore, a learning process is involved in the cognition and perception of the driver, as the information acquired through experience of earlier choices is processed in the next decision. However, inertia also plays a role: certain thresholds need to be crossed before changing habitual behavior.

3.3.1 The effect of Pre-Trip Information on route-choice behavior

The general framework of how pre-trip information influences route choice behavior is shown in figure 3-2. The rectangular boxes represent observable variables, while the oval ones represent unobservable or latent variables.

Before starting each trip a traveller decides whether or not to acquire information about the traffic conditions. Based on this information drivers adjust their schedule, departure time and route choice accordingly (see also figure 1.2). If drivers decide not to acquire pre-trip information, they will rely on their historical perceptions and experiences and therefore, start their trip following the habitual route.

When information is acquired by drivers, the perceived importance of indicated traffic conditions combined with the drivers' general attitudes and preferences, influence their pre-trip route choice decisions. The content of the acquired information could make drivers decide to follow an alternative route (if indicated conditions on usual route are worse than usual), or even convince them to follow their habitual route (if the indicated traffic conditions are better than usual). On the other hand, drivers might decide not to consider the acquired information on their pre-trip route choice decisions. In this case, the route choice process will not be influenced by pre-trip information: the drivers will rely on their previous experiences and follow their habitual route.

Drivers will use the benefits derived from their decisions, will be used as feedback to update their attitudes and preferences towards pre-trip information acquisition. Therefore, the pre-trip decisions for the following trip will depend on their perceived benefits on previous trips.

3.3.2 The effect of Enroute Traffic Information on Route Choice

After drivers make their pre-trip decisions, their attitudes towards traffic information acquisition will play an important role in their enroute choices. If drivers do not acquire pre-trip traffic information their route choice will be based on their past experiences. On the other hand, if information is acquired their route choice will be modified accordingly.

En-route information acquisition could be acquired either passively (from on-route variable message signs or by listening to the radio), or voluntarily. Voluntary en-route information acquisition is observed in those cases in which that the level of service on the preselected route is not the anticipated one; or when observing traffic conditions at an intersection which is usually congested. Notice that the driver might seek to acquire traffic information for both the actual and the alternative routes.

After traffic information is acquired, drivers process this information according to their personal characteristics, attitudes and preferences, as well as the characteristics of the information provided to them. Drivers might then choose not respond to the information and follow their preselected route, or they might respond by diverting.

The perceived benefits of drivers' actual decision, are going to affect the updating of his perceptions towards the acquisition and response to traffic information as well as his future route choice behavior (see figure 3-3). The general framework of enroute decision making is shown in figure 3-3.

3.4 Modeling Structure

In this section the modeling framework for the analysis of pre-trip information acquisition, the influence of pre-trip information on drivers' decisions and finally the en-route switching behavior is presented.

3.4.1 Modeling the Acquisition of Pre-Trip Information

Figure 3-4, presents the modelling of pre-trip traffic information acquisition and its influence on drivers' route choice. It is assumed that the acquisition of pre-trip traffic information depends on exogenous variables such as drivers' characteristics, travel and information characteristics, as well as on personality characteristics such as attitudes and preferences of the drivers. The acquired pre-trip information, is then processed and may influence drivers' route choice.

Binary choice models may be used to model the decision to acquire pre-trip traffic information. For these models the dependent variable is the acquisition of pre-trip traffic information; therefore, the choice is *acquired* if the driver acquired pre-trip traffic information or *not acquired* if he did not. The independent variables consists of two groups of variables: the first group includes the exogenous variables and the second group of variables includes attitudes and preferences of the drivers.

3.4.2 Modeling the Influence of Pre-Trip Information on Drivers' Behavior

As it is shown in figure 3-4 pre-trip traffic information acquisition might influence route choice decisions. A binary choice model is proposed to model drivers who acquired pre-trip traffic information and were influenced by this information. The dependent variable is the influence of pre-trip traffic information, therefore the choice is *influenced* if the driver was influenced by the traffic information and *not influenced* otherwise.

In all models the choice is assumed to be influenced by three principal categories of factors. The first category consists of exogenous variables which represent travel characteristics such as usual commuting time and familiarity of commuters with alternative routes. The second category includes variables reflecting the attitudes and preferences towards information acquisition, habit and diversion decisions related to information acquisition. Finally, the third category comprises variables related to the content of the pre-trip traffic information.

3.4.3 Modeling Drivers' Switching Behavior

To model the drivers' switching decisions the dependent variable is the decision to switch to an alternative route; therefore, the choice is *switch* for drivers who switched and *not switched* otherwise. The independent variables can be categorized in four groups. The first group consists of variables showing the perceived importance of certain factors when choosing the route to work. This factors are habit, time of the day, risk of delay and traffic reports. The second group includes variables which express the attitudes of the drivers towards switching decisions, such as *I like discovering new routes while driving* and *I often change my preselected route.* These variables show the propensity of the drivers to switch. The third group comprises variables related to the acquisition of pre-trip and enroute information; and the fourth includes a variable related to the actual traffic conditions encountered in the preselected route.

Different ways of representing attitudinal variables lead to three model formulations.

The first modeling approach consists of two stages (see figure 3.4.3). In the first stage, it is assumed that the attitudes and preferences of the drivers are the result of exogenous variables such as the socioeconomic characteristics of the drivers, the information characteristics and the trip characteristics. To model the above notion, ordered response models can be estimated, in which the dependent variables are the 5-point scale variables reflecting the attitudes and preferences of the drivers and the independent variables are the exogenous variables described above.

In the second stage, the switching behavior of the drivers is modeled using binary choice models as before. However, these models incorporated the fitted values of the dependent variables obtained from the ordered response models (first stage of modelling), as the group of independent variables reflecting the attitudes and preferences. In that way, any notion of circularity appearing in the model, is avoided. Circularity occurs when an independent variable is caused by the dependent variable. Since revealed preference data is used for the estimations, the inclusion of the reported attitudes as independent variables in the choice models, could render circularity implications.

The second and third models used as independent variables, the reported values of the drivers' attitudes and preferences (see, figure 3-5). As mentioned in section 3.2.2, a five-point scaling ranking from *Strongly disagree* to *Strongly agree* or from *Not important at all* to *Very Important*, was used to indicate the level of agreement or the level of importance of a number of statements which reflect the perceptions, attitudes and preferences of the drivers. In the second model the 5-point scale is used directly. However, the direct incorporation of ordinal categorical variables in the model does not make sense intuitively (the estimation was done for comparison reasons). Therefore, in the third model, from each categorical variable expressing a certain attitude or preference, two dummy variables are constructed, one indicating the *not important* or *strongly disagree* answer and one, the *important* or *strongly agree* answer. The middle category is used as a base for comparison.

