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16. Abstract

Advanced Traveler Information Systems (ATIS), by providing real-time traffic information, can assist trip-makers in selecting efficient travel choices, and aid the attainment of desirable system goals including reduced costs and increased efficiencies. The success of ATIS in achieving such goals critically depends on user behavior in response to information. This research focuses on investigating dynamic aspects in commuter behavior under real-time information. A dynamic interactive travel-behavior simulator, that enables a consistent representation of the nonlinear time-dependent interactions between network performance, trip-makers choices, and information, is used to observe trip-maker behavior. Using the simulator, interactive experiments are conducted where a range of experimental factors including network loading, day-to-day traffic evolution and ATIS information strategies are varied and the consequent trip-maker behavior is observed. Constituent models are proposed to analyze the choice dimensions of route, departure time, and compliance. The dynamic kernel logit (DKL) formulation is presented for analyzing these data and its theoretical and computational suitability established. The results confirm the significance of compliance and inertia as key mechanisms influencing route choice. Departure time adjustments appear to be based on a sequential heuristic search. Calibrated models also provide evidence of learning, adjustment, perception, judgment, and updating processes in trip-maker behavior. Empirical results indicate that real-time information and time-dependent network conditions are strong determinants of trip-maker behavior in a commuting context. The nature and quality of ATIS information (accuracy and reliability), the magnitude of network loading and its day-to-day evolution, and users' past traffic experience are important influences on how commuters select routes and departure times. At the unobserved level, general dynamic and stochastic patterns, including, heterogeneity, state-dependence, habit-persistence, and correlations are present in trip-makers' decisions. These substantive results have important implications for network state prediction, travel demand forecasting, design and evaluation of ATIS services and deployment of Intelligent Transportation System (ITS) programs. User behavior models developed here can be integrated with dynamic network traffic assignment models to obtain more accurate system performance modeling capabilities with considerable applications in tactical and strategic system planning and traffic operations.

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DYNAMIC DECISION AND ADJUSTMENT PROCESSES IN COMMUTER BEHAVIOR UNDER REAL-TIME INFORMATION

by

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Hani S. Mahmassani

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ABSTRACT

Advanced Traveler Information Systems (ATIS), by providing real-time traffic information, can assist trip-makers in selecting efficient travel choices, and aid the attainment of desirable system goals including reduced costs and increased efficiencies. The success of ATIS in achieving such goals critically depends on user behavior in response to information. This research focuses on investigating dynamic aspects in commuter behavior under real-time information. A dynamic interactive travel-behavior simulator, that enables a consistent representation of the nonlinear time-dependent interactions between network performance, trip-makers choices, and information, is used to observe trip-maker behavior. Using the simulator, interactive experiments are conducted where a range of experimental factors including network loading, day-to-day traffic evolution and ATIS information strategies are varied and the consequent trip-maker behavior is observed. Constituent models are proposed to analyze the choice dimensions of route, departure time, and compliance. The dynamic kernel logit (DKL) formulation is presented for analyzing these data and its theoretical and computational suitability established. The results confirm the significance of compliance and inertia as key mechanisms influencing route choice. Departure time adjustments appear to be based on a sequential heuristic search. Calibrated models also provide evidence of learning, adjustment, perception, judgment, and updating processes in trip-maker behavior. Empirical results indicate that real-time information and time-dependent network conditions are strong determinants of trip-maker behavior in a commuting context. The nature and quality of ATIS information (accuracy and reliability), the magnitude of network loading and its day-to-day evolution, and users' past traffic experience are important influences on how commuters select routes and departure times. At the unobserved level, general dynamic and stochastic patterns, including, heterogeneity, state-dependence, habit-persistence, and correlations are present in trip-makers' decisions. These substantive results have important implications for network state prediction, travel demand forecasting, design and evaluation of ATIS services and deployment of Intelligent Transportation System (ITS) programs. User behavior models developed here can be integrated with dynamic network traffic assignment models to obtain more accurate system performance modeling capabilities with considerable applications in tactical and strategic system planning and traffic operations.

EXECUTIVE SUMMARY

Advanced technologies allow tripmakers to receive real-time traffic information through a range of Advanced Traveler Information System (ATIS) devices. The effectiveness and impacts of ATIS critically depend on users choices over time, and the resulting time-dependent interactions between network conditions, real-time information, and user behavior. This research investigates dynamic decision and adjustment processes in user behavior under real-time traffic information.

The four principal objectives of this research are to a) develop a framework to model commuter behavior dynamics, b) investigate the influence of ATIS information strategies on commuter behavior, c) examine the role of network conditions on user behavior under real-time information, and, d) analyze cognitive and decision processes underlying observed commuter behavior dynamics and propose constituent models.

Capturing the influence of information attributes on user behavior will enable the design, and development of effective ATIS products and services. Understanding and quantifying the role of ATIS is also critical for the assessment of information impacts and evaluation of investment into alternative ATIS technologies. Research on user behavior dynamics has significant implications for traffic management since users' decisions during the peak period determine time-dependent congestion patterns and related system performance. Furthermore, route and departure time changes from day-to-day result in changes in O-D flows on the network, which are important for tactical and strategic planning purposes. It is expected that the development of more accurate dynamic behavioral models will translate into accurate and robust dynamic network modeling capabilities.

Overview of the Approach:

To model dynamics in commuter behavior under information, it is necessary to observe data on users' choice behavior (both within-day and day-to-day) simultaneously with the information supplied and network conditions. Since such data are currently not available from real traffic systems, an interactive travel-behavior simulator is used as an observational basis, to measure relevant behavioral data at a highly disaggregate temporal and spatial resolution. The following features of this simulator enhance its appeal to measure and observe user behavior dynamics (Chapter 3). The simulator's multi-user capability allows simultaneous data collection from several participants. The decisions of each participant are input into a dynamic traffic simulator as they occur. A dynamic traffic simulation engine determines the time-varying traffic stimuli experienced by each trip-maker (participant in the study) based on the interactions between the choices of all trip-makers, prevailing traffic conditions and network constraints. Unlike stated-preference approaches, users (respondents) experience the consequences of their choices in this simulator in the form of congestion-related delays, and schedule delays. Furthermore, arrival time constraints are imposed on the respondents in the study in order to simulate a commuting trip. Finally,

real-time information provided to each user is customized to reveal traffic conditions corresponding to his/her unique traffic experience.

This travel behavior simulator is used to design and conduct two sets of experiments for investigating key factors influencing commuter behavior under information. In the first set, the effect of varying network conditions (magnitude of network loads and its day-to-day evolution) on commuter behavior was investigated. The second set examined the role of varying ATIS information supply strategies on trip-maker behavior under information. A total of nearly 200 actual commuters (with 65 and 135 participants respectively in experiments one and two) from the city of Austin were recruited to participate in the study. In the experiments, the participants supplied departure time and route choice decisions (five per day) on a simulated commuting corridor for a series of 'simulated' days (up to 12 days). To assist users in these decisions, the ATIS provided them with the following information elements: travel time on alternative facilities, color-coded congestion information, auditory and visual cues when a user is stuck in traffic, and feedback on trip-time and arrival time along the user's chosen path. The decisions made by respondents, the information supplied, and the time-dependent traffic conditions on all network facilities were recorded.

The association between decision dimensions of interest (route switching, departure time switching and compliance decisions) and the experimental factors are analyzed using an array of statistical models. The statistical models are calibrated by specifying the behavioral framework, appropriate functional form, included variables, and error-term distributions. The departure time switching, route switching and compliance decisions are modeled using the Dynamic Kernel Logit formulation discussed below and estimated using Simulated Maximum Likelihood Estimation (SMLE). A range of other models including multinomial probit models, cross-sectional time-series models, and confirmatory factor analysis models are developed to analyze related choice dimensions. Following standard modeling practice, inferences are drawn based on the magnitude and statistical significance of model coefficients. The proposed models are also tested against alternative behavioral and functional specifications using both nested and non-nested statistical tests.

To internally validate the proposed models, the significant factors influencing the switching decisions are compared and contrasted across the two data sets, modeled using different behavioral paradigms. Many of the findings, presented below, appeared to be robust across the two data sets. Some differences pertaining to the different experimental treatments were noted across the two data sets. The results are also consistent with some of the earlier findings from a travel-diary survey of commuter behavior (Jou et al., 98), though in the absence of information. However, in view of the moderate sample size, nature of experiments and associated conditions, and assumptions in model specifications, caution is strongly advised in generalizing the results presented here. The model results and findings, discussed below, will need further external validation, as ATIS usage becomes prevalent, and as required data on network conditions, trip-maker choices and real-time information from real commuting systems become available at the desired temporal resolution.

Significant Findings and Implications:

Methodological Findings:

Modeling dynamics in commuter behavior over a period of several days involves the calibration of longitudinal discrete choice models of a large dimensionality. For example, modeling route switching data in this study requires developing models for 55 joint binary choice decisions per observation. The computational cost of the multinomial probit (MNP) formulation, typically used for longitudinal models, is prohibitive for such a large dimensionality. In fact, MNP models with more than 20 alternatives have hardly been reported in the literature. Therefore, the Dynamic Kernel Logit (DKL) formulation is presented as a methodological alternative to the multinomial probit (MNP) framework for modeling dynamics in choice behavior (Chapter 4). The suitability of this formulation to analyze the longitudinal analysis of discrete choice data is established based on theoretical and computational considerations. This formulation is shown to be asymptotically (as number of alternatives/panel periods increase) computationally more efficient than the MNP. However, for smaller problems (when NaltTpanels < 25 approximately), there is little computational advantage in using the DKL formulation relative to the MNP formulation. This suggests that MNP may be preferred to DKL for most cross-sectional discrete choice models. In terms of accuracy of estimates, numerical experiments and convergence results indicate that the DKL estimates are comparable to the MNP parameter estimates. It must
be noted, however, that both formulations are susceptible to the problems of local optima and identification issues due to the non-convex nature of the likelihood function.

Substantive Findings:

The DKL framework is applied to model the dynamics in various choice dimensions of interest. The first set of models analyze the influence of variations in network conditions on route and departure time switching decisions using data from the first experiment (Chapter 5). These models are based on well- established boundedly-rational behavioral rules for switching, where a user will switch routes (departure times), if the corresponding threshold (schedule delay indifference band) is exceeded. The results indicate a significant effect of both the magnitude of network congestion, and its day-to-day evolution (random or systematic). Network performance measures on alternative facilities, and opportunities for switching also strongly affect users' switching decisions under information. Other influential factors include interactions between users past choices and supply conditions, and adverse traffic experience. The strong impact of information and its differential effect on various user segments suggests that real-time information may be used to manage and control traffic through Variable Message Signs (VMS), in-vehicle devices etc. The findings also indicate that trip-maker behavior dynamics is influenced by dynamics in network conditions and vice-versa. Therefore, it is necessary to incorporate realistic user behavior components in dynamic traffic assignment methodologies to develop robust and more accurate models of system performance.

Users' dynamic compliance decisions are analyzed based on the utility maximization framework (Chapter 6). The model results suggest that users are particularly sensitive to the quality of information provided by the ATIS. When the ATIS provides inaccurate, incomplete (in terms of network coverage), or unreliable information, users display a markedly reduced compliance propensity. Users also exhibit a range of compliance behaviors in response to the nature, type, and feedback provided under various ATIS information strategies. In particular, users respond more favorably (in terms of compliance) to prescriptive information than descriptive information. Similarly, a greater compliance is noted in response to reliable predicted trip-time information compared to prevailing trip-time information. Providing feedback on trip performance on the chosen path in relation to optimal path also results in favorable compliance behavior. These findings highlight the need for accurate and reliable ATIS information in order to achieve desired behavioral response. The accuracy of such information is, in turn, predicated on the capability to accurately predict user behavior under information. The results also suggest that the scope of information (feedback provision), timeliness (predicted/prevailing trip time), and the extent of network coverage are important additional design criteria for ATIS services.

A joint route and departure time switching model is calibrated using data from the second experiment to investigate the presence of structural effects in commuter behavior dynamics (Chapter 7). This model captures various structural effects in commuter behavior including state-dependence, observed and unobserved heterogeneity, and habit persistence. The results indicate that these effects are indeed significant and considerably improve model fit in terms of the log-likelihood. The significance of state-dependence implies that a user's current choice can causally alter the decision-maker's preferences, choice sets and/or information sets for future decisions. Heterogeneity is observed in the inherent propensity to switch, and in the sensitivity of users to attributes affecting choices, as well. A general yet parsimonious error structure is proposed which considerably reduces computational cost of calibration. Many variables found significant in this model were earlier significant in the switching models from the first experiment and earlier investigations by Liu et al. (98). These findings imply that the application of conventional models (that disregard structural effects) can lead to serious mis-specification and forecasting errors. These results also suggest that idealized assumptions on user behavior (for e.g. equilibrium departure time choices, and shortest path choice) typically employed in network analyses are inappropriate for evaluating the impact of information.

Behavioral Findings:

The variability in user behavior over time suggests the presence of complex decision processes underlying observed choice dynamics. A preliminary examination of choice behavior revealed considerable support for the presence of four component processes, namely, learning, perception, judgment, and updating processes (Chapter 8). Instances of two types of learning processes - discrimination and trial-and-error learning are observed in user responses. The learning process is influenced by attentional and motivational factors, and the recency and frequency of experienced events.

Users' perceptions and attitudes, particularly towards schedule delay and congestion, play an important role in the choice process. The proposed perception model suggests that users' trip time perceptions differ significantly from the reported trip time, possibly due to uncertainty regarding traffic conditions and information accuracy. Models analyzing how expectations of arrival time are updated (in response to information and experience) indicate a greater influence of ATIS information under drastically fluctuating traffic environment (as in the random treatment) than when the traffic evolution is more gradual (as in the systematic treatment). These findings provide preliminary insight into the cognitive and decision processes underlying user behavior in the presence of ATIS and emphasize the need for further investigations.

Users are observed to adjust their route and departure time choices over time, in response to information and experience (Chapter 9). Explicit behavioral models are proposed to analyze these adjustment processes in terms of plausible underlying heuristic mechanisms and search strategies. Formal statistical tests indicate that these models significantly outperform conventional utility maximization based models of route and departure time choice. The departure time adjustment model suggests that users adjust their departure times from day-to-day in a manner consistent with a heuristic greedy search. In this search process, it appears that users evaluate alternatives in a sequential manner, with alternatives closer to the current choice being considered preferentially ahead of other alternatives. Models of path choice adjustment highlight the significance of inertial and compliance mechanisms. The inertial mechanism reflects the tendency of a user to continue on the current path due to cognitive, information and physical costs of switching. The compliance mechanism represents a user's propensity to follow the 'best' (least trip time) path reported by the ATIS. Statistical tests indicate that both the mechanisms operate simultaneously and the actual choice and vary dynamically with choice context, system performance measures, and network conditions. These findings cast a shadow on the suitability and behavioral realism of the utility maximization framework for representing trip-maker behavior dynamics under real-time information, or at least on our ability to derive a sufficiently realistic and operational specification of a possible underlying utility function. Further, they point out the need to consider the role of inertia and habit, users' judgment of ATIS information, information processing capabilities and the role of constraints in the environment on the dynamic decision processes of commuters.

The models and results presented here indicate the need for investigations along the following lines in the future: investigation of traveler behavior at a broader scope, development of psychometric and measurement frameworks to model user decision processes in real-time, dynamic network analysis and applications to traffic management. The scope of traveler behavior models presented here can be enhanced significantly by considering other trip purposes, more travel choice dimensions, interactions between activity and travel patterns, and behavioral adjustments over the long-term. Significant progress remains to be made in enhancing the psychometric and econometric frameworks to measure and quantify user decision processes in the presence of real-time information. In particular, investigations are much

needed with regard to mechanisms in trip-maker's learning and adjustment behavior over time, reliable data collection on latent cognitive processes, insights into the role of constraints, and the role of information acquisition, representation, and usage in choice decisions. The integration of richer user behavior models proposed here with dynamic traffic modeling in a micro simulation framework is yet another promising area for future research that will enable more realistic network performance analyses. As noted earlier, further external validation of the findings from this study with data from real commuting systems is also highly desirable.

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CHAPTER 1: INTRODUCTION

1.1 BACKGROUND

The advent of the information era offers promising new opportunities to enhance and improve users' travel experiences, and increases transportation system efficiency through Intelligent Transportation Systems (ITS) technologies. Existing system inefficiencies may be largely attributed to the limited network capacity available to support the growing mobility needs of the increasing number of users and the limited network capacity available to support it. Advanced Transportation Management Information Systems (ATMIS) seek to exploit real-time information to better match travel demand and system capacity to improve network performance. Advanced Traveler Information Systems (ATIS), a major component of ATMIS, attempt to induce the selection of more efficient trip choices by users, through the dissemination of timely and accurate information on network conditions (Schofer et al., 1993). Thus, ATIS offers considerable promise in influencing trip-maker behavior favorably for achieving desired system objectives.

The ability of ATMIS to accomplish its objectives critically depends on how successfully information influences driver behavior in the desired direction, and how effectively it supports traffic management decisions. User behavior directly determines network flow dynamics, both within-day and day-to-day. The provision of real-time information (both pre-trip and en-route) can influence users' route and departure time choices, thus determining the within-day distribution of vehicles on the network. In contrast, day-to-day dynamics result from users' learning about the traffic environment based on experience and information from ATIS, and consequent behavioral responses.

This work focuses on the dynamic aspects in the context of commuter behavior due to the following key considerations: Commuters contribute significantly to peak-period traffic flow in many urban areas. Second, the repetitive nature of commuting trips makes them better suited to learn about traffic and information environment (based on information and experience), than trips of an irregular nature. In modeling commuting behavior, the focus is primarily on the dimensions of route and departure time choice, as the dimensions of destination and mode choice are relatively fixed for most commuters (at least in many cities in the U.S). Furthermore, it is essential to analyze commuters' route and departure time choices as the interplay of these decisions with network supply constraints often determine the observed congestion build-up and dissipation patterns in many large urban areas around the world.

The effectiveness of ATMIS in addressing congestion and related problems depends on the time-dependent interactions between three major system components: trip-makers' choices, real-time information and network (supply) conditions. Among these factors, the interactions between trip-maker behavior and real-time information are critical in determining the evolution of network conditions (within-day) and system performance over time (day-to-day). Trip-maker behavior is arguably the most fundamental, yet one of the least understood areas. This research is, therefore, directed towards

investigating user behavior dynamics and its interrelationship with ATIS information, and network conditions.

In addition to the intrinsic scientific interest of understanding and describing the dynamics of travel behavior under real-time information, investigations in this regard have important practical implications for ATIS development and design, transportation planning, and traffic management and control. The next section elaborates on the motivation behind this line of research. Section 1.3 discusses the main objectives and the associated tasks. The next section presents an overview of the research methodology adopted in this study to accomplish these objectives. An overview of the major contributions from this study is provided in Section 1.5. The last section outlines the structure of this *Technical Report*.

1.2 MOTIVATION

As discussed previously, the success and effectiveness of transportation demand and supply management efforts critically depend on the interactions between the three major factors influencing system performance:

- User behavior in response to information and experienced network conditions,
- Network supply conditions, or the spatio-temporal distribution of users on the network, and,
- Real-time traffic information.

The nature of mutual interdependency between these three factors is illustrated qualitatively in Figure 1.1 and discussed below. The effectiveness of ATIS in promoting more efficient trip-making therefore depends on user response to ATIS information. Network conditions encountered and real-time information supplied by ATIS influence trip-makers' choice behaviors. For instance, users tend to avoid congested routes, and tend to select routes with lower travel time than other routes. Real-time information can influence trip-makers' choices by making them aware of more efficient opportunities on the network over time, even as the trip-maker traverses on the network.

Network performance and supply conditions, in turn, depend significantly on trip-makers' choices as well as real-time traffic information. User behavior influences evolving traffic conditions on the network through the collective interaction of users' choices (route and departure times) under the prevailing network constraints. The role of real-time information in influencing supply conditions is two-fold. First, information can be used to support traffic control and management decisions, which directly influence traffic flows and network performance. Second, information can also indirectly affect supply conditions by influencing user behavior through ATIS.

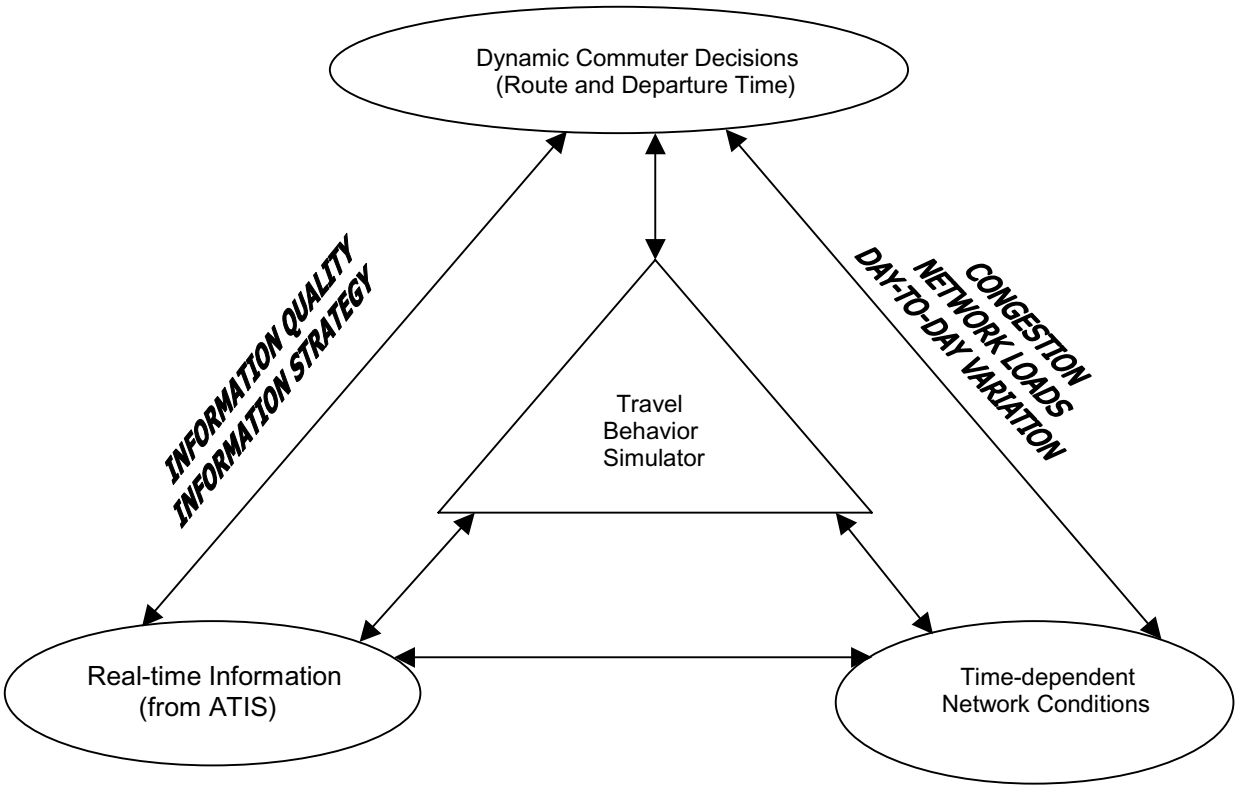

FIGURE 1.1

Interactions between trip-maker behavior, network conditions, and real-time information.

Real-time traffic information furnished by ATIS devices is directly influenced by supply conditions, as ATIS seek to convey information about changing traffic conditions (in turn, influenced by trip-makers' choices in the system). Furthermore, user behavior and supply conditions interact with each other to influence ATIS information in a manner that is not evident. To illustrate this effect, consider the role of perceived information quality on trip-maker behavior. The usage and effectiveness of ATIS information depend on the quality of information as perceived by the users. This perceived quality of information is likely to be based upon a comparison of supplied information with the user's experience and past knowledge (see for e.g. Bonsall et al., 1991; Mahmassani and Chen, 1993; Abdel-Aty et al., 1994). Users' experiences, in turn, are acquired as the result of past travel choices and the associated network supply conditions. Thus, network conditions and past user behavior act subtly in influencing perception of information quality. This interaction between choice behavior and the quality of ATIS information highlights the essential role of robust predictive models of user behavior in increasing the accuracy and credibility of ATIS information. Furthermore, this discussion also underscores the complex and time-dependent nature of interactions between user behavior, ATIS information and network conditions. In view of these interdependencies, it is necessary to examine commuter behavior, Advanced Traveler

Information Systems (ATIS), and network conditions as mutually inter-related components of the transportation system with time-dependent and non-linear interactions.

This investigation is partially motivated by the following applications. Commuter behavior research has important implications for traffic management, operations and control. Accurate behavioral models can translate into more robust network state prediction capabilities, with applications in the design of effective control strategies and traffic planning. Advances in commuter behavior research have important implications for the evaluation of congestion relief strategies and development of dynamic traffic assignment methodologies. This line of inquiry is also motivated by the need to obtain insights into trip-maker behavior, particularly with regard to its dynamic aspects.

In examining the role of real-time information as an essential element of the ATMIS framework, this work focuses on the effect of ATIS on commuter behavior and system dynamics. An important motivating consideration in this respect is the need to investigate the influence of various information attributes on user behavior. This will enable the design, development, and deployment of effective ATIS information strategies. Understanding and quantifying the role of ATIS is also critical for the design of ATIS-based composite strategies to improve system efficiency and an assessment of their impacts. This line of inquiry is also likely to provide valuable criteria and guidelines for evaluating investment into alternative ATIS technologies.

The importance of modeling trip-maker behavior has been recognized and documented in a large body of literature spanning over more than four decades. These research efforts have contributed significantly in developing a substantial body of empirical knowledge on modeling and forecasting traveler behavior in various choice dimensions, particularly in the absence of real-time information. Nevertheless, substantial progress remains to be made in unraveling the complex decision and cognitive processes underlying user behavior, especially under real-time information. The principal scientific interest in research along this line of inquiry stems from the need to model commuters' choice behavior in the presence of information as a complex decision process involving many independent decision-makers interacting with each other in complex and non-linear ways in the traffic system. Understanding and representing trip-maker behavior assumes greater urgency in light of availability of real-time information to support these decisions. ATIS, by providing real-time information enable faster and more frequent evaluations of alternative travel options than ever before.

Insights into the cognitive and decision processes in a real-time decision-making environment are necessary to associate, decision-makers' characteristics, attributes of the traffic environment, real-time information and constraints in the decision environment, with behavioral outcomes of interest. It is hoped that understanding the processes underlying user behavior will enable the identification and representation of stable aspects in behavioral processes, that can improve the predictive power of the relevant choice models. Such robust and parsimonious models are desirable because of their increased computational efficiency, enhanced forecasting accuracy, and improved interpretability. Inquiry into

cognitive processes also has important implications for the evaluation of policy measures aimed at managing demand, and assessment of traffic control strategies.