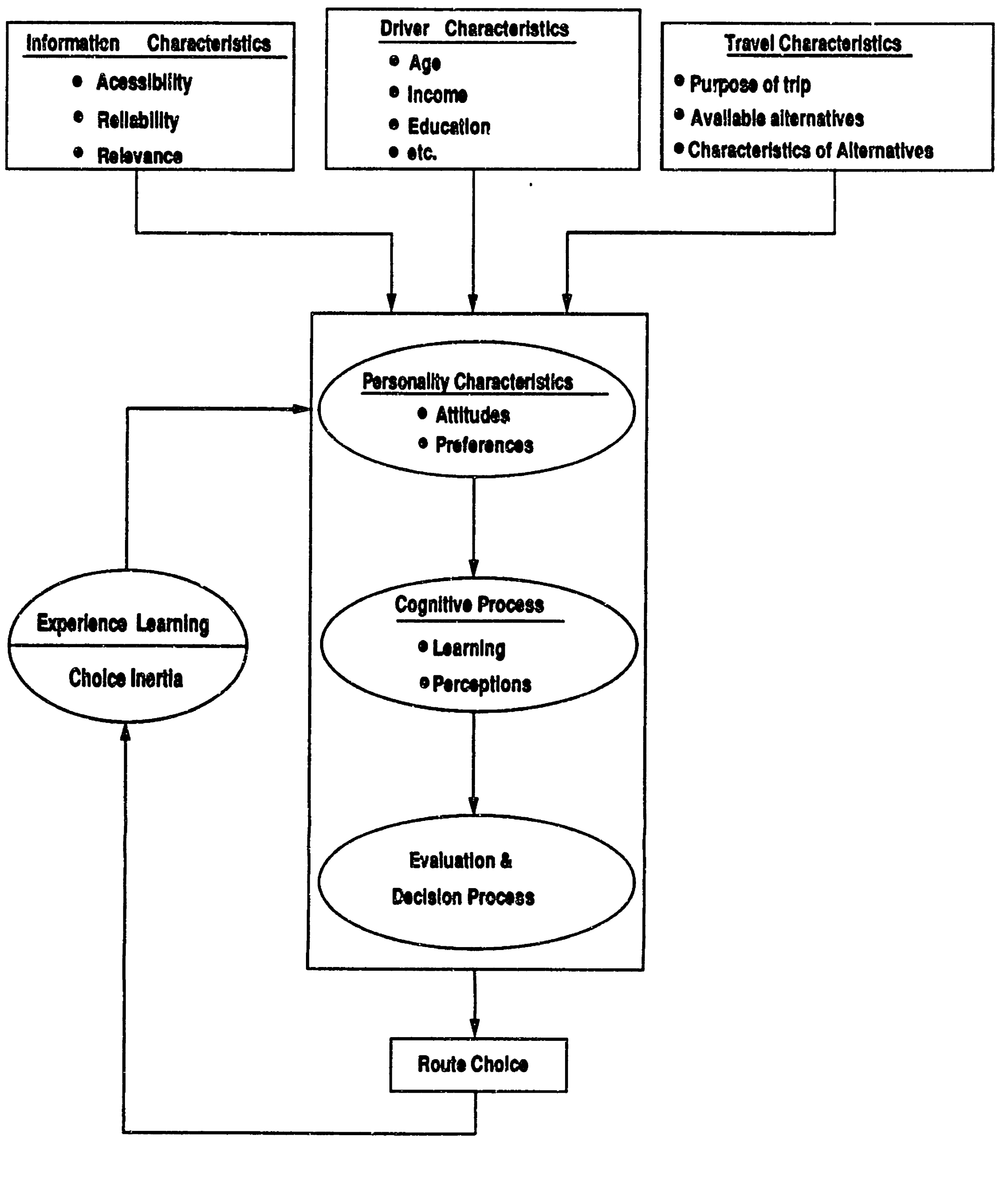

Figure 3-1: Framework for Route Choice Behavior

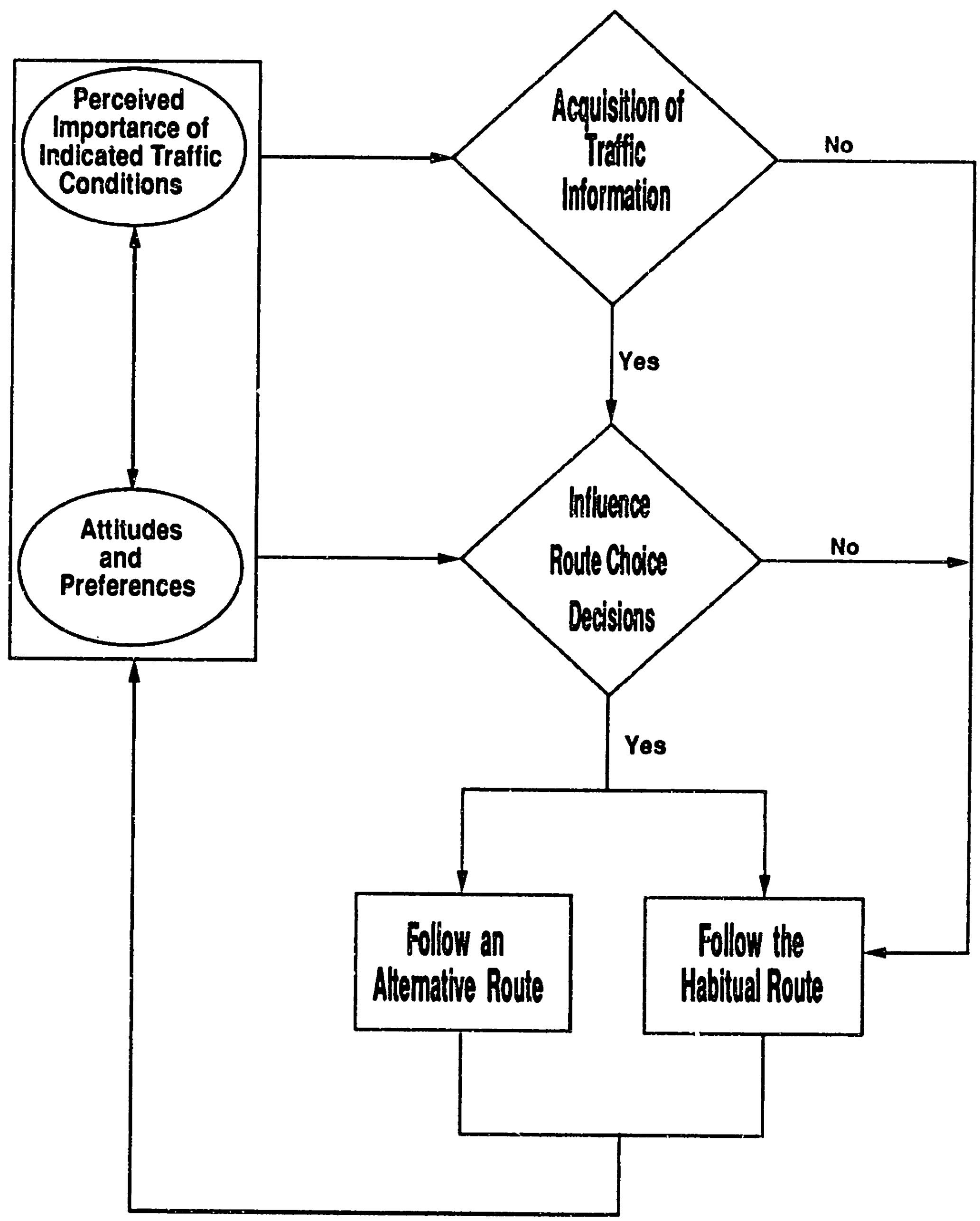

Figure 3-2: Pre-trip Choice Decisions

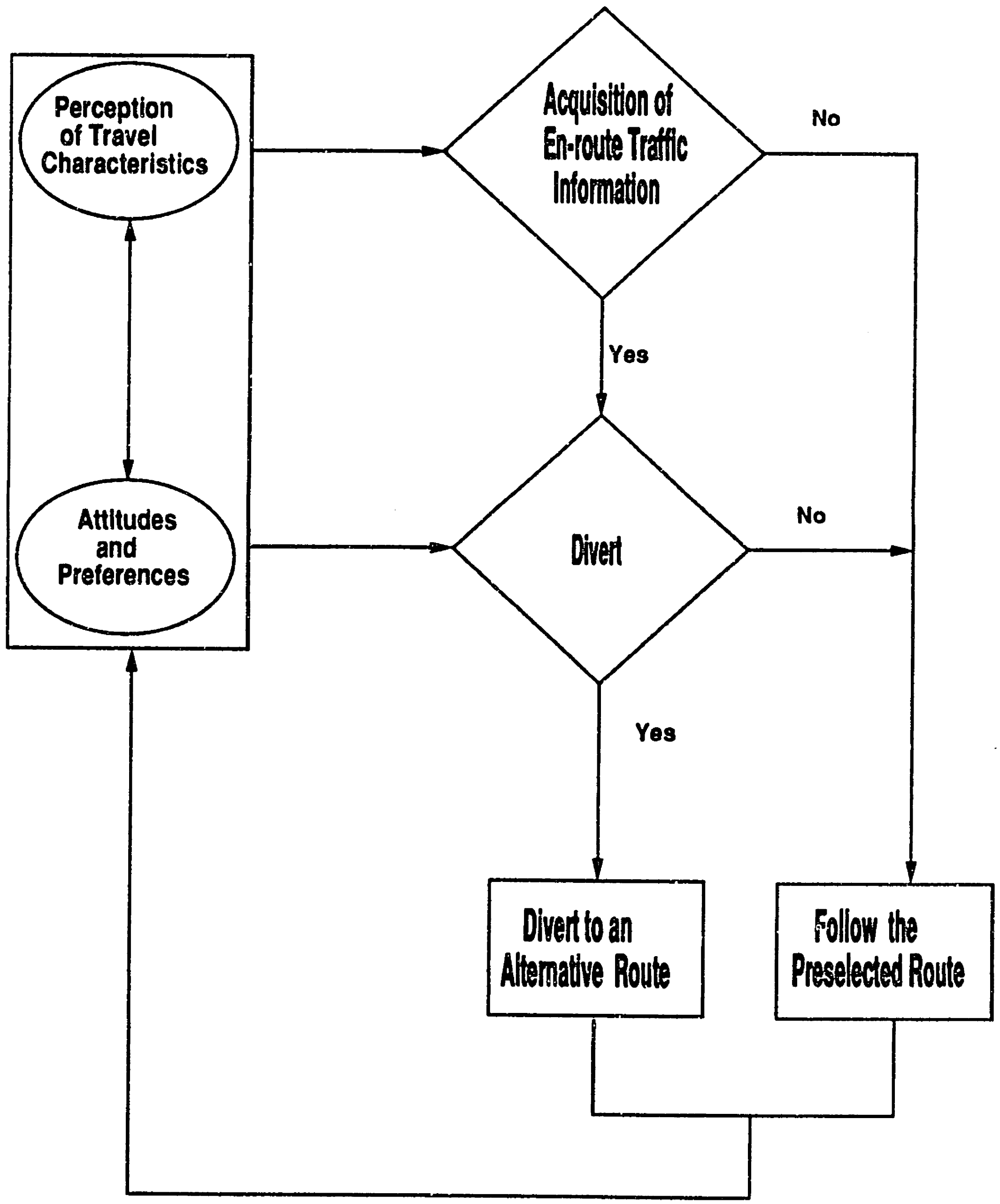

Figure 3-3: En-route Choice Decisions

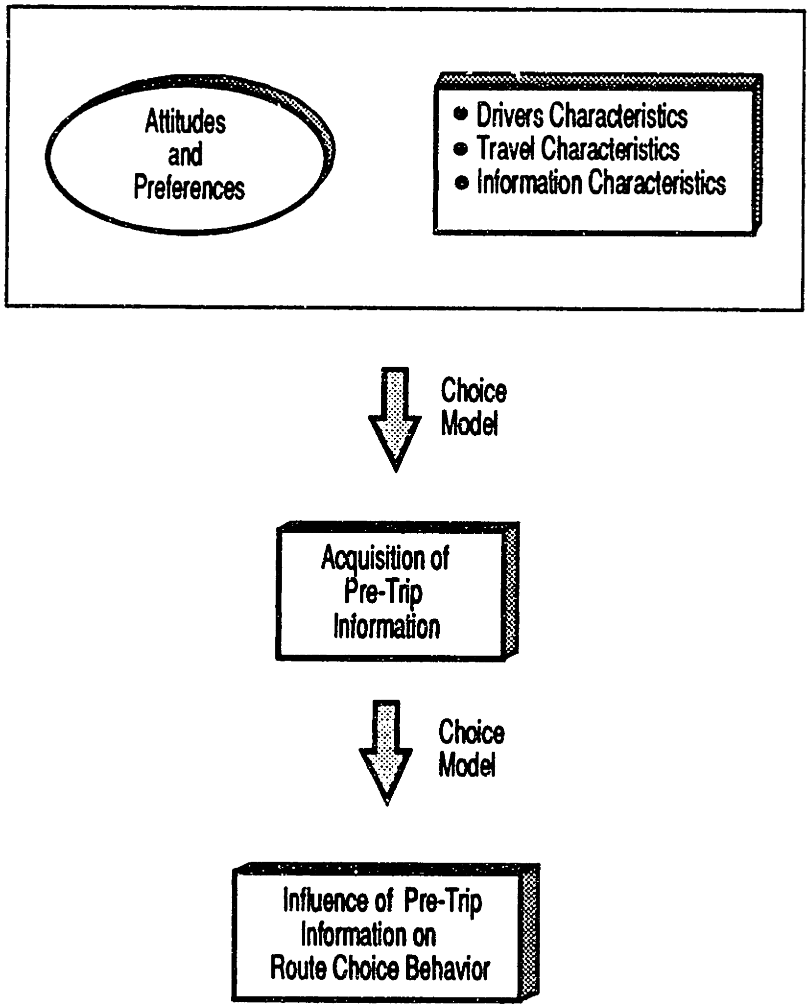

Figure 3-4: Modeling the Acquisition and Influence of Pre-Trip Information

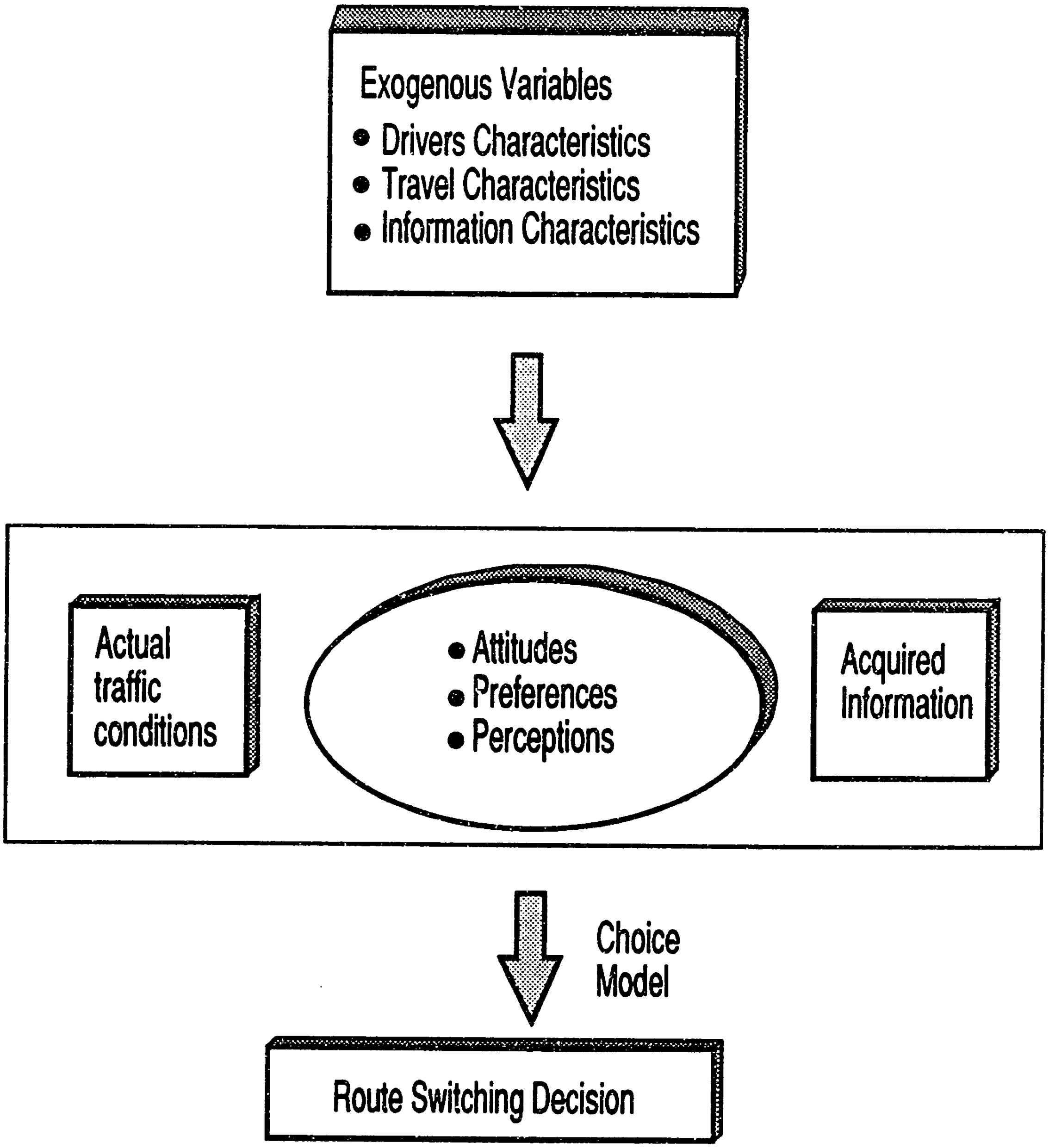

Figure 3-5: Modeling Switching Behavior with Reported Values

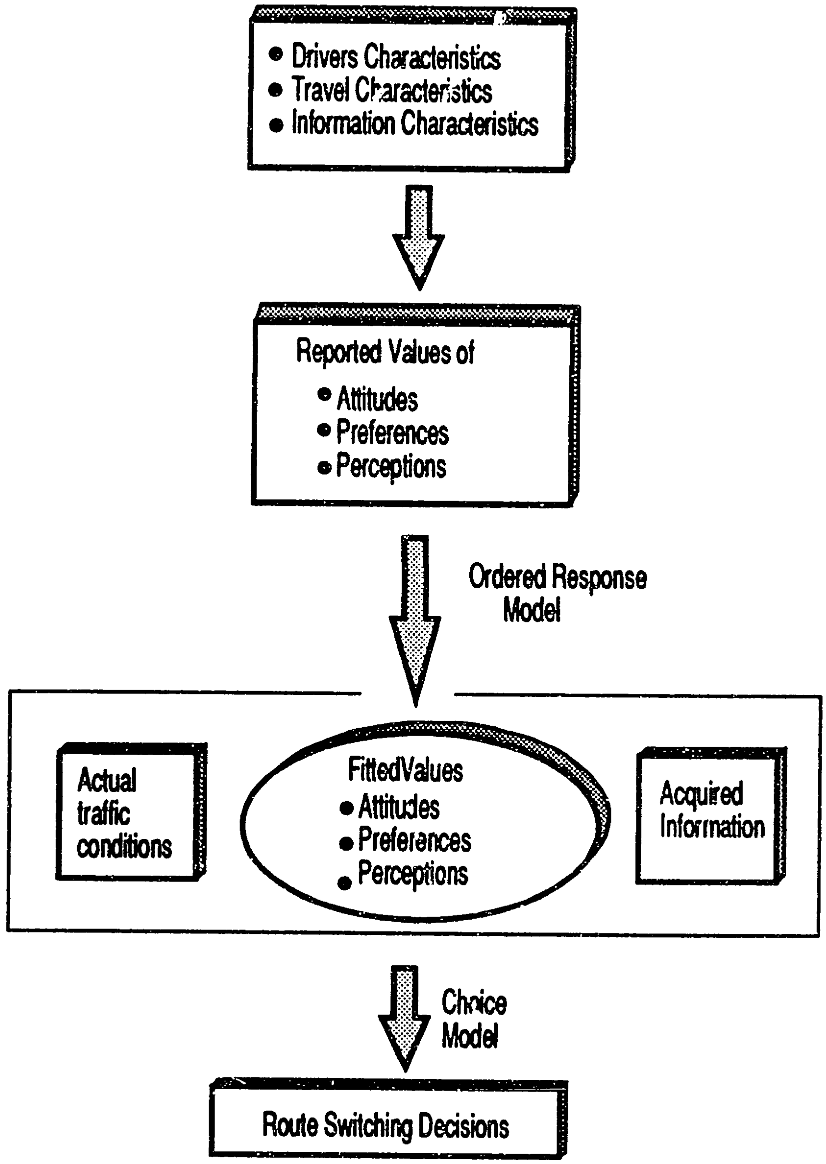

Figure 3-6: Modeling Switching Behavior with Fitted Values

Chapter 4

Data Collection and Analysis

The estimation of the models described in the previous chapter requires data on drivers' route choice behavior. In this chapter the data collection method - a survey of commuters - is presented. The main survey results are also reported.

4.1 Data collection

As described in Chapter 2, two kinds of preference data may be used to model route choice behavior: revealed preference data (RP) and stated preference data (SP). In this study we rely on RP data.

A survey was conducted during the Spring of 1991, to collect data from MIT commuters. (see also, Kaysi 1992 ; and Lotan 1992). The survey consisted of two parts[1].

The first part contained three groups of questions: the first group contained queries about the usual commuting trip to MIT, the second group about the drivers' socioeconomic characteristics and the third group about the drivers' attitudes and preferences. The questions about the commuting trip were related to the usual departure and arrival time, flexibility in the arrival time, traffic conditions encountered, number of alternative routes used, duration and purpose of stops made were asked. The second group of questions, related to the socioeconomic characteristics, asked the drivers'

[1]Appendix C contains the survey questionnaire

sex, marital status, education, income, profession, time lived in the same dwelling unit, as well as, time worked in the same job.

The third group of questions was related to the attitudes and preferences of the drivers. A five-point Likert-scale ranking from *Strongly disagree* to *Strongly agree*, was used to indicate the level of agreement with several statements that reflected these factors. These statements were classified in three major categories:

1. Statements that show the familiarity of the drivers with the network such as *I am very familiar with at least 2 significantly different routes to work*;

2. statements that reflect their general attitudes towards diverting such as *I like discovering new route* or *I often change routes while driving*; and finally,

3. statements that revealed the perceptions of the drivers towards the validity and effectiveness of traffic reports, such as *Radio traffic reports are usually reliable* or *I often change my route after listening to radio traffic reports.*

Finally another group of questions indicated the importance of several factors in choosing the route to work. For these statements a five-point Likert-scale from *Not important at all* to *Very important* was used to indicate the perceptions of the drivers related to factors such as time of the day, commuting time, habit, traffic reports, risk of delay and weather conditions.

The second part of the survey, consisted of a detailed diary of morning commute trip information, for the period of one week. This part included five identical questionnaires, each to be answered in five subsequent week days, and each related to that day's commuting (home to work) trip. The questions of this part were related to the pre-trip and en-route traffic information acquisition, their influence on the commuters decisions, the drivers' en-route diversion decisions, and the anticipated and observed traffic conditions. The questionnaire also included questions about the duration and purpose of stops made.

Finally, another group of questions was incorporated in this part of the survey, using a five-point scale, from *Strongly Disagree* to *Strongly Agree* to indicate day-specific perceptions about the commuting trip, such as: *Traffic conditions today were* *better than usual*, *I am satisfied with my route choice today*, and *Traffic information received today was useful*. In the next section an overview of the statistics obtained from the conducted survey is presented.

4.2 Results From the Conducted Survey

A total of 1300 individuals responded to PART I of the survey. From this group, 898 completed the second part and made 3218 trips in a five day period.

4.2.1 Results from Part I