1.3 OBJECTIVES

The four principal objectives of this research are:

1. Develop a framework to model commuter behavior dynamics,
2. Investigate the influence of ATIS information strategies on commuter behavior,
3. Examine the role of network conditions on user behavior under real-time information, and,
4. Analyze cognitive and decision processes underlying observed commuter behavior dynamics and propose constituent models.

The need for research into these four areas stem from wide ranging applications in the areas of commuter behavior modeling, network state prediction, traffic management and planning, ATIS design, deployment and evaluation discussed in the preceding section. A greater emphasis is placed on the first three objectives, namely, representing and modeling commuter behavior dynamics, in view of its significant role in determining several aspects of system performance during the peak period. The following discussion describes the tasks performed in accomplishing the objectives of this study.

The first objective is to examine dynamic aspects in commuter behavior. The relevant dimensions of within-day, and day-to-day dynamics are considered. Within-day dynamics refers to the time-dependent nature of commuters' trip choices on the same-day, more specifically within the peak-period (in the context of this study). Day-to-day dynamics refers to the variation in trip-maker decisions from one day to the next, possibly induced by real-time information and trip-makers' past experiences on the network. The main choice dimensions available to commuters (in most U.S cities) are those of route (pre-trip and en-route) and departure time. The choice dimensions of mode and destination tend to be relatively fixed for commuters at least in the short-term. Therefore, the primary tasks in investigating this objective can be summarized as:

1. Proposing an econometric framework to analyze within-day and day-to-day dynamics in route and departure time choices of commuters,
2. Developing an observational basis to yield commuter behavior data to calibrate dynamic models, and
3. Implementing the econometric framework through appropriate statistical models.

The second objective is to investigate the role of ATIS information strategies on commuter behavior. In this context, the following related tasks are performed. The first relates to investigating how alternative information strategies of ATIS are perceived by trip-makers and how they influence travel decisions. The second is to examine the impact of information quality on trip-maker behavior. The relevant subtasks include: identifying information strategies of interest, incorporating them in a suitable experimental design, observing, modeling, and analyzing traveler behavior under various information strategies, and investigating the role of key ATIS related variables.

The third objective is to study the influence of supply conditions on commuter behavior. The focus is on the influence of network loading and its day-to-day evolution on user behavior. Furthermore, the role of congestion on commuter behavior is also analyzed. The main tasks associated with this objective include developing a suitable observational basis for data-collection, and proposing a framework to model the observed data.

The final objective focuses on cognitive and decision processes underlying user behavior dynamics. To accomplish this objective the following tasks are undertaken:

1. Recognizing the presence of cognitive and decision processes in commuter behavior under real-time information,
2. Characterizing these processes and identifying and analyzing the major factors influencing these on the basis of empirical evidence,
3. Analyzing the effect of these processes on choice behavior through appropriate quantitative models, and,
4. Identifying behavioral mechanisms driving the variability in user choices over time and modeling them.

The next section presents an overview of the research methodology adopted in pursuing these objectives and the associated tasks.

1.4 OVERVIEW OF RESEARCH METHODOLOGY

A variety of measurement, substantive and methodological issues need to be addressed in modeling dynamic decision and adjustment processes in commuter behavior under real-time information. This section briefly outlines these issues in relation to the objectives of the study, and provides an overview of the research methodology adopted in this study to address these issues.

The primary measurement issue in observing commuter behavior dynamics arises from the need to obtain data at the desired level of sufficient spatial and temporal resolution to examine relevant dynamic aspects. In this context, it is necessary to ensure that the decisions supplied by the trip-maker are consistent with the encountered traffic conditions. The dynamic interactions between the traffic environment and commuter behavior under real-time information must be incorporated in the observational framework (Mahmassani and Herman, 1990). Information supplied by the ATIS should be consistent with both the supply conditions and user behavior. To accommodate these measurement requirements, a multi-user dynamic interactive simulator is used as an observational basis to measure trip-maker behavior under real-time information. The interactive simulation framework developed at the University of Texas at Austin (Chen and Mahmassani, 1993) is particularly suited to investigate trip-maker behavior under ATIS. Due to its multi-user capabilities, the trip decisions of a large number of trip-makers can be observed simultaneously. Information provided by ATIS is simulated to be consistent with each individual's decision state as well as the traffic reality for all users. This simulator ensures mutually consistent and time-dependent interactions between trip-makers' choices, network conditions and real-time information, by means of an underlying dynamic traffic simulation assignment model (DYNASMART).

The trip-maker decisions are input to the traffic simulation as they occur, and the experienced traffic supply conditions are a result of complex non-linear interactions occurring on the network. This simulation-based approach offers the advantages of cost-effectiveness, traffic realism, and statistical control compared to alternative approaches.

Several methodological challenges arise in modeling commuter behavior in the presence of information, due to the dynamic nature of the process. The provision of real-time information to the commuters allows the user to select from among alternative routes, possibly, several times during the commute on each day. If a trip-maker makes five route choice decisions per day, for a series of 12 days, it is necessary to model 60 route choice decisions for each user. In the real-world, it is possible that a user may encounter more than five switching opportunities on a given day, especially on long commutes. The duration over which learning and adjustment may occur may also exceed the 12 days considered in this example. Therefore, with real-world data it may be necessary to model more than 100 choice situations per decision-maker. Possible correlations over time can further complicate modeling efforts in these large dimensional decision problems. These decisions may be correlated with each other for two reasons. First, the effect of past experience on current choices is likely to be significant. Second, the choices made by the same user may exhibit persistence of error terms across different choice situations.

The Multinomial Probit (MNP) modeling framework is typically used to model correlated choice dimensions in longitudinal discrete choice data. However, this framework is admittedly computationally expensive to model large dimensional discrete choice data. The reason for this computational cost is that the likelihood computation involves the Monte-Carlo simulation of higher dimensional integrals of multivariate normal density function. To illustrate the computational complexity, consider the example discussed in the preceding paragraph. Modeling the 60 repeated route switching decisions for each trip-maker under the multinomial probit (MNP) framework would result in an equivalent probit model with 61 choice alternatives. With 61 alternatives, (assuming that the probability of switching at each instance is 0.5) the likelihood of an observation could be of the order of 10^{-25}. Therefore, about $O(10^{25})$ Monte-Carlo realizations are required for evaluating the likelihood for each observation in the sample. The computational cost of this framework is further increased as the likelihood evaluation is embedded in a non-linear optimization of parameters. Hence the likelihood computation procedure is invoked several times in the calibration procedure. Thus the calibration of multinomial probit model with a large number of alternatives is computationally prohibitively expensive. In fact, MNP results for more than 25 alternatives have not been reported using this framework before. The computational difficulty in the using the probit framework in this case is illustrated below.

In view of the computational impracticality of calibrating dynamic probit models of this dimensionality, the Dynamic Kernel Logit (DKL) framework is presented to model commuter behavior dynamics based on the logit kernel approach. This framework generalizes the 'mixed-logit' models proposed for modeling discrete choice data to model quite general dynamic effects in discrete choice panel data (Bhat, 1997; Revelt and Train, 1998). It is shown that under certain conditions, the DKL error-

structure converges asymptotically to a multi-variate normal distribution. Computational experiments are conducted, using synthetically generated longitudinal discrete choice data, to compare the accuracy and computational cost of the multinomial probit and dynamic kernel logit formulations.

The objectives regarding the role of supply conditions and ATIS on commuter behavior raise several substantive issues. To address these questions a series of experiments are designed and conducted to examine the influence of key factors on commuter behavior. Commuter behavior under real-time information is observed under varying experimental treatments using the interactive simulator described previously. In the first set of experiments, interest is centered on the effect of varying network conditions (magnitude of network loads and its day-to-day evolution) on commuter behavior. The second set of experiments focuses on the role of varying ATIS information supply strategies on trip-maker behavior under information. In each of these experiments, participants who are actual commuters supply their departure time and route choice decisions along a simulated commute in the presence of real-time information over a series of days. From these decisions, the outcomes of departure time switching, route switching, and compliance with information are inferred. The association between these discrete outcomes and the experimental treatments is analyzed according to alternative behavioral frameworks. Each behavioral framework is implemented by specifying the following components: appropriate functional form for the utility according to the underlying decision framework, included variables, and distributional assumptions regarding error terms. The effect of experimental treatments and other factors of interest are captured through suitably defined attributes that affect the utility of alternatives. By making suitable assumptions on the utility function and error structure, the DKL formulation is used to model the compliance and switching outcomes observed in the interactive experiments. Based on the observations from the experiments, the DKL models above are calibrated using the maximum likelihood technique (parameters are estimated so as to maximize the likelihood of observing the actual choices made by the decision-makers in the sample). The estimates, so obtained, have desirable asymptotic statistical properties of unbiasedness, consistency and efficiency, under mild regularity conditions.

Inferential testing of research hypotheses is performed based on the calibrated coefficients and associated statistics. The relative importance of various explanatory variables on the choice process is analyzed by examining the sign, magnitude and statistical significance of the estimated parameters. The suitability of alternative specifications is ascertained using various statistical tests. The substantive effects of network supply conditions on commuter behavior and the associated models are inferred based on model results from experiment one. The role of ATIS information strategies on compliance behavior of commuters is inferred from a compliance model calibrated using the data from the second set of experiments.

Behavioral issues arising in commuter behavior dynamics are examined at the following two levels. First, cognitive and decision processes in commuter behavior including learning, judgment, perceptional and attitudinal effects, and updating processes are analyzed by conducting exploratory tests

and statistical analyses on the data from the experiments. Major factors influencing these processes are identified through a series of linear statistical models.

At the second level, models representing how commuters adjust their route and departure time choices in response to experience and information, are proposed. The proposed models incorporate heuristic search procedures and behavioral mechanisms operating in commuters choice processes over time. It is hypothesized that the observed route choice is the consequence of heuristic mechanisms operating in commuter decision processes. Two plausible mechanisms, inertia and compliance, are identified based on the experimental data. A modeling approach is suggested to analyze the two mechanisms and their inter-relationship consistently. The relationship between these mechanisms and actual choice is also examined.

The departure time adjustments made by users from day-to-day is modeled as a heuristic greedy search. The proposed model is implemented by defining a suitable nesting structure for the alternatives. Alternative departure time adjustment models, including unordered choice mechanisms and ordinal response models are rejected in favor of the proposed model. The key factors influencing the adjustment process are assessed by examining the magnitude and significance of model coefficients.

1.5 SIGNIFICANCE OF RESEARCH OBJECTIVES AND CONTRIBUTIONS

Real-time traffic information delivered by Advanced Traveler Information Systems promises to offer significant potential benefits to users (both trip-makers and network managers). At the individual trip-maker level, the benefits may include trip-time savings, congestion avoidance, route guidance, and assistance in trip-planning. At the system level, the benefits could include increased system efficiency and reduced congestion and incident-related externalities. The effectiveness and success of ATIS in realizing these goals critically depend on users' response to real-time information and time-varying network conditions. Investigations into the dynamic aspects in trip-maker behavior have significant applications to travel demand modeling and forecasting, development and deployment of ATIS products and services, evaluation of ITS impacts, and the analysis of traffic management strategies, as described in the motivation section *(*Section 1.2*).* Despite its practical significance, considerable progress remains to be made in understanding, representing, and quantifying dynamic aspects in commuter behavior under real-time information. The primary sources of complexity in modeling user behavior relate to: the complexity of the dynamic decision environment (relatively large number of stimuli are encountered in quick succession), large dimensionality of choices made by trip-makers, correlation between choices over time, and non-linear time-dependent interactions between users choices on the network. Section 1.4 highlights several challenging substantive, methodological, and behavioral issues that arise in connection with efforts to model commuter behavior in the presence of real-time information. This Technical Report addresses these issues, and attempts to augment the growing body of knowledge on dynamic aspects in commuters' route and departure time choice behavior through the following contributions.

An interactive travel behavior simulator, developed earlier at the University of Texas at Austin, is used as an observational basis to represent and model non-linear interactions between user behavior,

information, and network conditions, consistently. For this study, the simulator is enhanced to incorporate the ability to examine the effect of day-to-day variations in network conditions on trip-maker behavior. Furthermore, the simulator also includes the capability to simulate ATIS information under varying information strategies. The simulator is well-suited to measure trip-maker behavior in the presence of information, as the stimuli encountered by trip-makers are consistent with their past choices, traffic conditions on the network, and the interactions between trip-makers on the network. The simultaneous measurement of trip-maker choices, network conditions, and information supplied to users, enables the observation of behavioral data at a highly disaggregate level and an adequate temporal and spatial resolution for dynamic modeling purposes.

At the methodological level, this research establishes that the Dynamic Kernel Logit (DKL) formulation is a suitable (from theoretical and computational perspective) methodological alternative to the multinomial probit (MNP) framework to model dynamic aspects in discrete choice dimensions in traveler behavior. This study also demonstrates the applicability of this formulation in modeling longitudinal-discrete choice data in both ordered and unordered decision contexts. Empirical application of this formulation to model commuter behavior dynamics, illustrate its suitability and versatility in accommodating alternative behavioral and decision frameworks (for example, utility maximization, and boundedly rational behavior rules). It is also shown empirically, that this formulation can represent general dynamic and stochastic patterns in choice behavior and can accommodate time-dependent interactions across multiple choice dimensions simultaneously (for instance, between route and departure time choices of a given individual).

Addressing the substantive issues of interest, this study analyzes the effect of network conditions (congestion level and its day-to-day evolution) on commuters' route and departure time switching behavior over time. In addition to the effect of experimental factors, the role of relevant factors including anticipated and experienced congestion, and quality of information on commuters' route and departure time switching decisions are also investigated. The findings from these models have important implications for the development of more accurate and robust network performance models that incorporate user response to varying network conditions.

The effect of varying information strategies on trip-makers' compliance with information is also investigated. In this regard, the influence of the following experimental factors and associated levels are explicitly modeled: the nature of information (descriptive and prescriptive information levels), type of information (prevailing, predicted, perturbed, differential, and random), and extent of feedback (feedback on own path, on recommended path, or on best path). In addition, the effect of costs and benefits of compliance, and the role of experience are also analyzed.

Unlike most existing dynamic models of trip-maker behavior (where only the switching decisions are analyzed), this study explicitly models path and departure time adjustment decisions. In other words, while modeling path choice, the decision to switch from the current path is modeled together with the path actually chosen. Analogously, the decision to adjust departure times is modeled simultaneously with the

magnitude of adjustments. These models have a direct relevance to the estimation and forecasting of time-dependent travel demand on alternative facilities in the network.

With regard to the behavioral issues of interest, this research relaxes several restrictive assumptions typically invoked under the utility maximization framework. For instance, the proposed models allow users to select alternatives that may not be globally optimal (in the sense of utility), especially in light of the cognitive constraints and limitations of trip-makers in real-time decision environments. Specifically, models based on alternative behavioral paradigms and decision rules (for instance based on boundedly rational behavior) are formulated and calibrated. The empirical models indicate a significant role of inertia, and search costs (involved in searching for a suitable alternative) in trip-maker behavior. It is proposed that inertia and compliance are two principal mechanisms underlying trip-makers route choice behavior in the presence of information. Departure time adjustment models suggest that trip-makers' adjustment decisions are consistent with a heuristic greedy search (by users) for an acceptable alternative. Evidence of cognitive processes including learning, judgment, perception, and updating, in user behavior are also presented.

1.6 STRUCTURE AND OVERVIEW OF THE TECHNICAL REPORT

This technical report is structured as follows. First, the introduction chapter provides an overview of the problem definition and motivation, as well as the research objectives and contributions of this study. A background review of related work is presented in the second chapter. The review pertains to three related areas: the role of real-time information on trip-maker behavior, dynamic models of commuter decisions, and the underlying cognitive and decision processes. The third chapter describes an observational framework used in this study to measure commuter behavior under real-time information. The dynamic travel behavior simulator used for this purpose is described, followed by the details of experimental design, treatment, and procedures for two sets of interactive experiments. Chapter 4 presents the Dynamic Kernel Logit (DKL) formulation and establishes its suitability for modeling longitudinal discrete choice data. In Chapter 5, commuters' departure time and route switching decisions under varying congestion levels on the network are modeled based on data from the first set of interactive experiments using the MNP and DKL formulations respectively. Chapter 6 presents the analysis of commuters' compliance decisions under varying information strategies based on data from the second set of interactive experiments. In Chapter 7, structural effects in commuter behavior under information are investigated. In this context, a joint model of route and departure time switching is specified and calibrated, that explicitly accounts for the presence of heterogeneity, state dependence, habit persistence, and a general variance covariance structure across decision dimensions and over time (within-day and day-to-day). Cognitive and decision processes underlying observed trip-maker behavior are explored in Chapter 8. Specifically empirical evidence is presented that indicates the presence of learning, judgment, perception and updating processes in trip-maker behavior under information. Chapter 9 examines processes governing adjustments in commuters' route and departure time choices. The empirical results presented in this chapter suggest that observed adjustments are consistent with heuristic mechanisms

and search processes. Chapter 10 describes the conclusions and contributions from this work and proposes directions for future research.

CHAPTER 2: BACKGROUND REVIEW

2.1 INTRODUCTION

This chapter discusses salient issues of relevance to commuter behavior dynamics and presents a review of existing modeling approaches. The purpose of this review is two-fold. First, an attempt is made to synthesize current knowledge on trip-maker behavior under information with reference to the objectives presented in Chapter 1. The second objective of this review is to recognize the essential characteristics of the process under study, outline the approaches adopted by various researchers and highlight their salient advantages and limitations with regard to the research issues of interest here. Therefore, this review is not intended to be comprehensive in the related streams of research which bear detailed investigations in their own right. In view of the objectives of this study, this chapter focuses on the following three areas: influence of Advanced Traveler Information Systems (ATIS) on trip-maker behavior, travel behavior dynamics, and decision processes in complex dynamic environments.

Accordingly, first, the literature pertaining to ATIS and its influence on trip-maker behavior is presented in Section 2.2. In Section 2.3, cross-sectional models of commuter choice behavior are reviewed. The limitations of cross-sectional models, particularly for representing and analyzing the impact of real-time information, highlight the need to model dynamic aspects in commuter behavior. However, the need to model dynamics introduces significant challenges associated with measuring trip-maker behavior dynamics in general, as discussed in Section 2.4. Section 2.5 examines existing research studies on trip-maker behavior dynamics. It is seen that the existing models of dynamics predominantly tend to investigate factors influencing choice, and not the decision processes underlying the choice. Insight into the cognitive and decision processes underlying commuter behavior dynamics will lead to behaviorally robust, transferable, and parsimonious models with wide ranging applications to demand modeling and forecasting. It may be noted that research directed at investigating decision processes underlying trip-maker behavior in the presence of real-time information is still in its infancy. Therefore, Section 2.6 reviews related literature from other fields including cognitive psychology and marketing, in addition to the few related studies in travel behavior modeling.

2.2 ROLE OF ATIS IN TRIP-MAKER BEHAVIOR

A substantial body of research on ATIS has emerged in various areas over the last decade. This review limits its attention to the influence of advanced traveler information on trip-maker behavior, specifically the effect of alternative ATIS information supply strategies on commuter behavior.

Through the provision of real-time information, ATIS aim to assist travelers in all facets of the trip-making process, from planning to en-route navigation and congestion avoidance. The scope of services has increased to include the wireless delivery of a wide range of web-based content. A considerable number of initial contributions have examined the potential benefits of providing real-time information to trip-makers. ATIS are empirically shown to result in reductions in trip time, incident clearance time,

congestion delays, and pollution externalities (Sengupta et al., 1998; Wunderlich, 1996). Trip-time savings on the order of 3-30% and reduction in congestion and incident delays of up to 80% for impacted vehicles have been reported (Tsuji et al., 1983; Reiss and Gartner, 1991). These estimates, though impressive, may overstate the potential benefits of ATIS, since they do not consider potential adverse effects of providing information such as oversaturation, overreaction, and concentration (Ben-Akiva et al., 1991, Mahmassani and Jayakrishnan, 1991). These studies are mostly based on data from hypothetical surveys and travel behavior simulators, where the information supplied by ATIS is assumed to be perfect. Another limitation of a majority of these studies is that they do not consider the interaction between user behavior and system performance. Based on a hypothetical example, Arnott et al. (1990) argued that providing information may not necessarily reduce congestion. In fact, providing imperfect information may exacerbate the congestion problem. The advantages and adverse effects of information are also shown to be influenced by the market penetration of ATIS (Mahmassani and Peeta, 1993; Emmerink et al., 1995). The decrease in system-wide benefits reported in these studies with increasing proportion of users may be attributable to concentration and oversaturation occurring on the network.

Relaxing the assumption in the earlier studies that ATIS supplies users with perfect information, some investigators have examined the impact of information quality on trip-maker behavior. Not surprisingly, they noted that information quality strongly influences trip choice behavior (Bonsall et al., 1991; Mahmassani and Liu, 1997; Vaughn et al., 1995). In fact, there is empirical evidence supporting the hypothesis that trip-makers adjust their behavior in response to the quality of information supplied by ATIS. Zhao et al. (1996) remarked that the perception band of trip time, (used in route choice decisions), reduces with increasing information accuracy. Mahmassani and Liu (1997) reported that users adjust their indifference band in route and departure switching decisions, to accommodate inaccurate information.

Given the strong influence of information quality on trip-maker behavior, it is essential to characterize and measure information quality. Mahmassani and Chen (1993) noted a fundamental difficulty in this regard. They remarked that there is no objective measure of information quality that is independent of user choice behavior, prevailing traffic conditions, and network interactions. This observation reinforces the need to model judgment processes of users, particularly with regard to perception and characterization of information quality of alternative ATIS technologies.

In addition to the quality of information, other attributes may also determine how trip-makers use real-time information to assist their choice process. Ben-Akiva et al. (1991) identified the following ATIS information attributes in this regard: nature of information (descriptive or normative), timeliness (higher temporal and spatial update frequency), and predictive ability (to predict evolving conditions based on user compliance with ATIS). However, the influence of these and various other information attributes and strategies on trip-maker behavior are yet to be assessed systematically.

2.3 CROSS-SECTIONAL MODELS OF COMMUTER BEHAVIOR

ATIS information may influence various trip-maker choice dimensions including mode, route, departure time, destination, and perhaps, in the long run, residential and work location decisions.

However, in the short run, route and departure time choices are the primary means of behavioral adjustment available to users in response to experienced congestion and information. This is particularly true for the commuting trips where the dimensions of mode and destination are relatively fixed in many urban areas in the U.S. For example, Conquest et al. (1993) reported that 75% of commuters change either departure time or route in response to information. Schedule delay and trip time are identified as key variables influencing departure time choice (Cosslet, 1977; Small, 1982; De Palma et al., 1983; Hendrickson and Plank, 1994; Tong and Mahmassani, 1987). The route choice process is shown to be strongly influenced by trip time, trip time variability, duration of delay, quality of information and congestion (Spyridakis et al., 1991; Adler, 1992; Mannering, 1994; Abdel-Aty et al., 1995). Other behavioral studies suggest that information provision will likely induce greater switching in both departure time and route choice behavior (Conquest et al., 1993; Mahmassani, 1990; Abdel-Aty et al., 1994). A majority of these models are based on the utility-maximization paradigm where travelers choose alternatives that minimize their disutility. While theoretically elegant, this framework (as typically implemented) fails to consider cognitive limitations associated with processing real-time information, the influence of imperfect/uncertain information, and the role of time constraints operating in the real-time decisions of trip-makers. Many of these models are also limited by their assumption of fixed and exogenous transportation system attributes that are unresponsive to user behavior. While providing valuable initial insight into factors influencing both route and departure time processes of commuters, they distinctly fall short of identifying and analyzing mechanisms underlying the decision processes. Furthermore, being cross-sectional in nature, these studies provide little or no insight into dynamic aspects of travel behavior.

2.4 MEASUREMENT ISSUES

As discussed in the previous section, cross-sectional commuter behavior models are not particularly suitable for investigating trip-maker behavior in the presence of real-time information. Modeling the time-dimension in trip-maker behavior is critically important under real-time information, as ATIS can influence the future decision states and choices of users by supplying them with real-time information. Several measurement issues arise in the context of observing commuter decision dynamics in the presence of real-time information. The essential requirements for an adequate observational basis have been summarized by Mahmassani and Herman (1990) as follows:

- Commuter decision dynamics must be measured simultaneously with associated service levels in congested systems,
- The observational framework should allow for the consequences of trip-makers' decisions to depend on the result of their own decisions and those of a large number of other decision-makers, and
- The process must be observed in a 'realistic' setting with complex non-linear interactions occurring between the users and the traffic system.

The range of approaches currently being employed to observe and investigate trip-maker decisions includes: analytical models, simulation models calibrated on micro-rules, laboratory experiments, surveys, field experiments and operational tests. Idealized analytical models are not appropriate for observing commuter behavior dynamics as they lack the ability to represent decision-making processes occurring in a complex dynamic environment. The lack of knowledge of micro-rules governing the decision processes significantly deters the applicability of pre-calibrated simulation approaches. Given the fact that ATIS are still in their infancy, it is perhaps premature to conduct expensive field operational tests and surveys, particularly considering the lack of theoretical constructs to usefully guide acquisition and analysis of such observations (Mahmassani and Herman, 1990). Realizing the limitations of other approaches, several researchers have invested considerable effort in laboratory experiments conducted using simulators (Adler et al., 1992; Koutsopoulos et al., 1994; Vaughn et al., 1993; Bonsall and Parry, 1991; Chen and Mahmassani, 1993), compared to alternative observational bases. These laboratory experiments enjoy the advantages of experimental control, limited resource requirements, and manageable number of participants.

2.5 DYNAMIC MODELS OF COMMUTER BEHAVIOR

Several researchers have investigated the dynamic aspects in commuter behavior, though these efforts have been limited by measurement difficulties as well as the methodological complexities involved. Three principal time frames of interest may be distinguished in the analysis of commuter behavior dynamics: within-day dynamics, day-to-day dynamics, and real-time dynamics as described below.

2.5.1 Within-Day Dynamics

Within-day dynamics concerns the time-dependent flow patterns that result from equilibrium choices of trip-makers. Within-day dynamic models relax the assumption of constant trip-time and flow rates in the peak period (invoked in the static models), by explicitly introducing the dimension of departure time decision in the framework. However, the primary research interest in these models has been to describe resulting equilibrium flow patterns, such that no trip-maker has an incentive to unilaterally change routes or departure times. This within-day dynamic equilibrium state, once achieved (if at all), is time-dependent (within-day) yet static (from one day to the next).