As stated above, the first part of the survey reflected drivers socioeconomic characteristics, travel characteristics and attitudes and preferences. The responses to this part of the survey are summarized in Table 4.1 to Table 4.4.

Socioeconomic and Travel Characteristics

Table4.1 reports the socioeconomic characteristics of the sample. Of the commuters, 59% were males while 41% were females. 66.7% of the commuters were married. Table 4.2 presents the travel characteristic of the commuters. The average commuting time was between 29 minutes and 40 minutes. The average number of routes used was 1.6, in spite of the fact that 43% of the drivers were very familiar with more than 2 routes. From the respondents, 14% had no flexibility in arrival time, 17% had flexibility up to 15 minutes, 16.6% 16 to 30 minutes, 15.3% from 31 to 60 minutes and 37% more than one hour.

22% of the commuters usually made stops while commuting to MIT, while 78% never made stops. The average duration of stops was 2.2 minutes. Approximately 38% of the stops had as purpose dropping off a passenger while only 4.9% of the stops were made to pick up a passenger. Almost 60% of the respondents had a post-graduate degree. Approximately 28% were administrative staff, 20% support staff, 26% faculty and 7.5%students.

Attribute		Percentage
Age Group	<=20	0.0
	20-29	12.4
	30-39	29.3
	40-49	29.6
	50-64	24.6
	>=65	4.1
Gender	Male	59.1
	Female	40.9
Marital Status	Married	66.7
	Unmarried	33.3
Education level	High school or less	4.8
	Some College	13.2
	Graduate College	24.0
	Post Graduate Work	57.90
Annual Income	<=20K	1.2
	20-40K	18.7
	40-60K	23.4
	60-80K	18.8
	80-100K	13.7
	>=100K	24.1
Position	Undergraduate Student	0.0
	Graduate Student	7.5
	Academic Staff	6.0
	Tenured Faculty	15.0
	Non-tenured Faculty	5.1
	Administrative Staff	27.6
	Service	1.90
	Support Staff	18.4
	Research Staff	15.1
	Other	3.6

Table 4.1: Socioeconomic Characteristics

Attribute		Average
Commuting Days per Week		4.7
Number of Different Routes Known		
	One	56.8%
	Two	32.6%
	Three	8.5%
	Four	1.6%
	Greater than Five	0.4%
Number of Different Routes Used		1.6
Flexibility with Arrival Time		
	None	14.2%
	<=15 minutes	17.1%
	16-30	16.6%
	31-60	15.3%
	>60	36.8%
Make Stops on the Way to Work		
	Yes	22.1%
	No	77.9%
Purpose of stops		
	Drop off passenger	37.7%
	Pick up passenger	4.9%
	Eat	10.3%
	Run errands	20.2%
	Fill gas	14.4%
	Child	9.5%
	Other	6.8%
Duration of stops		2.2 minutes
Usual minimum commuting time		29 minutes
Usual maximum commuting time		39.6 minutes

Table 4.2: Travel Characteristics

Attitudes and Preferences

Table 4.3 presents the answers of the statements reflecting the attitudes and preferences of the drivers. Caregory 1 corresponds to response *Strongly Disagree*, while category 5 corresponds to response *Strongly Agree*. While 52.5% of the drivers never change their planed route while driving, 16% often change their preplanned route. From the sample, 37% often listen to radio traffic reports and 27% usually follow the recommendations. Only 25% of the drivers think that radio traffic reports are reliable while 22% consider them as not relevant. From the drivers that listen to radio traffic reports, 20% often change their routes after listening to them, while 50% completely ignore traffic reports when these are different than their observations. In the latter case only 10% continues to follow the radios' advice. From all the surveyed commuters 10% were willing to pay more to get more useful information, while 50% do not.

Table 4.4 presents the importance of different travel attributes when drivers choose their route to work. Caregory 1 corresponds to response *Not important at all*, while category 5 corresponds to response *Very important*. Almost 66% of the drivers perceive time of the day as a very important factor when choosing their route to work. However, 80% of the drivers perceive commuting time as the most important factor in their route choice. 40% of the commuters consider habit as an important factor in their route choice , while 18% radio traffic reports and approximately 56% the risk of delay.

The results show that commuting time is the most important route choice factor. At the same time, the small percentage of the importance given to radio traffic reports can be attributed to their poor reliability and lack of relevance. Therefore, a route guidance system that provides accurate and relevant instructions and ensures the minimization of travel time between each O-D, would be a more useful information tool for the drivers. Moreover, it would be utilized by a higher percentage of them.