Research efforts relating to within-day dynamics have pursued the following major lines of inquiry. Under the first, several researchers have analyzed commuters' trip scheduling decisions under fixed, exogenous, and known values of system performance attributes. Investigations in this category have focused on formulating and estimating trip-scheduling (departure time) choice models under the standard Random Utility Maximization (RUM) paradigm (Cosslett, 1977; Small, 1982). Empirical models suggest that schedule delay and trip time play a crucial role in the departure time decisions of trip-makers. However, these models can not be considered definitive, in view of the small size and other data limitations (Mahmassani, 1997).

The second stream of research relating to within-day dynamics focuses on describing time-dependent flow patterns together with the associated network performance measures, thus explicitly

recognizing the endogeneity between trip-maker choices and network conditions. As noted earlier, models in this category have attempted to characterize equilibrium flows on the network (Hendrickson and Kocur, 1981; Mahmassani and Herman, 1984). However, the analytical tractability of these models decreases significantly for larger (and realistic) networks, leading to the development of iterative simulation schemes to solve for the equilibrium flows in larger networks (Mahmassani and Jayakrishnan, 1991). A majority of these models, however, are limited by questionable assumptions about trip-maker behavior (for instance, trip-makers always tend to select paths that minimize their trip time). Furthermore, this framework is only concerned with network flows under equilibrium conditions. However, it is not clear yet, whether such equilibrium conditions exist. Even if equilibrium states exist, the time till convergence and the path to equilibrium may be a significant determinant of network states, their stability and associated costs. This framework also does not explicitly represent and model adjustments in choices over time, as users have no incentive to unilaterally change their trip-choices under equilibrium conditions.

2.5.2 Day-to-day Dynamics

In contrast to previous models, models of day-to-day dynamics allow trip-makers to adjust their choices from day-to-day in response to pre-trip information and past experience. This representation is inherently more dynamic than within-day dynamic models, as it explicitly captures the daily adjustment process. Several researchers report considerable variability in trip-maker behavior from one day to the next (Hatcher and Mahmassani, 1992; Jou et al., 1998). Possible sources of such variation include trip-maker characteristics, travel time uncertainty, changed objectives, trip-changing behavior, etc. Mahmassani and Chang (1985) proposed a two-stage framework to analyze the day-to-day adjustments in user behavior under real-time information. In the first stage, a commuter decides whether to change route/departure time on the next day based on current experience and information. In stage two, conditional on the decision to change either, the user selects a new route or determines the magnitude of departure time adjustment.

Mahmassani and Chang (1987) proposed that drivers' decisions (route and departure time choices) are based on boundedly rational behavioral rules. According to this framework, a trip-maker will switch routes only if the travel-time saving realized by switching exceeds a pair of indifference band thresholds (relative trip time saving and minimum trip time saving). Analogously, a user will switch departure times only if he/she arrives (early or late) outside the corresponding schedule delay indifference band. These models were calibrated using data from interactive simulation experiments. The insights from these models have been summarized below by Mahmassani (1990) as follows:

- Indifference bands tend to vary with experienced congestion and information,
- Users are more likely to switch departure time than route,
- Users tolerate greater schedule delays when faced with increasing trip-time fluctuations, and
- The impacts of unsuccessful experiences (arrival on time) are generally more drastic and longer lasting than successful ones.

Many of these findings have subsequently been independently validated based on travel diary surveys of commuters in actual traffic systems (Mahmassani et al., 1993; Mahmassani and Jou, 1998).

For the second stage, these researchers proposed a simple departure-time adjustment mechanism from day-to-day (Chang and Mahmassani, 1998). It is assumed that users are assumed to anchor their departure times on their desired or preferred arrival time at the work place. The departure time for the following day is determined by subtracting the predicted or estimated trip time for the next day from this preferred arrival time. Commuters supply preferred arrival times in a set of interactive experiments. These preferred arrival times are regarded as being fixed for each commuter over a series of hypothetical commutes. Predicted trip times are then calibrated as a function of experienced trip time, schedule delay, trip time variability, and cumulative number of unsuccessful arrivals (measured by the number of previous departure time switches).

While this work provides some fundamental insights into the factors influencing day-to-day dynamics, it also offers adequate scope for further exploration in detail. A general dynamic framework that can represent a variety of dynamic and stochastic processes is presented and implemented as well. However, several limitations were recognized in this study that offer the scope for further investigation. First, the models presented do not represent heterogeneity adequately (although the indifference bands are modeled as random variables). Second, the simple departure-time adjustment heuristic considered allows considerable scope for further exploration of alternative mechanisms. Additional research is required to enhance and extend the simple learning model proposed in this framework. The dynamic framework, proposed by the authors, may be generalized to explore cognitive decision processes and behavioral mechanisms underlying commuter behavior.

2.5.3 Real-Time Dynamics

Real-time dynamics refers to the time dependent flow patterns that result from real-time decisions of trip–makers in the network in response to perceived or anticipated traffic conditions and information supplied by ATIS (Mahmassani 1996). Thus, models of real-time dynamics allow for continuous adjustments (over time) in trip-maker decisions, unlike day-to-day dynamic models which allow for periodic (daily) adjustments.

Several researchers have analyzed within-day trip-maker behavior in the presence of real-time information, particularly, the dimensions of pre-trip and en-route choice and departure time choice. Departure time choices influence time-dependent O-D demands and hence the temporal distribution of vehicles in the network, and may be considered within-day in this sense. Several researchers have modeled and analyzed these choice dimensions using laboratory-like experiments with simulators, as well as data from travel diaries (see Caplice and Mahmassani, 1992; Mahmassani et al., 1993, for choice models based on travel diaries). Empirical studies report that network conditions, particularly, experienced trip-time, trip-time variability, delays associated with congestion and incidents, and trip-maker attributes are significant determinants of route choice. (Spyridakis et al., 1991; Mannering, 1994; Abdel-Aty et al., 1995). Other researchers have noted the influence of cognitive (motivational improvement,

conflict tolerance) and situational factors (arrival constraints, schedule delay) on en-route choice behavior of trip-makers (Adler, 1992; Liu and Mahmassani, 1998). Major factors that affect departure time choices of users (in the presence of information) include trip-time, trip-time variability, schedule delay, and past experiences in the network (Mahmassani et al., 1993; Mahmassani and Chang, 1985; Tong et al., 1987).

Many of these studies (with a few notable exceptions) observed and measured dynamic behavior within a static experimental or analysis framework. Two serious limitations can be identified in existing research efforts on trip-maker behavior dynamics. First, in many observational bases used to measure trip-maker behavior, the time-dependent effects of past choices of trip-makers do not influence network conditions in the future. Thus, the traffic stimuli encountered by users are assumed to be exogenous to their past choices. Hence the realism of the stimuli relating to the traffic and decision environment in these studies is somewhat questionable. Second, most analyses (with a few exceptions) do not model the temporal correlation between repeated decisions made by a trip-maker. Even studies that explicitly model these effects, do not analyze structural effects such as state-dependence and heterogeneity in trip-maker behavior.

2.6 DYNAMIC DECISION PROCESSES AND COGNITIVE MECHANISMS

Most existing models of commuter behavior (both cross-sectional and dynamic) are based on the utility maximization paradigm. The application of this behavioral framework to model trip-maker behavior under information has been questioned behaviorally on the following counts. The framework assumes that trip-makers, at each decision instance, evaluate alternatives and select the one with the highest utility. However, the repetitive nature of the choice context, and the attentional conflict of information acquisition with the driving task, suggest the possibility of heuristic search processes in trip-maker behavior (Chang and Mahmassani, 1988; Garling, 1998). There is considerable evidence of inertia, habit formation, and cost of implementing selected choices that is unaccounted for by the utility maximization framework (Liu and Mahmassani, 1998). The absence of behavioral frameworks that explicitly recognize these effects and the considerable unexplained variability in existing models indicate that the cognitive and decision processes underlying trip-maker behavior under real-time information are not sufficiently understood. In view of the limited body of research contributions into dynamic decision processes of travelers, the review, hereafter, goes outside the immediate scope of the commuting context to examine relevant investigations in other fields, particularly, cognitive psychology and consumer behavior.

Dynamic decision-making processes possess the following four essential characteristics (Edwards, 1962; Brehmer, 1992):

- A series of decisions are required to reach the goal,
- The decisions are not independent,
- The state of a decision problem changes as a consequence of the decision-maker's actions, and
- The decisions are made in real-time.

Dynamic commuter behavior, in addition to satisfying the characteristics above, bears several interesting parallels with consumer purchase behavior for non-essential items over time. This decision is

postulated to be an outcome of a disconfirmation process that accounts for a consumer's' satisfaction with alternative brands of a product. It is assumed that this disconfirmation process is based on user's previous experience and information regarding alternative product brands (Latour and Peat, 1980; LaBarbera and Mazursky, 1983). Analogously, in the boundedly rational behavior model of trip-making, the decision to switch routes/ departure times is based on a satisficing process depending on actual experience and information about alternative trip options. Marketing researchers have proposed detailed cognitive models of human learning and judgment processes to analyze product purchase decisions, which may be of relevance to commuter behavior (Cardozo, 1965; Oliver, 1977; Olson and Dover, 1979).

However, the analogy of consumer behavior and commuter behavior under real-time information is not perfect for the following two reasons. First, the decision environment in commuter behavior is more dynamic than the purchase decision environment in the sense that drivers can review and change their previous decisions within relatively small time intervals (say, on the order of 5-10 minutes or less). Second, the environment is more complex because the experiences and decisions of each trip-maker depend on the collective network effects that are the result of the interaction of a large number of individual decisions. Thus it is necessary to recognize and analyze driver behavior and response to real-time information, to a consequence of complex decision processes.

The processes of perception, learning, judgment, updating and adjustment decision-making have been observed empirically in complex decision situations in empirical studies in Psychology (Slovic et al., 1977; Einhorn and Hogarth, 1981; Howell and Cooke, 1989; Edland and Svenson, 1993). Empirical research indicates the presence of these processes in driver behavior as well. Several researchers have employed a simple exponentially weighted moving average learning model, where users learn by linearly combining past experience with trip-time reported by ATIS (Iida et al., 1992; Horowitz, 1984). Polak and Hazelton (1998), in the context of the exponential smoothing learning model above, suggest the existence of weighting factors that represent the effect of length of memory and rate of forgetfulness. Mahmassani and Chang (1988) provided evidence of adjustment processes, when they noted that the indifference bands influencing route and departure time switching are adjusted dynamically by trip-makers, in response to experience and information.

Recognizing the imperfect nature of ATIS information in dynamic environments, some analysts argue that trip choice decisions are based not on objective information supplied by ATIS, but on subjective information as perceived by users (Ben Akiva et al., 1991; Zhao et al., 1996). A simple model of perception has been proposed by some researchers, where the perceived trip- time is the sum of a weighted combination of experienced trip-time and a random perception error (Horowitz, 1984; Polak and Hazelton, 1998). Though a simple and elegant construct, this model needs to be compared and validated against alternative perception models. Ben-Akiva et al. (1991) proposed a similar mechanism for perception updating from day-to-day except that, in this case, information is linearly combined with perception of trip-costs, as opposed to experienced trip costs. This model, however, has not been implemented or calibrated using empirical data.

There is very little empirical work addressing how users judge the information provided by ATIS and accordingly form perceptions. Nevertheless, the importance of information quality on trip-maker behavior observed in several studies, highlights the existence and operation of judgment processes in trip-maker behavior in the presence of information (Bonsall and Parry, 1991; Abdel-Aty et al., 1994; Liu and Mahmassani, 1998).

Finally, the literature pertaining to adjustment and updating processes in commuter behavior is reviewed next. In modeling day-to-day dynamics of commuter behavior, Mahmassani and Chang (1988) proposed a plausible adjustment mechanism. Under this mechanism, users adjust their departure time from day-to-day by predicting the trip-time for the next day, and offsetting the estimated trip-time from the preferred arrival time. The authors also suggest an updating mechanism for the indifference bands to reflect users' learning in the traffic system. The important factors influencing the updating process are found to be past experience, schedule delay and trip-time variability.

It is evident from this brief review that commuter decision processes occur in a complex and dynamic environment. There is sufficient empirical evidence to support the presence of complex judgment, perception, adjustment, updating, and learning processes under such dynamic decision environments. The factors influencing these processes are not well understood, and the few models proposed to represent these processes cannot yet be considered definitive, pending further testing. Investigating the role of these processes and mechanisms in commuter behavior dynamics promises to be a rich and challenging line for further inquiry.

2.7 SUMMARY

This chapter briefly outlines current research on modeling commuter behavior dynamics, discusses the deficiencies of existing approaches, and identifies opportunities for further investigations. From among these areas, this Technical Report seeks to address several methodological and substantive questions regarding commuter behavior dynamics that are as yet unanswered. In this regard, the following lines of inquiry are pursued in the subsequent chapters:

- Investigating the role of ATIS and influence of network supply conditions on commuter behavior,
- Modeling cognitive mechanisms and rules operating in commuter decision processes, and,
- Examining learning and adjustment processes influencing day-to-day dynamics in commuter behavior.

CHAPTER 3: OBSERVATIONAL FRAMEWORK AND INTERACTIVE EXPERIMENTS TO MEASURE COMMUTER BEHAVIOR DYNAMICS UNDER REAL-TIME INFORMATION

3.1 INTRODUCTION

To model trip-maker behavior under real-time information, it is necessary to observe or measure it dynamically, along with the information supplied and the associated network performance measures (at a disaggregate level). Two major approaches are generally employed to measure behavioral data of interest. In the first, broadly referred to as stated preference (SP) methods, respondents are asked to supply choices, under hypothetical decision-making scenarios. In contrast, in the second approach, referred to as revealed preference (RP), respondents' actual behavior is observed in a real-world setting along with the relevant variables of interest, though often in a self-reported mode.