Number	Statement	1 %	2 %	3 %	4 %	5 %	Not relevant %
1	I am very familiar with at least 2 different routes to work	7.3	4.4	5.0	6.4	74.5	2.4
2	I often change my planned route while driving	41.0	21.6	18.8	7.9	8.0	2.5
3	I like discovering new routes	22.4	11.6	25.0	15.6	18.0	7.3
4	I am willing to try new routes to avoid traffic delays	5.2	5.5	13.4	22.4	50.5	3.0
5	I always listen to radio traffic reports	24.4	13.5	21.0	12.1	25.2	3.9
6	I usually follow the recommendations of radio traffic reports	19.1	15.5	21.9	15.8	11.4	16.3
7	Radio traffic reports are usually reliable	8.5	14.7	30.9	17.3	7.9	20.7
8	When traffic reports are different from my own observation I ignore them	5.1	5.4	16.2	18.9	31.3	23.1
9	I often change my route after listening to radio traffic reports	13.6	19.5	25.9	14.0	6.4	20.7
10	I trust my own judgement more than the traffic reports	8.1	13.8	26.5	20.2	16.2	15.2
11	Traffic reports do not provide relevant information	16.9	23.6	23.7	11.7	10.1	14
12	I am willing to pay in order to get more useful traffic information	54.5	13.9	12.5	5.3	3.4	10.4

Table 4.3: Respondents' Attitudes and Preferences

4.2.2 Results from part II

A summary of the results for the second part of the survey, which reflected daily commute characteristics, are reported to tables 4.5 to 4.8. Table 4.5, presents questions relevant to the acquisition of pre-trip information. In approximately 24% of the trips made, pre-trip traffic information was acquired. 7% of the drivers were influenced by this information.

Table 4.6, presents questions relevant to the acquisition of enroute traffic information. En-route traffic information was acquired for 23.6% of the trips made. Table 4.7, presents questions relevant to the route switching behavior. 66.9% of the trips made presented the opportunity of switching routes. From these trips, route switching was observed in 6.3% of them. From the trips in which route switching was observed, 8.4% received traffic information before switching. The reason to switch, was split as follows: 10% was due to radio traffic reports, 52% was due to drivers' own observations and the remaining 38% switched for other reasons.

Table 4.8 presents the daily specific perceptions about the conducted trip and the information acquired. Caregory 1 corresponds to response *Strongly Disagree*, while category 5 corresponds to response *Strongly Agree*. 18% of the individuals found that the acquired traffic information was useful. Only 8% of the respondents thought they would have saved at least 5 minutes had they taken another route or relevant traffic information. 41% of the respondents were confident about their decision to switch to an alternative route; 38% were not confident and 21% were undecided. In spite of the fact that in 64% of the trips made, drivers thought that the commute time was worse than unusual, diversion to another route was observed only in 4.9% of the total trips.

From the above results, it can be inferred that drivers need stronger incentives in order to divert, since they don't know the length of delay in advance. In addition note that almost half of the drivers who diverted were not confident if they would be better off when they diverted. Therefore, provision of clear and precise information on delays and congestion would contribute favorably to the congestion reduction and eliminate the uncertainty in route choice. In Chapter 5, the estimation results of the models introduced in section 3.3 are presented and discussed.

Number	Attribute	1 %	2 %	3 %	4 %	5 %
1	Time of day	15.7	7.1	11.1	16.3	44.9
2	Commute time	9.2	4.6	10.0	20.6	55.5
3	Habit	12.3	8.6	29.8	26.1	23.3
4	Time spent stopped in traffic	5.3	5.3	10.3	29.0	50.1
5	Number of traffic lights	10.9	11.5	24.2	25.4	27.9
6	Traffic reports	30.7	22.7	28.1	12.4	6.1
7	Risk of delay	8.6	8.5	26.1	30.6	26.2
8	Weather	25.9	16.7	19.3	15.9	22.1

Table 4.4: Importance of factors affecting route choice behavior

Question		Percentage
Receive traffic information		
	From radio	22.09
	From TV	5.17
	No	72.76
Pre-trip information influence route choice		
	A lot	4.15
	Somewhat	12.35
	Very little	11.82
	Not at all	68.05
Indicated traffic conditions for the route taken		
	Much worse than usual	0.89
	Worse than usual	6.85
	Usual traffic conditions	35.40
	Better than usual	4.32
	Much better than usual	1.31
	No information	23.00
	Other	3.76

Table 4.5: Acquisition of Pre-trip Information

Question		Percentage
Receive traffic information		
	Yes	23.64
	No	76.35
Observed traffic conditions on the route taken		
	Much worse than usual	1.54
	Worse than usual	10.92
	Usual traffic conditions	67.35
	Better than usual	16.17
	Much better than usual	3.59
	Other	0.42
Indicated traffic conditions on the route taken		
	Much worse than usual	2.61
	Worse than usual	14.55
	Usual traffic conditions	57.34
	Better than usual	7.96
	Much better than usual	1.34
	No information	12.94
	Other	0.99

Table 4.6: Acquisition of En-route Traffic Information

Statement		Percentage
Receive traffic information before switching for new route		
	Yes	8.37
	No	91.63
Indicated traffic conditions for new route		
	Worse than usual	6.67
	Usual traffic conditions	50.00
	Better than usual	3.33
	No information	36.67
	Other	3.33
Reasons for switching		
	Radio Traffic Reports	11.82
	Own observation	61.58
	Forced detour	4.93
	Other	21.67

Table 4.7: Route Switching Behavior

Number	Statement	1 %	2 %	3 %	4 %	5 %
1	Traffic conditions today are better than usual	12.89	16.6	42.17	16.48	11.86
2	Traffic information today was useful	32.81	19.34	30.35	10.87	6.63
3	My commute time today was worse than usual	42.42	21.51	20.85	9.74	5.47
4	I am satisfied with my route choice today	3.10	3.26	16.76	23.90	52.98
5	I could have saved at least 5 min. had I taken another route	58.10	23.29	10.58	4.27	3.76
6	I could have saved at least 5 min. had I gotten relevant info	59.15	22.97	11.50	3.36	3.11
7	When I made my decision to switch routes today I was confident I would be better off	30.17	7.35	21.66	16.63	24.18

Table 4.8: Level of agreement

Chapter 5

Estimation Results

This chapter presents the estimation results from the modeling of the acquisition of Pre-trip traffic information, the influence of this information on drivers' behavior and route switching decisions.

5.1 Estimation Methods

As discussed in Chapter 4, 3218 trips were made by 898 individuals in a 5-days period. In the estimations the totality of these trips is used to estimate discrete choice models using standard maximum likelihood estimator (MLE) techniques. (See Ben-Akiva and Lerman (1985) for further discussion on discrete choice models.) Since choices over time were observed, the dynamic complications of serial correlation were present. Therefore, the error terms of our utility functions are correlated over time. By using the standard statistical packages the obtained parameter estimates are consistent[1] but not efficient[2]. Therefore, the standard errors and consequently the t-statistics obtained are overestimated (see. Amemiya (1985) for formal proof).

The Jackknife Method was used to calculate the correct standard errors of the modeling coefficients. This method[3] (presented in appendix B) gives a nonparametric

[1] An estimator that is consistent has a distribution that collapses on the true parameter value as the sample gets larger.

[2] An efficient estimator has the smallest variance of all other estimators.

[3] first introduced by Tukey in (1958) .

estimation of the statistical standard errors. The tables in this chapter report the correct standard errors and t-statistics.

In order to incorporate the attitudes and preferences[4] of drivers in the models, dummy variables are generated as follows: a *not important/disagreement* variable is generated when values of 4 and 5 are chosen as response in the ordinal scale. Respectively, an *important/agreement* dummy variable is generated for responses of 1 and 2. Ordinal value 3 in the scale, is considered as the base case.

5.2 Modeling the Acquisition of Pre-Trip Information

Binary logit models were used to model the acquisition of pre-trip traffic information (see also Figure 3-2). For these model the dependent variable was: 1 if the commuters acquired pre-trip information and 0 otherwise.

To model the acquisition of pre-trip information, three major groups of independent variables were used: socioeconomic characteristics, travel characteristics and perceptions about radio traffic reports. Table 5.1 presents the results of this model. It also provides a summary with relevant statistics obtained from the estimation. The analysis of the results related to each group of factors follows.

Socioeconomic characteristics

Marital status appear to be a significant socioeconomic characteristic. The negative sign of the coefficient indicates that married people are less likely to acquire pre-trip traffic information. Therefore, one can assume that a married commuter is less anxious or more conservative than an unmarried individual. However we can justify this as a result of a less flexible schedule that married drivers have due to situational constraints such as "drop the children to school". On the other hand, women appear to acquire more traffic information than men. The higher the income is, the more

[4]Questions answered with an ordinal value in a scale from 1 to 5 (see section 4.1)

likely drivers are to acquire information. However, for income of more than $100000, a sudden drop in the willingness to acquire information is observed. This could reflect a different attitude adopted due to a highei income position. Students, academic staff and faculty are less likely to acquire information than the rest of the support and administrative staff working at the university. Maybe due to more flexible schedule and off-peak departure time.

Travel characteristics

The larger the duration of stop made before arriving to their destination, the more drivers tend to acquire pre-trip information. This can be explained as follows: suppose that someone acquires traffic information that indicated congestion in the usual route. Then he might decide to make a stop or to extend the duration of his stop until traffic conditions on his usual route ameliorate. When travel time never exceeds the usual range of expected time, drivers are less likely to acquire traffic information. On the contrary, it is when travel time usually exceeds the normal range of time that drivers are willing to acquire traffic information. This is one of the most important findings in the model presented in table 5.1. It shows that unstable traffic conditions that cause unexpected and frequent delays, lead drivers to acquire pre-trip information in order to plan their trip efficiently. No flexibility in arrival time or flexibility of less than sixteen minutes (in comparison with flexibility of more than sixteen minutes), make drivers to acquire more pre- trip traffic information. Finally, familiarity with both less than two and more than two alternative routes, make no difference in the decision to acquire pre-trip traffic information.

Perceptions about Radio Traffic Reports

The perceptions of the drivers about the reliability and relevance of radio traffic reports, influence pre-trip traffic acquisition. It can be seen that when traffic reports are perceived as unreliable or irrelevant, drivers are less likely to acquire pre-trip traffic information. The acquisition of pre-trip information depends strongly on the characteristics of the information provided.

In this model socioeconomic characteristics and travel characteristics appeared significant. The most important result is that the drivers perceptions about the quality of information provided influences positively or negatively the acquisition of pre-trip information.

5.3 Modeling the Influence of Pre-Trip Information

To model the influence of pre-trip information on drivers' behavior (see also, Figure 3-4) only drivers who acquired pre-trip traffic information were taken into account (800 drivers approximately) (see Table 5.4). Binary logit models were estimated where the dependent variable was: 1 if the driver stated that he was influenced by the radio reports and 0 otherwise.

Three major groups of independent variables can be distinguished:

1. travel characteristics,
2. attitudes, preferences and perceptions of the drivers, and
3. pre-trip traffic information characteristics.

The analysis of the results of the model follows.

Travel Characteristics

The more often travel time exceeds its usual range, the more drivers' decisions are likely to be influenced by the traffic reports. Also, the larger the number of different routes used, the more pre-trip information influences route choice. The longer the time commuters make the same trip[5] the more traffic information influences their decisions. Drivers who are familiar with the network will utilize the pre-trip information to plan their trips accordingly.

[5]This time is the minimum between the years working at the same job and years residing at same dwelling unit

However, the reliability of traffic reports as well as the willingness to try different routes to avoid traffic congestion, appear insignificant factors. The above result could be explained as a loss of information because it considered only trips in which drivers acquired pre-trip traffic information.

Attitudes, Preferences and Perceptions

Habit does not affect negatively the influence of pre-trip traffic information on drivers behavior. The reliability of traffic reports as well as the willingness to try different routes to avoid traffic congestion, appear insignificant factors. The above result could be explained as a loss of information because it considered only trips in which drivers acquired pre-trip traffic information. However, if commuters rarely use to change their routes after listening to radio traffic reports, their decisions are not influenced by the pre-trip traffic information.

Pre-trip Traffic Information

When the acquired traffic information was not relevant for the area under interest, then, as expected, this information did not influenced drivers decisions. In any other case traffic information influenced commuters' decisions. This can be explained as follows: if the traffic conditions were better than usual in the preselected routes, then the drivers might decide to stay in this route. However, if the traffic conditions were worst than usual in the preselected routes, then the driver might decide to use an alternative route. Therefore, in both cases pre-trip information determine the drivers' decisions about the route to follow.

Note that no socioeconomic characteristics appeared significant in the estimation of the above model. The most important factors were the traffic conditions indicated by the media. Note that information influences drivers' behavior only when it is relevant to their interests. This indicates that the broad implementation of route-guidance systems might successfully influence drivers' behavior, as these systems provide specific details and instructions about each drivers trip.

5.4 Modeling En-Route Switching Behavior

To model the drivers' switching decisions three different modeling approaches were used. In all three models the dependent variable was 1 for drivers who switched and 0 otherwise.

The first modeling approach incorporated the fitted values of attitudes and preferences (see figure 3.4.3. These fitted values were acquired by estimating an ordered probit model for each attitude variable. Binary logit models were then used to estimate the drivers' switching behavior.

The other two modeling approaches (section 5.4.2 and 5.4.3) included as dependent variables the reported values of the attitudes and preferences of the drivers (see also, figure 3-5). In section 5.4.1, the analysis of the results of the logit model that includes the fitted values of attitudes of the drivers is presented.. Furthermore, a comparison with the results acquired by the logit model estimations that include the reported values of attitudes is then presented.

5.4.1 Modeling with Fitted Values of Attitudes

In this section, the analysis of the results of the logit model that includes the fitted values of attitudes of the drivers is presented (see Table 5.6).

Table 5.8, table 5.9 table 5.10, table 5.11, table 5.12, table 5.13 and table 5.14 show the estimation results of the ordered probit models. As explained in section 3.4.3 the dependent variables reflect the attitudes and preferences of the drivers, while the independent variables represent the socioeconomic and travel characteristics. The fitted values of the dependent variables are used as independent variables in the binary logit model of table 5.6. Note that the socioeconomic characteristics and the travel characteristics are not such good predictors of the attitudes and preferences of the drivers. That implies that there is a large portion of unexplained variability depending on the personality of each driver, which can not be captured by the above factors. However, the insignificance of the socio-economic variables in all models that included attitudes and preferences, supported our apriori notion that the psychological factors determine route choice behavior.

Six main categories of factors affecting route switching are included in the modelling:

1. perceived importance of factors, affecting route choice,
2. attitudes and preferences
3. pre-trip information,
4. en-route information about pre-selected route,
5. en-route information about alternative routes and
6. actual traffic conditions.

The analysis of the results related to each group of factors is presented in sections 5.4.1 to 5.4.1.

The negative sign of the constant in table 5.6 shows that people prefer to follow their preselected route. A "switch" is a deviation from their habitual behavior.

Factors affecting route choice

If *habit* is perceived to be an important route choice factor, then the probability of switching from the preselected route decreases. The more *time of the day* is an important route choice criterion, the more drivers are likely to switch. (Note that in this case study we are dealing with the everyday commuting trip to work).

The *risk of delay* is an important factor in the route choice behavior. As it increases drivers are more likely to divert. When travelers are under time pressure, they try to avoid traffic congestion by switching to alternative routes, which they perceive as less congested and will faster lead them to their destinations.

The more *traffic reports* play an important role on drivers' route choice, the less likely they are to divert. That means people who tend to acquire pre-trip information choose more efficiently the route to follow and therefore have no need to divert.

Attitudes

Drivers who change often their preselected routes while driving are more likely to divert from the preselected route. Moreover, drivers who like to discover new routes are more prone to switch from their usual route.

The two factors above show the general attitude of the drivers towards diverting. A person with a risk-taking attitude is more likely to switch to another route than one who prefers following the same route and does not like changes. Moreover, drivers who like discovering new routes are more prone to switch than those who do not.

Pre-trip Information

The more drivers are likely to acquire pretrip information, the less likely they are to divert. However, drivers who are influenced by pre-trip information are more likely to divert.

This result confirms the hypothesis that route choice is a hierarchical sequence of decisions. Each route from home to work is partitioned into major segments with different traffic conditions (highways, streets, bridges). Each commuter knows a priori (with the exception of incidents) in what segment worse traffic conditions might be encountered. Therefore, an intersection that precedes segments with heavy traffic conditions, is a decision point. Pre-trip and en-route information can provide the necessary information that will allow drivers to enhance this hierarchical decision process.

Observed Traffic Conditions

This is one of the most important factors in the estimation results in table 5.6. The worse the traffic conditions the driver observes while driving, the more likely he is to divert. The process of adaptive route choice is usually observed when drivers are under time-pressure (commute to work is usually characterized by time pressure) and choices are made in intermediate node according to what is termed "myopic view" (Shefi, 1982), where driver chooses between continuing links according to the distance between him and the last queuing car in each of the links ahead.

En-route information for Pre-selected Route

The acquisition of en-route information does not enforce a diversion from the usual route (drivers might acquire information passively by radio or variable message signs, or voluntarily because traffic conditions are worse than expected or they might just want to update their pre-trip information). However, if the information provided indicates worse traffic conditions than the usual ones, for the route actually followed, then the probability of switching to an alternative route is greater.

En-route Information for Alternate Routes

A driver who is interested in acquiring en-route traffic information for an alternate route, is more prone to divert. When the information about traffic conditions on an alternate route is usual or better than usual then drivers are more likely to switch to the new route.

While estimating the drivers' diversion behavior, socioeconomic, travel or information characteristic were not significant. The non-significance of the socioeconomic variables was also a result found by Hatcher and Mahmassani (1992) who concluded that *some of these characteristics may be reflected through drivers trip chaining patterns, as well as commuter preference indicators.*

As stated above, socioeconomic characteristics such as age, sex, income, education or position do not play any role in route switching behavior. This finding is very important, as it shows that for actual commuting trips only perceptions traffic conditions provided and general attitudes towards switching influence their decisions.

In addition, the duration of trip or the number of years making the same commute do not affect switching behavior. That shows that for the trip to work. drivers reach a steady state, in which their route choice set is formulated and only day to day fluctuations of traffic conditions (mainly caused by incidents) are important.

5.4.2 Modeling with Reported Values of Attitudes (Direct Scale)

The model presented in Table 5.7 has as independent variables the reported values of attitudes and preferences of the drivers. This model uses the direct ordinal response scale (see section 4.1). The results shown in table 5.7, are very similar to the results of table 5.6. The only difference is the signs of the coefficients of risk of delay and traffic reports importance (negative and positive respectively). However, these signs make more sense intuitively than the ones presented in table 5.6. When risk of delay is an important factor in route choice behavior, drivers are more likely to divert. When travellers are under time pressure they prefer to stay in the familiar route. Moreover, the more traffic reports play an important role on users' route choice the more likely they are to divert. That means people who tend to acquire pre-trip information are more prone to divert. This can be attributed to the fact that they might encounter heavier or unstable traffic conditions more often than other drivers and, therefore, they tend to acquire traffic information more frequently. However, as mentioned in section 5.4.1 there is a large portion of unexplained variability depending on the personality of the drivers which can not be captured by the ordered probit models. Therefore, the difference in the sign of these two coefficients reflecting the attitudes of the drivers could be attibuted to the above factor. . Although, one can argue that the incorporation of the categorical variables as independent variables does not make any sense, or is inaccurate, the better fit of this model and the relatively easy estimation should be further considered.

5.4.3 Modeling with Reported Values of Attitudes (Dummy Variables)

The model presented in Table 5.8, has as independent variables the reported values of attitudes and preferences of the drivers. This model incorporates the attitudinal variables as dummy categorical variables. This model has the better fit of all the models. It can be seen that the only difference with model presented in Table 5.6, is related to the variable *habit* where its coefficient is now positive. That means that people who select their route by habit, are more likely to divert. This result is counter intuitive and might be the effect of the use of the dummy variables. However, the signs of the factors expressing risk of delay and traffic reports importance coincide with the results of the model presented in Table 5.7. Moreover, the latter model is more difficult to interpret as in the initial model the independent latent variables are directly expressing drivers preferences. In addition, the first and second models include eight less independent variables, a fact that makes them more efficient than this modeling approach.

To conclude, pre-trip information acquisition depends on drivers' socioeconomic and travel characteristics, as well as the perceptions of the drivers about the reliability and relevance of traffic reports. Drivers route choice is strongly influenced by the content of pre-trip information. Finally, en-route diversion depends on drivers' attitudes and preferences, pre-trip and en-route information acquisition and the observed traffic conditions.

	Variable number	Variable name	Coefficient estimate	Assymptotic st. error	t statistic
	1	Constant	-1.710	0.652	-2.62
Socioeconomic Characteristics	2	Gender male	-0.193	0.184	-1.05
	3	Marital status married	-0.494	0.257	-1.92
	4	Age 30-40 years old	0.079	0.045	0.32
	5	Age 40-50 years old	0.410	0.123	1.40
	6	Age more than 50 years old	0.620	0.096	1.53
	7	Income <\$20K and <=\$40K	0.356	0.328	1.08
	8	Income <\$40K and <=\$60K	0.454	0.156	2.91
	9	Income <\$60K and <=\$80K	0.710	0.274	2.60
	10	Income <\$80K and <=\$100K	0.283	0.247	1.15
	11	Student	-0.459	0.522	-0.88
	12	Faculty	-1.536	0.162	-3.03
	13	Academic Staff	-0.271	0.211	-1.28
Travel Characteristics	14	Duration of Stops	0.005	0.004	1.08
	15	Travel time rarely exceeds usual range	-0.296	0.236	-1.25
	16	Travel time often exceeds usual range	0.394	0.202	1.94
	17	No flexibility in arrival time	0.163	0.213	0.76
	18	Flexibility in arrival time less than 15 min	0.231	0.175	1.32
	19	Familiar with less than 2 alt. routes	0.295	0.604	0.49
	20	Familiar with more than 2 alt. routes	0.378	0.45	0.83
Perceptions	21	Traffic reports are not *reliable*	-0.419	0.115	-1.53
	22	Traffic reports are very *reliable*	0.194	0.456	0.68
	23	Traffic reports are not *relevant*	-0.658	0.456	-0.23
	24	Traffic reports are *relevant*	0.288	0.045	1.29
		Summary statistics			
		Number of observations = 2492			
		$\mathcal{L}(0) = -1727.31$			
		$\mathcal{L}(\mathbf{c}) = -1547.94$			
		$\mathcal{L}(\hat{\beta}) = -1429.67$			
		$-2[\mathcal{L}(0) - \mathcal{L}(\hat{\beta})] = 595.29$			
		$\rho^2 = .172$			
		$\bar{\rho}^2 = .158$			

Table 5.1: Estimation Results of a Binary Logit Model-Acquisition of Pre-trip Information

	Variable number	Variable name	Coefficient estimate	Assymptotic st. error	t statistic
	1	Constant	-2.509	0.427	-5.9
Travel Characteristics	2	Time using the the same O-D	0.020	0.011	1.8
	3	Number of different routes used to work	0.133	0.103	1.3
	4	Travel time exceeds often the usual range	0.824	0.190	4.3
Perceptions Attitudes and Preferences	5	Habit is not an important route choice factor	0.799	0.249	3.2
	6	Habit is an important route choice factor	0.336	0.217	1.6
	7	Radio traffic reports are not reliable	0.249	0.264	0.9
	8	Radio traffic reports are reliable	0.340	0.202	1.7
	9	Not willing to try different routes to avoid traffic congestion	0.788	0.480	1.6
	10	Willing to try different routes to avoid traffic congestion	0.299	0.292	1.0
	11	Rarely change route after listening to radio traffic reports	-0.631	0.244	-2.6
	12	Often change route after listening to radio traffic reports	0.162	0.220	0.7
Pre-trip Information	13	Indicated traffic conditions : none	-0.622	0.243	-2.6
	14	Indicated traffic conditions worse than usual	0.976	0.268	3.6
	15	Indicated traffic conditions better than usual	1.229	0.308	4.0
		Summary statistics			
		Number of observations = 758			
		$\mathcal{L}(\mathbf{0}) = -525.41$			
		$\mathcal{L}(\mathbf{c}) = -447.33$			
		$\mathcal{L}(\hat{\beta}) = -306.04$			
		$-2[\mathcal{L}(\mathbf{0}) - \mathcal{L}(\hat{\beta})] = 258.73$			
		$\rho^2 = .246$			
		$\bar{\rho}^2 = .218$			