The advantage of the SP approach is that it affords statistical control over experimental factors or treatments of interest and is relatively inexpensive. However, the data are susceptible to selectivity and reporting biases introduced in the experimental design due to differences between the hypothetical and real-world scenarios. Furthermore, SP respondents do not generally experience the consequences of their choices. Hence it is necessary to validate the results from SP surveys for the behavioral setting in question. RP data, on the other hand, though more realistic by definition, offer less inferential power and are often more expensive to obtain. RP data are often based on recall of past experiences, which can be biased or unreliable with the passage of time. RP approaches are also inflexible to the extent that they do not enable modeling actual responses to new alternatives or policy measures (that are yet to be implemented). SP data have been obtained through stated preference surveys, questionnaires, and traditional factorial experiments (Bovy and Bradley, 1985; Khattak et al., 1993; Hensher, 1994; Bates, 1998; Widlert, 1998). RP data sources in travel behavior include commuter diaries, ex-post facto surveys of behavior, field operational tests etc. (Abu-Eiseh and Mannering et al., 1987; Mahmassani et al., 1990; Mahmassani et al., 1993; Jou and Mahmassani, 1998).

Recognizing the limitations of these two approaches, recent efforts in travel behavior measurement and data collection have focused on developing hybrid approaches that take advantage of these two approaches while avoiding their respective limitations. Instances of hybrid approaches include join-stated and revealed-preference surveys, and interactive simulation experiments. In joint surveys, choice information is elicited on both actual/revealed behavior (in real-life) and stated response to hypothetical choice scenarios. By correlating the stated preference to the revealed response, this approach attempts to externally validate the SP data (Ben-Akiva and Morikawa, 1990; Morikawa, 1994; Caldas and Black, 1997).

Interactive simulators form the core of an alternative hybrid approach for behavioral data measurement. Under this observational framework, the decision-makers are placed in simulated choice contexts, and interact with the simulated system as they would in the real-world. It is possible to embed hypothetical factors of interest in the simulated setting, while retaining a consistent relationship between

the stimulus and response. In contrast to the SP methods, the choice context is not hypothetical in the sense that the decision-maker encounters it in the simulated setting and faces the consequences associated with the choice of different alternatives. Furthermore, unlike the SP method, users do not report their choices themselves, but their choices are observed and recorded in the simulated system. Thus simulator-based measurements can serve as an effective compromise between SP and RP approaches to data collection (Louviere and Hensher, 1982; Mahmassani and Herman, 1990). With increasing realism of experienced stimuli, and greater fidelity of the simulator model (relative to real-world conditions), the data measured from the simulation setting could closely approximate revealed preference data, while still enjoying the advantages of experimental control associated with stated preference approaches. To ensure external validity of simulator based data, however, it is essential to maintain consistency between stimuli and responses of the participants. The obvious tradeoffs between the realism of the simulator and the need for experimental control on factors of interest can be resolved based on the objectives of the study, cost and other experimental design constraints.

The objectives of the present study necessitate the measurement of user responses to ATIS jointly with the network's dynamic characteristics. These objectives suggest the following essential features of the measurement framework.

a) Users responses need to be measured over time (both within-day, and day-to-day variations need to be accounted for).
b) It is necessary to capture associated supply conditions and ATIS information provided to the user (consisting of the stimuli presented to different users) at an adequately rich temporal and spatial resolution. This implies that there must be sufficient variation in the time-dependent conditions experienced by different users on the network (for different departure times on the same day as well as from day-to-day).
c) A related condition is the need to ensure consistency between user responses (trip-choices made by respondents) and the stimuli that are encountered. In other words, the traffic conditions encountered by a user should be consistent with his/her past choices and the collective trip-decisions of all network users. In view of these requirements, the interactive simulator approach is particularly well suited, practically, to measure and observe user behavior dynamics in response to ATIS.

The reminder of this chapter is organized as follows. Behavioral studies based on simulators are reviewed in Section 3.2 The following section provides an overview of the main features of the interactive simulator used in measuring user behavior dynamics. Section 3.4 discusses the interactive simulator-based experiments, the commuting context in these experiments, and the experimental procedures. The next section presents the experimental treatments considered in the first set of experiments aimed at examining the role of varying network conditions on trip-maker behavior. Section 3.6 presents the experimental factors from the second set of experiments, investigating the effect of varying information strategies on commuter behavior. Finally, the chapter is closed with a few concluding remarks.

3.2 TRAVEL BEHAVIOR MEASUREMENT IN SIMULATED ENVIRONMENTS

The advent of Intelligent Transportation System (ITS) technologies, especially ATIS, has spurred several investigations focussing on the impacts of information on trip-maker behavior (see for example, Adler et al., 1992; Conquest et al., 1993; Abdel-Aty et al., 1994; Hanowski et al., 1994; Koutsopoulos et al., 1994; Emmerink et al., 1995; Chen and Jovanis, 1997). Research into this line has also been motivated by the desire to inform (guide) the design and deployment of ATIS products and services. In view of their limited real-world deployment, and the absence of substantial conceptual and theoretical frameworks to guide data collection, researchers have relied on simulator-based approaches to perform these investigations. As a result, controlled laboratory-like interactive experiments conducted in simulated networks have led to preliminary insights into traveler behavior in the presence of ATIS. Below some salient simulator-based studies are reviewed. These studies are aimed at examining diverse aspects of traveler behavior and ATIS impacts. These studies are referenced below, variously, by means of acronyms of the simulators, names of the developers, or the institutions where the simulators were developed.

3.2.1 Interactive Guidance On Routes (IGOR)

Among the earliest simulators, IGOR was developed to investigate route guidance under ATIS (Bonsall and Parry, 1991). IGOR simulated en-route travel through a network and emulated an in-vehicle navigation system that provided participants with real-time route guidance. The traffic conditions experienced by a user were exogenously defined with a systematic component reflecting time-of-day variations, in addition to a random component. The information is supplied to users through a personal computer screen interface. Information supplied included trip time till the current intersection, trip time on the previous link, qualitative description of traffic conditions on the alternative routes, and route guidance information. The ATIS supplied snapshots of traffic conditions when a user reached an intersection, but no network representation was provided. Information quality, familiarity with the network, user's experience, and trip-maker characteristics were found to be major determinants of compliance behavior.

3.2.2 Allen (1991)

Allen et al. (1991) investigated the influence of alternative information systems on route diversion decisions. The driving simulator provided stimulus in the form of sequential slides and auditory feedback. This simulator provided a realistic representation of the driving task, as the interface provided for simulated steering, speed control and maneuvering capabilities. Respondents who incurred delays were penalized, and those who minimized their trip times were rewarded in the experiment. ATIS information was assumed to be perfect, and traffic conditions were predetermined. Older drivers were observed to be less likely to switch routes as compared to younger drivers. This study also reported that route familiarity and gender were significant determinants of route switching behavior.

3.2.3 University of California, Irvine

Researchers at the University of California, Irvine, developed FASTCARS (Freeway and Arterial Street Traffic Conflict Arousal and Resolution Simulator). This simulator was intended to capture en-route

driver behavior in response to real-time information (Adler, 1992). Based on conflict assessment and resolution theories, drivers' preferences were obtained using a multi-objective scoring function. The study simulated information provision through various ATIS devices including Variable Message Signs (VMS), Highway Advisory Radio (HAR), and In-Vehicle Navigation Systems. However, the information supplied was always accurate and the traffic conditions were exogenously determined, so that a user always encountered preset conditions. Thus while the user interface and interaction between user and the ATIS were realistic, the stimuli encountered by users is behaviorally questionable. The results from this study highlighted the significance of attentional and motivational factors on trip-choices in the presence of information. Trip-maker characteristics such as familiarity with the network and perception of information value also influenced diversion behavior and information acquisition.

3.2.4 University Of California, Davis

Vaughn et al. (1995), at the University of California, Davis, developed a travel behavior simulator to investigate the purchase propensity of ATIS and route choice decisions in the presence of real-time information based on a set of empirical experiments. The simulated network consisted of a corridor with three parallel facilities. The ATIS is emulated through an information display window. Information on network conditions (determined exogenously) is supplied to the user along with an advice on the route to follow. In this set of experiments, the traffic conditions were exogenously generated and a relatively simplistic representation of network and driving task was adopted. The results from this set of experiments highlight the role of information quality, trip-maker attributes, and congestion and incident information on the choice process.

3.2.5 Massachusetts Institute Of Technology

Researchers at MIT calibrated a route choice model under ATIS based on fuzzy set theory and approximate reasoning (Koutsopoulos et al., 1994). The data was obtained using an interactive simulator loosely structured after IGOR, with an enhanced graphical user interface. This simulator also included the capability to simulate a wide range of ATIS devices (radio, VMS, in-vehicle devices). The traffic scenarios used in the study varied based on randomly generated congestion and accident and information availability parameters. The experimental network conditions, limited number of subjects (10), and lack of interactions between vehicles in the simulator pose significant limitations on the generalizability of the findings from this study.

3.2.6 University of Texas, Austin

Mahmassani and Chen (1993) developed a dynamic interactive travel behavior simulator, which consists of a dynamic traffic simulator and a graphical user interface through which ATIS information is supplied to the user. The interface is used to elicit trip-maker decisions, which are then input into the traffic simulator. Another notable feature of the simulator is that it can be used to observe trip-makers' route and departure time choices on a given day as well as their variation from day-to-day. In contrast to the previous simulators, this simulator ensures a consistent representation of user behavior, network conditions and ATIS information supplied. The multi-user capabilities of the simulator enables data

collection from many system users simultaneously. Furthermore, the simulator is set-up to enable data collection regarding pre-trip, en-route, and day-to-day route and departure time choices. An elaborate description of this simulator, and its modifications in relation to the objectives of this study are presented in the following section.

To summarize, a variety of simulators have been used to elicit and observe traveler behavior in the presence of ATIS. The basic capabilities common to most of these simulators include representation of the driving task, representation of ATIS information devices and information supply, and a representation of network traffic conditions. The existing simulators differ in their representations of these capabilities, since their design is often guided by different sets of objectives. For instance, a more realistic representation of driving task and user interface is desirable in a study of human factors issues regarding information acquisition en-route. Similarly, greater fidelity in representing traffic conditions and interactions between network performance and user decisions is preferable for measuring user behavior dynamics.

3.3 DYNAMIC INTERACTIVE TRAVEL BEHAVIOR SIMULATOR

It is clear from the preceding discussion that the travel behavior simulator design should enable the representation of ATIS information provision to users, while simultaneously eliciting their trip choices over time. Toward this end, the travel behavior simulator for the present study is designed with a dynamic network assignment simulator at its core (Figure 3.1). The actual respondents' vehicles are assigned to the network links according to their route and departure time choices. The traffic simulator assigns the background (simulated) traffic on the basis of boundedly-rational switching rules calibrated in previous studies (Chang and Mahmassani, 1988; Mahmassani, 1996). The vehicles of commuters (simulated and actual) are moved on the network links, by the traffic simulator, consistent with the prevailing traffic conditions, capacity constraints, and vehicular interactions on the network, in fixed time steps (six second intervals). The resultant traffic conditions on the network form the basis for ATIS information supplied to the users through a Graphical User Interface (GUI). The GUI also displays the movement of each user's vehicle, through the network links, on his/her screen. The actual participants are asked to select routes (both pre-trip and en-route) as they travel through the network and departure times from day-to-day. This cycle of user-decisions, information supply, and traffic (movement simulation) is repeated over time for each day’s peak-period. A detailed description of the major simulator components and its capabilities, that make it suitable for the observation and measurement of traveler behavior dynamics, is provided next.

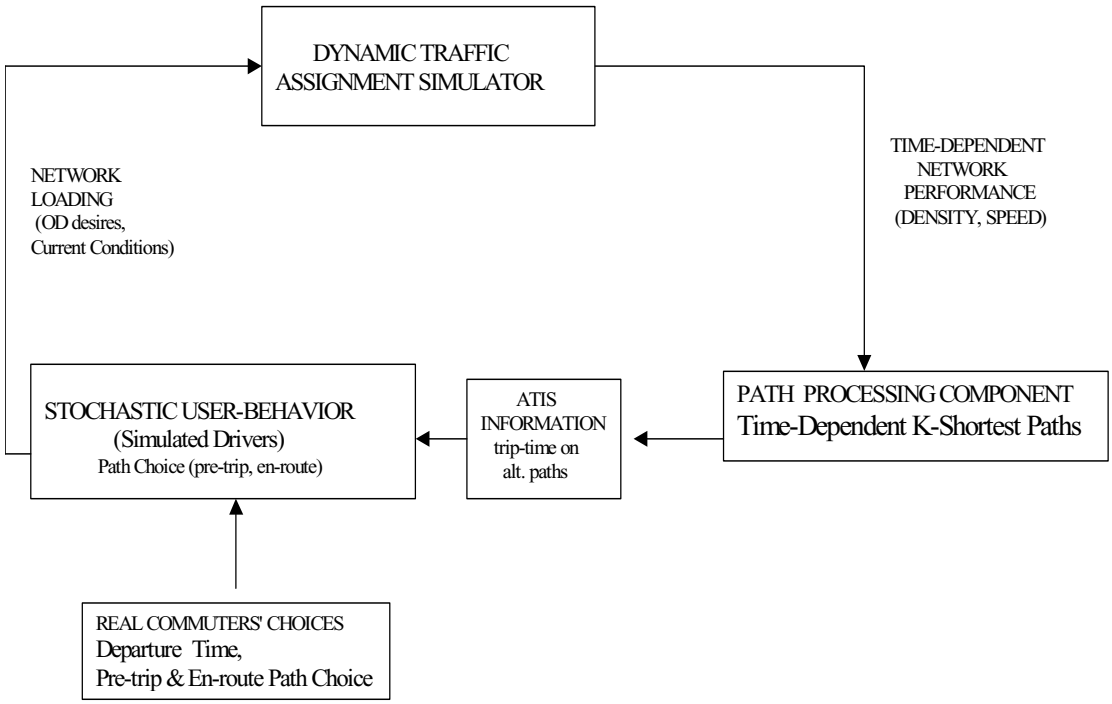

FIGURE 3.1
Schematic representation of travel behavior simulator.

3.3.1 Graphical User Interface

Each user interacts with the simulator via a graphical user interface (GUI), as depicted in Figure 3.2. The GUI serves two major purposes. First, it emulates an in-vehicle information device that supplies ATIS information to users. Second, it enables eliciting users real-time decisions in response to supplied information. The GUI consists of three display windows. The leftmost window (occupying half the display screen) displays the network links, and the location of the participant's vehicle on the network. Each participant's vehicle is moved according to his/her decisions in real-time, and the corresponding movement is displayed through animation. The second window is located on the right top half of the screen.

This window serves as an ATIS message window and conveys trip-times on alternative routes when a participant reaches a junction (an intersection) in the network (decision point). The user is alerted to an approaching decision location by an auditory beep. Further, the ATIS alerts a user by displaying a message when he or she is stuck in a traffic queue, in addition to emitting an auditory beep. This information window also displays a simulated clock, conveying to the user the amount of time elapsed during the commute. A third window, located on the right hand side bottom half of the screen, is used to elicit each user's trip choice.

The user can select from the available alternative routes by clicking on the corresponding buttons with a computer mouse (Figure 3.2). Users can choose departure times by typing in the desired time

using the keyboard. Thus the GUI provides ATIS and driving task information, through both visual and auditory media, by means of a computer monitor, and speakers. The user inputs his/her choices via the mouse and keyboard. The GUI design was guided by human factors considerations including cognitive burden, amount of information, information visibility, task-feedback etc. (Crosby et al., 1993; Rubenstein and Hersh, 1994; Koutsopoulos et al., 1995) and refined through pilot-testing.

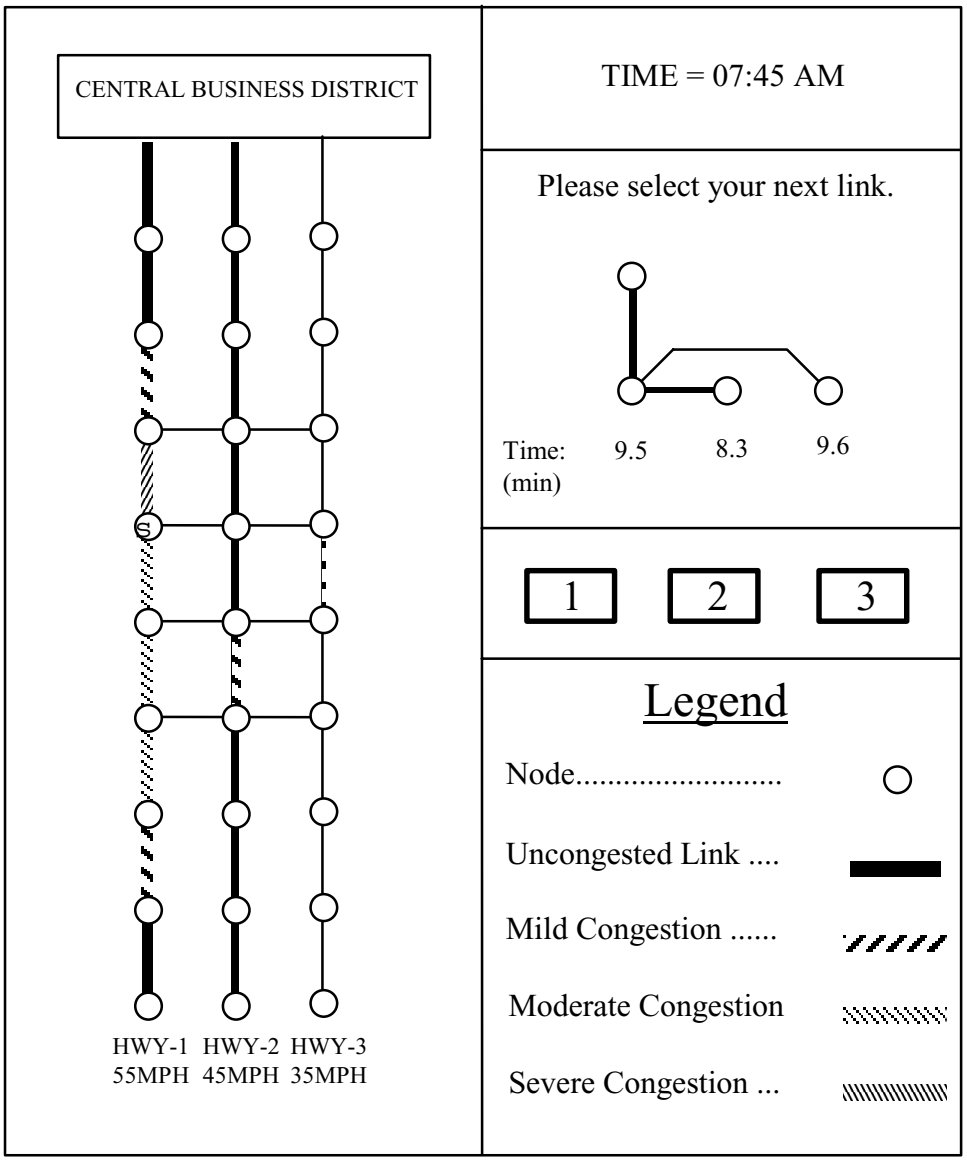

FIGURE 3.2
GUI display depicting the commuting corridor and information supplied by ATIS.

3.3.2 Driving Task Description

Each participant is provided with a view of the basic network configuration along with his/her vehicle's location on it. The vehicle is depicted as a green triangle on the network. The driving task is represented

by an animation of the vehicle's movement on appropriate network links. This animation is simulated consistently according to the prevailing speed of vehicle movement on that link, and the traffic interactions on the network. To further simulate a realistic driving experience, a decision time constraint (ten seconds real-time) is imposed on route choice decisions. This is intended to represent the time-sensitive character of en-route responses to ATIS information. Another feature is intended to enhance the realism of the queuing experience in the simulation. When a user is stuck in traffic, the driver experiences associated delays (till the queue gets cleared), albeit as per the simulated clock. During such instances, he/she will be stationary (till clearance) in traffic, while the time (in the simulated clock) continues to elapse However, as the simulated clock is speeded up about five times faster than real-time, a delay of one hour incurred in traffic is represented by a delay of about 12 minutes on the simulator. It was observed, informally, that several participants displayed signs of restlessness even when faced with such simulated delays. In order to simulate constraints governing commuter behavior, an arrival time constraint at the work-place is also imposed. While driving, the traffic conditions on the network links are displayed through color code as discussed in the next sub-section. Once a driver reaches the destination, the actual path chosen by the driver is highlighted on the network, and the associated trip-time and arrival time are displayed to the user.

3.3.3 ATIS Information

The ATIS conveys traffic information to the participant through the following information elements:

1. Trip times on alternative paths: This information is supplied to each user whenever he/she reaches a decision point. The decision points (located pre-trip and en-route) represent intersections or other opportunities where a user can switch from one facility to any of the others. The time at which a user reaches each decision point depends on his/her departure time and past path choice(s).
2. Congestion information on network links: Prevailing link concentrations are displayed graphically through the use of the following color coding scheme. Links depicted in black correspond to uncongested segments, yellow denotes a mildly congested link, brown represents moderate congestion, while red indicates a severely congested link. The prevailing link concentrations are obtained through the traffic simulator as described in the next sub-section. This congestion information is updated in each simulation interval (every six seconds) and refreshed to ensure visual continuity of the displayed information.
3. Queue build-up and clearance: A user is alerted of entry into a queue and clearance from it, by means of, both, visual messages and auditory beeps. This information is displayed only to those users who enter or leave a queue.
4. Post-trip feedback: Following the completion of each day's trip, the user is furnished feedback on that trip including a graphical display of the path chosen, along with the trip-time on the chosen path, and arrival time at work.

Modifications of these basic information elements in accordance with the study objectives are discussed in the experimental design sections (Sections 3.4 and 3.5).

3.3.4 Traffic Simulation and Path Assignment Model

The traffic simulation and path assignment model used in this study is based on the corridor network version of the DYNAMSART model developed at the University of Texas at Austin (Mahmassani and Jayakrishnan, 1991). The model consists of three main components: the traffic simulator, the network path processing component, and the user decision-making components, as shown in Figure 3.1.

The traffic performance simulator is a fixed time-step 'mesoscopic' traffic simulator. In the simulator, vehicles are moved on the network links at the prevailing local speeds consistent with macroscopic speed-density relations (as per the modified Greenshield's model). Inter-link transfers are subject to capacity constraints. For a given network representation, the simulator uses a time-dependent input function to determine the movement of vehicles on the network links. The traffic simulator also updates the time-dependent network performance measures accordingly. The performance measures obtained from the traffic simulation model include time-dependent link trip times, congestion on various links, queue lengths, and estimated queue clearance times. These form the input to the path processing component, which calculates the pertinent path trip times. The trip times, so obtained, form the basis for the information provided by ATIS to the participants in the study and simulated drivers (with access to ATIS information). In this context, the simulator has the ability to provide information corresponding to a wide range of information strategies, from supplying prevailing trip times on the network links with no predictive capability, to providing route guidance based on reliable travel time predictions, to be described in Section 3.6. Further detail on the simulation-assignment methodology can be found in the paper by Mahmassani and Jayakrishnan (1991).

3.3.5 Architecture

The travel behavior simulator applies the client/server concept to ensure multi-user capabilities as shown in Figure 3.2. The dynamic traffic simulator is implemented in Fortran and resides as an X-Client on a IBM RISC/6000 host computer (Chen, 1998). The GUI is implemented using a C program (calling X-Windows library functions), and is displayed to each user through an X-Server (Macintosh, P.C., or DEC - Digital Equipment Corporation, computer with monitor and corresponding X-Windows software). The GUI and traffic simulator are linked by C library interface routines (available under IBM operating environment AIX version 3.2).

3.3.6 Unique Features of the Simulator

This section is concluded with a few remarks on the suitability of this simulator to observe user behavior together with the dynamic patterns therein, in the presence of real-time information.

Three unique features of the travel behavior simulator described previously enhance its appeal to measure user behavior dynamics. The simulator has multi-user capabilities, thus allowing simultaneous data collection from respondents who interact with each other in real-time on the network. This capability

is especially useful in measuring heterogeneity in user behavior across respondents facing the same choice situation at the same time (path choice across respondents choosing the same departure time).

Secondly, the simulator is specifically designed to enable investigations of two principal dimensions of dynamic behavior – within-day and day-to-day. The latter time frame has typically not been included in other travel behavior simulators, even though it may be expected that the learning and behavioral change resulting from receiving ATIS information can occur over a duration of at least a couple of days. The incorporation of a dynamic traffic simulation component enables capturing the network conditions encountered by each user at a sufficiently high temporal resolution. In addition, this component of the simulator also ensures that the vehicles on the network interact with each other in real-time in accordance with the prevailing network conditions, capacity and queuing restrictions, thus enhancing the realism of traffic stimuli encountered by the respondents. In contrast, a majority of travel behavior simulators, described previously, observe user behavior in response to hypothetical and exogenously determined traffic scenarios. This simulator is also behaviorally more realistic because of the constraints placed on the choice context (arrival time constraints, decision time constraints) to emulate real-world commuting conditions, as well as the consistent and time-dependent interactions between user behavior, supply conditions, and ATIS.

Finally, the information supplied to each user is customized to reveal network conditions pertaining only to his/her commuting experience (in relation to his/her location and departure time) in a time-dependent manner. In effect, this emulates an in-vehicle device that updates information corresponding to the driver's current location (remaining trip-time to his/her destination etc.) as determined by his/her previous choices. Thus a user cannot obtain detailed trip-time information on departure times or routes other than those that correspond to his/her choices. However, the user may obtain general network information (visual congestion information) on all routes through the ATIS device.

3.4 SIMULATOR-BASED INTERACTIVE EXPERIMENTS

Two sets of interactive experiments are conducted in this study. The focus in the first set of experiments is on the influence of network conditions, specifically, the magnitude of network loads, and its day-to-day evolution on trip-maker behavior. In the first experiment, the simulated ATIS supplies information on prevailing traffic conditions to users. Details of the experimental factors and loading levels are presented in the next section. In contrast, in the second set of experiments, the primary interest is on the effect of varying information strategies on commuter's choice behavior. In this experiment, the ATIS supplies information according to different information strategies, to be described in Section 3.6. However, in the second experiment, the same network loading level is maintained across the different information strategies, thus statistically controlling for day-to-day variations in network loads.