Table 5.2: Modeling the influence of Pre-Trip Information

	Variable number	Variable name	Coefficient estimate	Assymptotic st. error	t statistic
	1	Constant	-3.242	0.516	-6.28
Factors affecting route choice	2	Habit Importance	-0.617	0.420	-1.47
	3	Time of the day Importance	0.616	0.420	1.47
	4	Risk of delay Importance	0.485	0.393	1.23
	5	Traffic reports Importance	-0.516	0.420	-1.23
Attitudes	6	Like to discover new routes	0.013	0.379	0.03
	7	Often change planned route while driving	0.066	0.330	0.20
Pre-Trip information	8	Acquired pre-trip information	-0.006	0.254	-0.02
	9	Information had little influence on route choice	0.506	0.336	1.50
	10	Information somehow influenced route choice	0.688	0.277	2.48
	11	Information had a lot of influence on route choice	0.988	0.334	2.65
Actual traffic conditions	12	Observed conditions at the beginning of the trip: Worst than usual	1.014	0.123	8.24
En-Route information for actual route	13	Acquired en-route information	-0.138	0.334	-0.41
	14	Indicated conditions for preselected route worst than usual	0.535	0.295	1.81
En-Route information for new route	15	Acquired information for alternate route	0.287	0.223	1.28
	16	Indicated conditions for alternate route better than usual	0.156	0.155	1.00
		Summary statistics			
		Number of observations = 2978			
		$\mathcal{L}(\mathbf{0}) = -2064.17$			
		$\mathcal{L}(\mathbf{c}) = -879.92$			
		$\mathcal{L}(\hat{\beta}) = -824.77$			
		$-2[\mathcal{L}(\mathbf{0}) - \mathcal{L}(\hat{\beta})] = 2478.79$			
		$\rho^2 = .600$			
		$\bar{\rho}^2 = .593$			

Table 5.3: Modeling Route Switching Behavior - Using fitted values of attitudes

	Variable number	Variable name	Coefficient estimate	Assymptotic st. error	t statistic
	1	Constant	-2.606	0.467	-5.58
Factors affecting route choice	2	Habit influence a little on the route choice	0.484	0.271	1.78
	3	Habit influence a lot the route choice	0.214	0.237	0.90
	4	Time of the day is not important	-0.442	0.484	-0.91
	5	Time of the day is very important	-0.112	0.249	-0.45
	6	Risk of delay is not important	0.111	0.350	0.32
	7	Risk of delay is very important	-0.194	0.347	-0.56
	8	Traffic reports are not important	-0.195	0.288	-0.68
	9	Traffic reports are very important	0.164	0.254	0.64
Attitudes	10	Do not like discovering new routes	-0.055	0.206	-0.27
	11	Like to discover new routes	0.444	0.190	2.34
	12	Rarely change planned route while driving	-0.579	0.369	-1.57
	13	Often change planned route while driving	0.369	0.070	1.78
Pre-Trip information	14	Acquired pre-trip information	-0.060	0.243	-0.25
	15	Information had little influence on route choice	0.322	0.384	0.84
	16	Information somehow influenced route choice	0.586	0.402	1.46
	17	Information had a lot of influence on route choice	1.012	0.527	1.92
Actual traffic conditions	18	Observed conditions at the beginning of the trip were worst than usual	1.997	0.189	5.25
En-Route information for actual route	19	Acquired en-route information	-0.257	0.236	-1.09
	20	Indicated conditions for preselected route worst than usual	0.547	0.477	1.15
En-Route information for new route	21	Acquired traffic information for alternate route	0.221	0.437	0.51
	22	Indicated conditions for alternate route better than usual	0.210	0.189	1.11
		Summary statistics			
		Number of observations = 2978			
		$\mathcal{L}(\mathbf{0}) = -2064.17$			
		$\mathcal{L}(\mathbf{c}) = -879.92$			
		$\mathcal{L}(\hat{\beta}) = -802.38$			
		$-2[\mathcal{L}(\mathbf{0}) - \mathcal{L}(\hat{\beta})] = 2523.58$			
		$\rho^2 = .611$			
		$\bar{\rho}^2 = .600$			

Table 5.4: Modeling Route Switching Behavior - Using reported values of attitudes (direct scale)

	Variable number	Variable name	Coefficient estimate	Assymptotic st. error	t statistic
	1	Constant	-4.099	0.556	-7.10
Factors affecting route choice/ preferences	2	Habit Importance	-0.016	0.089	-0.19
	3	Time of the day Importance	0.064	0.121	0.53
	4	Risk of delay Importance	-0.102	0.119	-0.85
	5	Traffic reports Importance	0.088	0.115	0.76
Attitudes	6	Like to discover new routes	0.168	0.084	1.99
	7	Often change planned route while driving	0.302	0.120	2.52
Pre-Trip information	8	Acquired pre-trip information	-0.062	0.216	-0.28
	9	Pre-trip information had little influence on route choice	0.392	0.336	1.01
	10	Pre-trip information somehow influenced route choice	0.612	0.414	1.48
	11	Pre-trip information had a lot of influence on route choice	0.992	0.472	2.10
Actual traffic conditions	12	Observed conditions at the beginning of the trip: Worst than usual	0.992	0.190	5.20
En-Route information for actual route	13	Acquired en-route information	-0.234	0.221	-1.06
	14	Indicated conditions for actual route worst than usual	0.535	0.460	1.18
En-Route information for new route	15	Acquired information for alternative route	0.247	0.388	0.65
	16	Indicated conditions for alternative route better than usual	0.207	0.165	1.26
		Summary statistics			
		Number of observations = 2978			
		$\mathcal{L}(\mathbf{0}) = -2064.17$			
		$\mathcal{L}(\mathbf{c}) = -879.92$			
		$\mathcal{L}(\hat{\beta}) = -807.41$			
		$-2[\mathcal{L}(\mathbf{0}) - \mathcal{L}(\hat{\beta})] = 2513.52$			
		$\rho^2 = .609$			
		$\bar{\rho}^2 = .6011$			

Table 5.5: Modeling Route Switching Behavior - Using reported values of attitudes (dummy variables)

variable number	Variable name	Coefficient estimate	Assymptotic st. error	t statistic
1	Constant	-0.222	0.314	-0.708
2	Number of days coming to MIT	-0.017	0.592	-0.30
3	No stops	-0.183	0.091	-2.03
4	Travel time exceeds often the usual time range	0.293	0.105	2.80
5	Travel time exceeds rarely the usual time range	-0.246	0.090	-2.72
6	Number of different routes used	0.487	0.005	9.71
7	Age25-40	0.091	0.057	1.00
8	Age > 50	0.011	0.091	0.121
9	Faculty	-0.118	0.114	-1.04
10	Administration	-0.041	0.113	-1.84
11	Staff	-0.041	0.109	-0.38
12	Thresh 1	0.690	0.014	19.31
13	Thresh 2	1.392	0.040	35.09
14	Thresh 3	1.860	0.055	33.76
	Summary statistics			
	Number of observations = 801			
	$\mathcal{L}(0) = -1158.1$			
	$\mathcal{L}(\hat{\beta}) = -1066.1$			

Table 5.6: Estimation Results of Ordered Probit Model: Often Change Route While Driving

Variable number	Variable name	Coefficient estimate	Assymptotic st. error	t statistic
1	Constant	0.425	0.465	0.91
2	No flexibity in arrival time	-0.173	0.115	-1.50
3	Stop less than 10 minutes	0.277	0.456	0.61
4	Number of different routes used	0.262	0.080	5.24
5	Travel time exceeds rarely the usual time range	-0.136	0.080	-1.71
6	Marital status	-0.239	0.115	-2.85
7	Age25-40	0.059	0.089	0.67
8	Age > 50	-0.154	0.916	-1.68
9	Education - High-school	-0.623	0.192	-3.24
10	Education - Colege	-0.370	0.123	-3.02
11	Education - Graduate Studies	0.020	0.096	-0.21
12	Thresh 1	0.386	0.030	12.61
13	Thresh 2	1.112	0.034	32.42
14	Thresh 3	1.688	0.045	37.74

Summary statistics
Number of observations = 748
$\mathcal{L}(0) = -1538.8$
$\mathcal{L}(\hat{\beta}) = -1149.5$

Table 5.7: Estimation Results of Ordered Probit Model - Like Discovering New Routes

Variable number	Variable name	Coefficient estimate	Assymptotic st. error	t statistic
1	Constant	1.913	0.326	5.87
2	No flexibility with arrival time	0.089	0.112	0.79
3	No stops	-0.008	0.008	-0.90
4	Usual minimum travel time	-0.005	0.003	-1.89
5	Travel time exceeds rarely the usual time range	0.146	0.785	1.86
6	Number of different routes used	-0.092	0.048	-1.89
7	Number of days coming to MIT	-0.009	0.057	-1.53
8	Income >= 80000	0.007	0.086	0.81
9	Faculty	-0.147	0.113	-1.30
10	Administration	-0.099	0.106	-0.94
11	Staff	-0.062	0.112	-0.55
12	Thresh 1	0.339	0.032	10.51
13	Thresh 2	1.158	0.035	32.71
14	Thresh 3	1.881	0.045	42.21
	Summary statistics			
	Number of observations = 796			
	$\mathcal{L}(0) = -1604.4$			
	$\mathcal{L}(\hat{\beta}) = -1199.1$			

Table 5.8: Estimation Results of Ordered Probit Model - Habit Importance

Variable number	Variable name	Coefficient estimate	Assymptotic st. error	t statistic
1	Constant	-0.417	0.152	-2.74
2	Age > 50	0.219	0.081	2.70
3	Inc $20000 - 60000$	0.135	0.100	1.40
4	Inc 80000+	-0.141	0.104	-1.35
5	Faculty	-0.132	0.108	-1.22
6	Administration	0.168	0.091	1.83
7	No flexibility in arrival time	0.322	0.108	2.97
8	Usual minimum travel time	-0.005	0.009	-0.55
9	Usual maximum travel time	0.022	0.008	2.25
10	Travel time exceeds often the usual time range	0.267	0.094	2.84
11	Number of different routes used	0.102	0.049	2.07
12	Thresh 1	0.672	0.036	18.86
13	Thresh 2	1.528	0.043	35.83
14	Thresh 3	2.205	0.063	34.80
	Summary statistics			
	Number of observations = 802			
	$\mathcal{L}(0) = -1398.4$			
	$\mathcal{L}(\hat{\beta}) = -1139.6$			

Table 5.9: Estimation Results of Ordered Probit Model - Importance of Traffic Reports

Variable number	Variable name	Coefficient estimate	Assymptotic st. error	t statistic
1	Constant	1.441	0.502	2.87
2	Inc 20000 – 60000	0.007	0.105	-0.07
3	Inc 80000+	-0.133	0.108	-1.24
4	Faculty	-0.112	0.119	-0.99
5	Administration	0.191	0.138	1.68
6	Staff	0.297	0.125	2.37
7	No stops made	-0.124	0.097	-1.28
8	Stop less than 10 minutes	-0.707	0.496	-1.43
7	No flexibility in arrival time	0.192	0.133	1.44
10	Flexibility upto 16 minutes	-0.142	0.095	-1.50
11	Travel time exceeds rarely the usual time range	-0.129	0.082	-1.58
12	Number of different routes used	0.284	0.054	5.27
13	Thresh 1	0.263	0.025	10.55
14	Thresh 2	0.577	0.026	22.05
15	Thresh 3	1.055	0.037	28.65
	Summary statistics			
	Number of observations = 809			
	$\mathcal{L}(0) = -1349.4$			
	$\mathcal{L}(\hat{\beta}) = -1056.3$			

Table 5.10: Estimation Results of Ordered Probit Model - Importance of Time of the Day

Variable number	Variable name	Coefficient estimate	Assymptotic st. error	t statistic
1	Constant	1.754	0.439	4.00
2	Inc 20000 – 60000	-0.009	0.098	-0.09
3	Inc 80000+	0.085	0.101	0.84
4	Faculty	-0.117	0.113	-1.03
5	Administration	-0.056	0.110	-0.51
6	Staff	0.154	0.119	1.29
7	Sex	-0.139	0.084	-1.66
8	Stop less than 10 minutes	-0.649	0.421	-1.54
9	No flexibility in arrival time	0.071	0.122	0.58
10	Flexibility upto 16 minutes	0.025	0.090	0.28
11	Travel time exceeds often the usual time range	-0.139	0.093	-1.49
12	Number of different routes used	0.228	0.049	4.62
13	Thresh 1	0.442	0.038	11.52
14	Thresh 2	1.264	0.038	33.56
15	Thresh 3	2.100	0.047	44.69
	Summary statistics			
	Number of observations = 800			
	$\mathcal{L}(0) = -1724.6$			
	$\mathcal{L}(\hat{\beta}) = -1156.8$			

Table 5.11: Estimation Results of Ordered Probit Model - Importance of Risk of Delay

Chapter 6

Conclusions and Further Research

6.1 Contributions

The major contributions of this thesis consist of the following:

- *Proposed Framework*:

  A general framework for drivers' route choice behavior was formulated. In this framework, major importance was given to the attitudes and perceptions of the drivers, as the principal factors affecting their decisions. Moreover, the analysis of the impact of pre-trip and en-route information on drivers' route choice and route switching behavior, was presented.

- *Modeling Approach*:

  The modeling framework for the analysis of pre-trip and en-route driver behavior in conjunction with traffic information acquisition was developed. A two-stage methodology for incorporating attitudes and preferences was proposed.

- *Evaluation of the results*

  The case study provided insights into:

  - Acquisition of pre-trip traffic information;
  - Influence of pre-trip traffic information on commuters' decisions; and
  - Drivers' switching behavior.

Comparing this work with other researchers' revealed preference (RP)- based experiments investigating route choice behavior, the following can be said:

Khatak *et al* (1992) used a survey that asked the respondents their relevant decisions, for trips in which the experienced en-route delay was longer than 10 minutes. In their models, they compared switching decisions due to drivers' own observations and those due to the acquisition of traffic information. The researchers concluded that drivers divert more when they acquired information about traffic delay than when they relied on their own observations. The models use a *Stated Preference Index* which indicated the inherent tendency to divert, and an *Adventure and Discovery* Personality Index. As used in the models, these indices are biased indicators of diversion behavior.

Mahmassani *et al* (1991) addressed the day-to-day variability of individual trip scheduling and route decisions based on two-week diaries of actual commuting trips. Although traffic information was implicated as an important factor affecting diversion decisions, no specific questions about pre-trip and enroute information were incorporated in the survey. Moreover, the drivers' personality factors were not explicitly explored.

This thesis implements a modeling approach which is more complete. The systematic and detailed questions in the survey, related to pre-trip and en-route information acquisition, gave the opportunity to evaluate the direct impact of traffic information on users' decisions. Therefore, for modeling the route switching behavior, both pre-trip and enroute information were taken into account. In addition, the way that attitudes and perceptions were incorporated in the models did not introduce inconsistencies or biases in the estimations. The following section describes the major findings of the research conducted in this thesis.

6.2 Major Findings

Socioeconomic characteristics appeared significant only in the model of the acquisition of pre-trip traffic information. Travel characteristics and perceptions about the relevance and reliability of the radio traffic reports were also important factors affecting radio traffic information acquisition. Therefore, it can be said that a more reliable and frequently updated traffic information system than radio, would stimulate the acquisition of traffic information.

The key finding was that en-route diversion is influenced only by attitudinal factors of the drivers and by the information acquisition and not by socioeconomic characteristics or travel characteristics. This indicates that real-time information provides the basis for making en-route decisions. It was also found that the drivers' own observations are still a very important factor towards route switching. This finding is very important for the efficient implementation of route guidance systems. Only a system that gives accurate and precise directions, that really correspond and reflects actual traffic conditions will be successful. Only then will drivers follow the systems' instructions for choosing their route.

In this study, the mechanism by which individuals process information and perform adjustments in their perceptions, under the influence of inherent characteristics and travel experience, was examined. However, much remains to be learned about the interrelationship between commuters' information acquisition, processing, and decision making. This thesis contributed towards the exploration of the complex mechanisms governing users' behavior and its interaction with the facilities' performance and the provision of information.

6.3 Directions for Further Research

As stated in chapter 2, *revealed preference* (RP) and *stated preference* (SP), are the two basic approaches of data collection used to model route choice behavior.

As explained in Chapter 2, SP and RP data contain different levels of accuracy and various types of biases. Therefore their combination is proposed to profit from the relevant advantages and obtain reliable parameter estimates.(A method of combining estimation with RP and SP data, is presented by Morikawa (1989)).

SP data can be generated by using a driver simulator (see section 2.3.2 f driving simulator developed at MIT). This data will allow the calibration of models of drivers' responses in hypothetical scenarios. Moreover, the descriptive and prescriptive information provided by the simulator, will allow the simulation of the day-to-day dynamics of drivers' behavior. RP data can be collected by a pilot study using route-guidance systems or by conducting a detailed diary survey similar to the one used in this study, but involving other population (not restricted to MIT commuters).

Under this approach (combining RP and SP data), route choice behavior wil be modeled by taking into account the effect of the information provided, the learning process through the experience and the role of inertia. Therefore RP and SP data combination provides a valuable continuation of this research.

Appendix A

Ordered Probit Model

The use of the ordered probit model is appropriate when the observed dependent variable is ordinal. The model assumes a linear effect of each independent variable as well as a series of break points between categories for the dependent variable. The ordinal scale is supposed to represent the true underlying variable.

The ordered probit model was described by McKelvey and Zanoiva in 1975 , as follows:

- Assume that the variable of theoretical interest U^* satisfies:

  $$U^* = X\beta + u$$

  where

  $$u \sim N(0, \sigma I)$$

  the error term, is a multivariate normal with expectation **0** and variance - covariance matrix $\sigma^2 I$.

- Assume that Z is a categorical variable with M response categories $R_1, \ldots, R_M$ which is derived from U^* as follows:

  - assume there are $M + 1$ real numbers $\mu_0, \mu_1, \ldots, \mu_M$ with:

$$\mu_0 = -\infty,\ \mu_M = \infty \text{ and } \mu_0 \leq \mu_1 \leq \ldots \leq \mu_M$$

such that:

$$Z_j \in R_k \Longrightarrow \mu_{k-1} < U_j^* \leq \mu_k$$

for $1 \leq j \leq n$ and $1 \leq k \leq M$

- Since Z is ordinal. it can be also represented a series of dummy variables. Therefore, we can define:

$$Z_{jk}n = \begin{cases} 1 & \text{if } Z_j \in R_k \\ 0 & \text{otherwise} \end{cases}$$

$$for\ 1 \leq j \leq n.\ 1 \leq k \leq M$$

- Therefore, the model to be estimated is:

$$Pr[Z_{jk} = 1] = \Phi[\mu_k - \sum_{i=0}^{K} \beta_i X_{ij}] - \Phi[\mu_{k-1} - \sum_{i=0}^{K} \beta_i X_{ij}]$$

where, $\Phi(t)$ represents the cummulative standard normal density function and under the assumption that $\mu_1 = 0$, $\sigma = 1$

- Note that the estimation give us $(k+1)$ values of$\beta(\beta_0 \ldots \beta_k)$ and $(M-2)$ values of M $(\mu_2 \ldots \mu_{M-1})$. Therefore, the total number of estimated parameters are $Q = M + K_1$

For example, assume Z is an observed categorical dependent variable, such that:
$Z = 1$, if response = I strongly disagree
$Z = 2$, if response = I moderate disagree
$Z = 3$, if response = I do not agree or disagree
$Z = 4$, if response = I moderately agree
$Z = 5$, if response = I strongly agree
Therefore the estimated probabilities for the example are:
$P(Z = 1) = P(U^* < \theta_1) = \Phi(\theta_1 - \beta' X)$

$P(Z = 2) = P(\theta_1 \leq U^* < \theta_2) = \Phi(\theta_2 - \beta'X) - \Phi(\theta_1 - \beta'X)$

$P(Z = 3) = P(\theta_2 \leq U^* < \theta_3) = \Phi(\theta_3 - \beta'X) - \Phi(\theta_2 - \beta'X)$

$P(Z = 4) = P(\theta_3 \leq U^* < \theta_4) = \Phi(\theta_4 - \beta'X) - \Phi(\theta_3 - \beta'X)$

$P(Z = 5) = P(\theta_4 \leq U^*) = 1 - \Phi(\theta_4 - \beta'X)$

and the number of estimated parameters is $Q = k + 4$

The main advantage of the ordered probit model comparing to regression, logit or probit models, is that it provides "thresholds" which indicate the levels of importance allocated to each factor, so there are no arbitrary assumptions about the magnitudes of differences between categories of the dependent variable.

To be more specific the two sets of parameters included in the ordered probit model can be explained as follows: The constant and other threshold parameters indicate the range of normal distribution associated with specific values of the explanatory variables. The remaining parameters represent the effect of changes in each explanatory variable on the underlying scale. These parameters indicate the relative importance of each variable in determining the likelihood that a factor play or not an important role in their behavior.

In the ordered probit model the effect of a variable on the changes in probabilities of the dependent variable at the two extremes (dependent variable being 1 and 5) is clear. However, changes in probabilities of the intermediate categories are not clear. Thus a positive sign would imply a decrease of the probability of disagreement (coded by 1) and an increase of the probability of agreement with the related factor (coded as 5) relative to the base.

Appendix B

The Jackknife Method

The jackknife estimate of standard error was introduced by Tukey in 1958 (see Miller (1974)). The jackknife gives a nonparametric estimation of the statistical error. The attractive properties of this method is that it acquires very little in the way of modeling assumptions and can be applied in an automatic way to any situation no matter how complicated. The jackknife can be applied to any statistic that is a function of n independent and identically distributed variables.

The jackknife variance can be estimated in 5 steps:

1. Let our sample ψ, which consists of N observations. Partition ψ as $\psi' = (\psi'_1, \psi'_2, \ldots, \psi'_G)$ where G is the number of groups and m is the number of observations in each group such that $G * m = N$

2. Let $\hat{\beta}$, the estimator acquired using all the data. Let $\hat{\beta}_{-i}$, the estimator obtained by omitting ψ_i, for $i = 1, 2, \ldots, G$.

3. Calculate the pseudovalues:

$$\beta_i^* = G\hat{\beta} - (G - 1)\hat{\beta}_{-i}$$

for $i = 1, 2, \ldots, G$.

These β_i^* can be treated like G observations on $\hat{\beta}$ (though not independent)

4. Calculate $\bar{\beta}^*$ as:

$$\bar{\beta}^* = \frac{1}{G}\sum_{i=1}^{G}\beta_i^*$$

5. Estimate the variance of $\hat{\beta}$ as:

$$Var(\hat{\beta}) = \frac{1}{(G-1)G}\sum_{i=1}^{G}(\beta_i^* - \bar{\beta}^*)(\beta_i^* - \bar{\beta}^*)'$$

For each coefficient, after the estimation of the variances the correct t-statistics were calculated as the ratio of the $\hat{\beta}$ over the $\sqrt{(Var)}$. In the tables the correct standard errors and t-statistics are reported.

Appendix C

A Survey of Your Home to M.I.T Commute

Center for Transportation Studies Massachusetts Institute of Technology

May 1991

Attached is a questionnaire prepared by a research team in the Center for Transportation Studies at MIT, in cooperation with the MIT Planning Office. This questionnaire is part of an on going research at MIT in the area of Intelligent Vehicle Highway Systems (IVHS), which aim at reducing congestion by providing on-line and user specific information to commuters using a variety of technologies. It is designed to provide transportation planners with a better understanding of the routes you follow on your daily commute, your preferences when it comes to choosing those routes, your reliance on traffic reports, and your parking needs at MIT.

You are kindly requested to fill out this questionnaire. By filling out this questionnaire you will help us design systems which will provide drivers with relevant, useful, and reliable information. It will also allow the MIT Planning Office to be more responsive to your preferences and needs in the future. All responses are **strictly confidential.**

How to fill out this questionnaire:
The questionnaire consists of two parts; **Part I** asks you about your usual commute to MIT, and **Part II** about your specific commute during the week of May 6 to May 10. Please fill out both parts and return them in the envelope provided by May 16, 1991.
Please feel free to write comments in the margins wherever appropriate.

Thank you in advance for your time and effort.

PART I: Your Usual Commute to MIT

1. In a typical 5 day work week, **how many times** do you use each of the following modes to commute to work:
   __ Drive Alone   __Carpool Driver   __Carpool Passenger
   __ Public Transportation   __other:__________

2. In a typical 5 day work week, how many days do you come to MIT? ____ days

3. Do you come to MIT on weekends? ☐ often ☐ occasionally ☐ never

*FOR THE REST OF THIS SURVEY WE ARE INTERESTED IN **DRIVERS** BEHAVIOR AND CHOICES. IF YOU NEVER DRIVE TO WORK, PLEASE DO NOT FILL THE REST OF THE SURVEY. THANK YOU FOR YOUR WILLINGNESS TO PARTICIPATE.*

4. When **driving** to MIT:

a. What time do you usually leave home? hour ___ min ___ ☐ a.m ☐ p.m.

b. What time do you usually arrive at MIT? hour ___ min ___ ☐ a.m ☐ p.m.

5. How much flexibility do you have in choosing the time you arrive at work on a daily basis?

☐ none ☐ up to 15 minutes ☐ 16 - 30 minutes

☐ 31 - 60 minutes ☐ more than an hour

6. Think about a **typical** car trip from your home to work. Assume "**regular**" traffic conditions, i.e. **no** extreme traffic delays, **no** major incidents and **no** weather related problems. Under these conditions, how long does it **usually** take you to drive from your home to work? Please specify a range (e.g. from 40 to 55 minutes): from _____ to _____ minutes.

7. How often does your driving time to work **exceed** the range you specified in question 6?

☐ very often (more than once a week) ☐ often (approx. once a week)

☐ occasionally (approx. twice a month) ☐ rarely (approx. once a month)

☐ very rarely (less than once a month)

8. What is the <u>shortest</u> driving time you have <u>ever</u> experienced during your home to work commute? ___ minutes

9. What is the <u>longest</u> driving time you have <u>ever</u> experienced during your home to work commute? ___ minutes

10. In a **typical** 5 day work week, how many significantly different routes from home to MIT do you use? ____ routes (by "significantly different" we mean routes which almost do **not** overlap, for example: Mass. Pike and Route 9, or 93 and Morrissey Blvd.)

11. Please describe below your **most frequently used route** to MIT by indicating the **major streets, highways, and** bridges that compose the route:______________________________

____

12. Do you usually make stops on your way to MIT? ☐ no → proceed to question 14

☐ yes, total duration of stops is approx. ____ minutes

13. What is the purpose of your stops? ☐ drop a passenger ☐ pick a passenger

☐ eat ☐ run errands ☐ fill gas ☐ other:__________________

14. Where do you usually park your car?

☐ at an MIT parking lot ☐ on street

☐ on street at a meter ☐ other:__________

15. To which MIT parking facility do you have a sticker? ______________

16. How long does it usually take you to get from your parked car to your MIT destination? ___ minutes

17. What time do you usually leave MIT? hour____ min____ ☐ a.m ☐ p.m.

Your Attitudes and Preferences

18. On a sc·ie of 1 to 5, where 1 indicates "strongly disagree" and 5 indicates "strongly agree", indicate your level of agreement with the following statements by checking th· appropriate box:

	strongly disagree 1	2	3	4	strongly agree 5	not relevant
I am very familiar with at least 2 significantly different routes to work						
I often change my planned route while driving						
I like discovering new routes						
I am willing to try new routes to avoid traffic delays						
I always listen to radio traffic reports						
I usually follow the recommendations of radio traffic reports						
Radio traffic reports are usually reliable						
When traffic reports are different from my own observation, I ignore them						
I often change my route after listening to radio traffic reports						
I trust my own judgement more than traffic reports						
Traffic reports do not provide relevant information						
I am willing to pay in order to get more useful traffic information						

19. On a scale of 1 to 5 where 1 indicates "not important at all" and 5 indicates "very important", indicate the importance of the following factors in choosing your route to work:

	not important at all 1	2	3	4	very important 5
Time of day					
Commute time					
Habit					
Time spent stopped in traffic					
Number of traffic lights					
Traffic reports					
Risk of delay					
Weather					

PART II: YOUR COMMUTE TODAY

THIS PART OF THE QUESTIONNAIRE RELATES TO YOUR DRIVING BEHAVIOR DURING A SPECIFIC WEEK. IT CONTAINS 5 IDENTICAL SECTIONS, ONE FOR EACH DAY FROM **MAY 6 TO MAY 10**. PLEASE FILL OUT EACH SECTION AFTER YOU HAVE COMPLETED YOUR COMMUTE TO MIT FOR THAT DAY.
EVEN IF YOU MISS FILLING OUT THE SURVEY FOR ONE DAY DUE TO ANY REASON, PLEASE FILL OUT THE INFORMATION FOR THE SUBSEQUENT DAYS.

Would you be willing to respond to a follow-up questionnaire about your driving behavior during the next year?
If so, please fill out the following:

Name:______________________
MIT address:_________________

Participants will also receive a summary of our findings.

If you wish to remain anonymous, please take the time to fill out PART II anyway.

All responses are **strictly confidential**.

This part is designed to monitor your daily commute from home to MIT. We need to know whether the route you followed to work everyday was influenced by traffic information you listened to, by unusual traffic conditions you encountered on your way to work, or by commuting experience on the previous day. We are also interested in diversion decisions you made while on your way to MIT.

YOUR COMMUTE FOR MONDAY, MAY 6, 1991

(1) How did you get to MIT today? ☐ Drive Alone ☐ Carpool Driver
☐ Carpool Passenger ☐ Public Transportation ☐ other:__________

IF YOU DID NOT DRIVE YOURSELF TO WORK TODAY, PLEASE IGNORE THE QUESTIONS FOR TODAY. CONTINUE TOMORROW WITH THE NEXT SECTION.

(2) Did you receive traffic information **before** you left home today?
☐ yes, from radio ☐ yes, from TV
☐ no → proceed to question 5

(3) Did the information that you received **before** leaving home influence your route choice for today?
☐ a lot ☐ somewhat ☐ very little ☐ not at all

(4) What did the **information** you received indicate about traffic conditions on **the route you decided to take?**
☐ much worse than usual ☐ worse than usual ☐ usual traffic conditions
☐ better than usual ☐ much better than usual ☐ I don't remember
☐ no information ☐ other:____________

(5) Once you started your trip, what were the traffic conditions **you observed** at the beginning of your trip?
☐ much worse than usual ☐ worse than usual ☐ usual traffic conditions
☐ better than usual ☐ much better than usual ☐ other:____________

(6) **While driving**, did you receive any information about the route you were following?
☐ yes, which radio station? ________ ☐ no → proceed to question 8

(7) What did the **information** indicate about traffic conditions on the route you were following?
☐ much worse than usual ☐ worse than usual ☐ usual traffic conditions
☐ better than usual ☐ much better than usual ☐ I don't remember
☐ no information ☐ other:____________

(8) After you started your trip to work, was there a way to switch to another route that will take you to your destination?
☐ yes ☐ no → proceed to question 14

(9) While driving, did you switch from the route you were following ?
☐ yes ☐ no → proceed to question 14

(10) Before you switched routes, did you get any radio information about the route you switched to?
☐ yes ☐ no → proceed to question 12

(11) What did the **information** indicate about traffic conditions on the route you switched to?
☐ much worse than usual ☐ worse than usual ☐ usual traffic conditions
☐ better than usual ☐ much better than usual ☐ I don't remember
☐ no information ☐ other:____________

(12) Based on your observation, what were traffic conditions on the route you switched to?
☐ much worse than usual ☐ worse than usual ☐ usual traffic conditions
☐ better than usual ☐ much better than usual ☐ other:________________

(13) Why did you switch? check all boxes that apply:
☐ radio traffic reports ☐ your own observation on traffic conditions
☐ forced detour ☐ other (please specify):____________________

(14) Did you make any stops on your way? ☐ yes, total duration of stops was ___ minutes
☐ no → proceed to question 16

(15) What is the purpose of your stops? ☐ drop a passenger ☐ pick a passenger
☐ eat ☐ run errands ☐ fill gas ☐ other:________________

(16) When did you arrive at your MIT destination? hour__ min____ ☐ a.m. ☐ p.m.

(17) Please describe the route you took today to MIT by indicating the major streets, highways, and bridges that compose the route:____
____

About Your Trip Today

(18) On a scale of 1 to 5, where 1 indicates "strongly disagree" and 5 indicates "strongly agree", indicate your level of agreement with the following statements:

	strongly disagree 1	2	3	4	strongly agree 5	not relevant
Traffic conditions today were better than usual						
Traffic information received today was useful						
My commute time today was worse than usual						
I am satisfied with my route choice today						
I could have saved at least 5 min. had I taken another route						
I could have saved at least 5 min. had I gotten relevant information						
When I made my decision to switch routes today, I was confident that I would be better off						

(19) Write any other comments related to your trip to work today (optional):
____
____
____

ABOUT YOURSELF

The information requested in this section relates to your personal and household data. We need this information to better understand how personal and family characteristics affect commuting choices. All information collected will remain strictly confidential.

20. Sex: ☐ Male ☐ Female

21. Marital status: ☐ Married ☐ Unmarried

22. What is your age group?
☐ Less than 20 years ☐ 20 - 29 years ☐ 30 - 39 years
☐ 40 - 49 years ☐ 50 - 64 years ☐ 65 or older

23. What is the highest level of education you have completed?
☐ High school or less ☐ Some College
☐ Graduated College ☐ Post graduate work

24. What is your home Zip Code? ___________

25. How long have you lived at your present home address? ____ years

26. Do you own or rent your dwelling unit?
☐ own ☐ rent

27. How many persons including yourself live in your household? ______ persons

28. What is the total number of automobiles owned by your household? ____ automobiles

29. What is your household's approximate yearly income from all sources (before taxes)?
☐ Less than $20,000 ☐ $20,000 - $40,000 ☐ $40,000 - $60,000
☐ $60,000 - $80,000 ☐ $80,000 - $100,000 ☐ More than $100,000

30. How long have you worked at your present job location? ____ years

31. Which of the following categories best describes your position?
☐ Undergraduate Student ☐ Graduate Student ☐ Academic Staff
☐ Tenured Faculty ☐ Non-Tenured Faculty ☐ Administrative Staff
☐ Service ☐ Support Staff ☐ Research Staff
☐ Other:___________

General

32. Write any other comments related to your daily commute to work, the way you choose and follow routes, your attitude towards traffic reports, and your parking needs (optional):

____
____
____
____
____

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