3.4.1 Commuting Context

In these experiments, the participants interact with each other within a simulated traffic corridor as shown in Figure 3.3. The simulated commuting corridor consists of three parallel facilities, Highways 1, 2, and 3, with speed limits of 55, 45, and 35 mph respectively (Figure 3.3). The cross-over links have a free

mean speed of 45 mph. Each of these highways is nine miles long, and is discretized into nine one-mile segments as shown. There are four cross-over

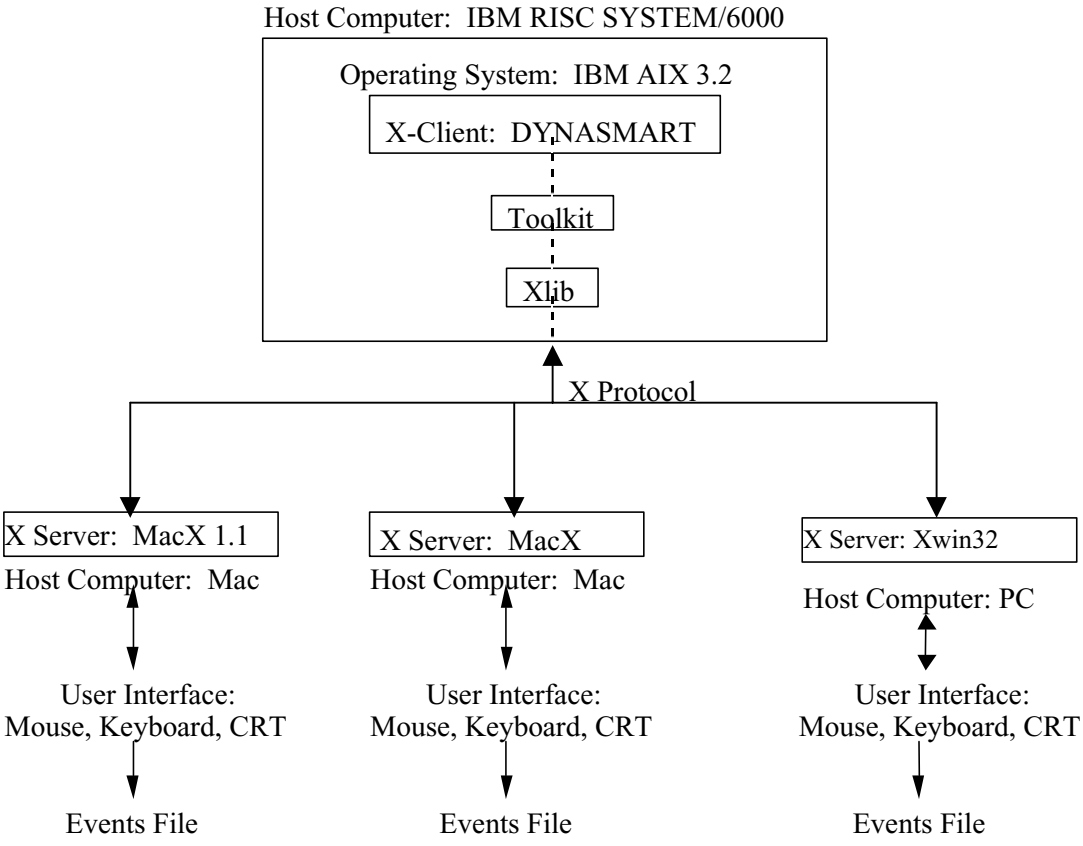

FIGURE 3.3
Client/server model used in travel behavior simulator.

locations (j = 2,...,5), located at the end of the third, fourth, fifth, and sixth miles, where a driver may switch en-route from one facility to another.

The commuters on this simulated corridor can be classified into three categories: actual participants, simulated commuters with information, simulated commuters without information. The first two categories of trip-makers contribute to the real-time decisions on the network on the basis of information. The decisions made by the actual participants are directly incorporated in the simulation, immediately affecting the paths of the corresponding simulated vehicles. The second source of real-time decisions corresponds to simulated drivers with information. Twenty five percent of the simulated commuters are selected, randomly and independently, to receive ATIS information. The informed user receives information on trip-times (from the current location on the network to his/her destination) along the three alternative paths. The decisions of these drivers are modeled using boundedly rational behavioral rules based on a satisficing decision framework, calibrated and validated in earlier studies

(Chang et al., 1988, Jou et al., 1998). In this framework, it is postulated that a user will not switch routes unless the relative trip time saving exceeds a relative band, and the minimum trip time saving exceeds the corresponding indifference band. Each simulated driver who receives information is assigned a randomly generated relative indifference band drawn from a triangular distribution with a mean value of 0.2 and a range of 0.1. This expected value is adopted based on route switching models calibrated in previous studies (Liu et al., 1998). Furthermore, the relative indifference band is allowed to vary across simulated drivers. The minimum indifference band, set at one minute, is taken to be identical across simulated users with information. Simulated commuters, without information, do not switch routes and follow pre-specified paths during their commute.

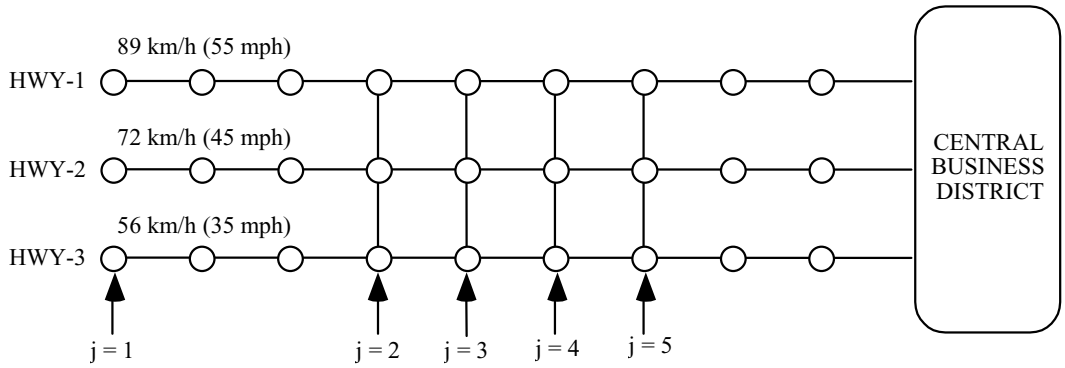

FIGURE 3.4
Commuting corridor with three parallel facilities used in experiments 1 & 2.

In this corridor, commuting trips of the simulated trip-makers (background vehicles on the network) originate from the first six 'residential' sectors (one-mile segments). The simulated commuters, in each sector, depart uniformly over a 20-minute period. The loading periods between adjacent sectors are staggered by five minutes from each other, with commuters in sector one starting first. The simulated drivers enter the corridor through ramps feeding into the first six segments on each facility and commute to a single common destination downstream (such as the Central Business District). It is assumed that in this corridor network, users perceive and identify a path in terms of its major highway facility. Thus, a path is defined, in this study, as a single major facility (to the destination) along with its connecting links. Therefore, for the purpose of this study, it is assumed that a commuter effectively considers only three paths at each decision location (node), one for each major facility.

The participants recruited in the study are required to travel from home to a work location in the central business district for a series of days in the simulated corridor, corresponding to a series of morning commutes. An arrival time constraint (at the work-place) of 8:00 a.m. is imposed, and lateness at work is not permitted. During their commute, the informed users are supplied with the following information by the ATIS to assist in their trip choices. The trip-choice decisions available to actual

participants in the study include pre-trip departure time and route selection, and en-route path choices. The information supplied includes trip times on the three facilities (at decision locations), congestion indicated by color code (updated in real-time), message alerting the driver when he/she is stuck in a queue, and post-trip feedback (departure time, arrival time and trip time on the chosen path). A more detailed description of the experimental procedures and tasks in the two experiments are presented in the following subsection.

3.4.2 Experimental Procedures

The subjects in the two experiments are selected randomly from a pool of commuters at the University of Texas at Austin. Care is taken to exclude potential respondents with unrepresentative commute patterns (such as students or faculty) from the sample. Further, a screening process was used to ensure that the participants in the experiment predominantly commuted to work by driving.

Each participant was given a brief orientation prior to engaging in the experiments. After the briefing, data on socio-demographic and attributes related to actual commute characteristics are obtained using a pre-experiment questionnaire. Initially, the participants were asked to drive through the corridor network in order to familiarize them with the network configuration, and the basic information elements supplied by ATIS.

When the participants were comfortable with the experimental setup and the simulator, they were requested to complete a series of trips to the CBD, corresponding to a series of morning commutes. Initially, each participant's time of departure is pre-assigned for the first day of simulation. When the simulation of the peak period begins, each subject is provided with a display of the commuting corridor. The level of congestion on each link in the network is updated in real-time and a clock displays the current (simulated) time on his/her screen (Figure 3.2). At the participant's designated departure time, his/her screen is updated to display all available paths to the destination. The ATIS then reports trip time information corresponding to each path and the congestion levels on each link are displayed using a color coding scheme discussed in Section 3.3.3. At the designated departure time, the participants are asked if they wish to depart at that time or delay their departure to a later time. When they decided to depart for the commute, the participants could point and click using the mouse at links labeled 1, 2, and 3 in the right-middle of the display window (see Figure 3.2) to select a path.

Once the participant enters the network, he/she receives real-time updates of the vehicle's position (represented by a green triangle symbol) in the corridor, on his/her screen. When the vehicle reaches a decision location where route switching is possible, i.e., crossover links were available, the ATIS displays available paths from the user's current location, along with the information on trip times on alternative paths (see Figure 3.2). Based on this information, and congestion displayed visually on the network links, the subject can then decide on the path to follow from the current decision location to the destination.

When the participant reaches the destination, he/she is supplied with feedback regarding the path chosen, and the associated trip summary statistics, including departure time, arrival time, and total travel

time for that commuting trip. The participant is then required to select a departure time for the commuting trip on the next day.

After the experimental runs have been completed, information on post-experiment questionnaire is used to elicit data on users' preferences for information system attributes, attitudinal factors influencing route and departure time switching decisions, and their evaluation of ATIS information quality.

3.5 EXPERIMENTAL DESIGN AND TREATMENTS IN THE- CONGESTION EXPERIMENT

The first experiment is designed to investigate the role of congestion and day-to-day evolution of network conditions on user behavior in the presence of real-time information. Two experimental factors are examined here. The first experimental treatment considered is the network load. Three loading levels are simulated in the network as shown in Table 3.1. These levels are chosen to ensure a significant difference in trip times and concentrations on the three facilities over a wide range of departure times. The resulting time-dependent congestion levels experienced by the user depend on his/her departure time, and the behavior of other drivers in the network. The simulated commuters are distributed in the network such that the rerouting opportunities on it decrease, with increasing network loading.

The second experimental factor relates to network state evolution from day-to-day, and consists of the following two levels. In the first, referred to as the sequential or systematic treatment, each commuter encounters the three loading levels in a sequential manner, a given loading level being applied for four consecutive days. The order in which these loading levels are administered is varied between different batches of participants as shown in Table 3.1. This level is intended to simulate a relatively gradual change in network states over time. In this level, a given state persists for four successive days, thus allowing the user a reasonable amount of time to get adjusted to the changed network states. In contrast, the second level of the second factor is intended to represent the effect of random fluctuation in network states from day-to-day. This is simulated by providing the three levels of network loads (factor one) in a random order.

The commuting context in this experiment is discussed in Section 3.4.1. Sixty-four respondents were recruited for this set of experiments, using the selection procedure described in Section 3.4.2. The random treatment was administered to half the respondents (in three batches of about 10 participants) for a period of six days. The systematic treatment was administered for a duration of twelve days to the other three batches of participants (Table 3.1).

TABLE 3.1

LOADING LEVELS AND DAY-TO-DAY EVOLUTION FOR THE SYSTEMATIC AND RANDOM TREATMENTS

Batch	Loading Level Systematic Treatment (4 days/ level)	Loading Level Random Treatment
1	A, B, C	C, A, C, B, B, A
2	B, C, A	B, B, A, B, C, C
3	C, A, B	A, A, C, B, C, C

Note: A,B,C correspond to 60 veh/min, 75 veh/min, 90 veh/min loads respectively

Due to the non-linear and time-dependent interactions on the network, the magnitudes of network congestion cannot be represented in a closed-form. Therefore, the level of congestion on the network is represented in terms of the magnitude of network loads in this experiment. The network loading levels in the experiment correspond to light, moderate and severely congested conditions on the network during the peak-period. For instance, volume to capacity ratios in excess of 0.85, were observed for a significant time-interval during the peak-period at the highest loading level. The lowest loading magnitude corresponds to uncongested conditions on the network. The loading levels were chosen to allow considerable variability in trip-times on the alternative facilities across different departure times. Furthermore, the simulated commuters are assigned to alternative facilities such that the rerouting opportunities on the network decrease as the network loading magnitude increases.

The profile of the 62 randomly selected commuters (from a pool of commuters to the University of Texas, Austin) recruited to participate in the experiments is as follows. The majority of subjects are between the ages of 20 and 60 (84%). The mean travel time (actual) to work is approximately 31 minutes with a standard deviation of about 19 minutes. The average work start time for the respondents in this sample was 8:01 a.m. with a standard deviation of about 32 minutes. Nearly 42% of the participants reported tolerance to lateness of less than fifteen minutes at the workplace; the average preferred arrival time is 7:56 a.m., 4 minutes before the work start-time. The profile of the participants is comparable to the commuter profile obtained from a field survey of 638 respondents in the city of Austin in 1990, with a few minor differences (Mahmassani et al., 1993). The average trip-time reported then was 21 minutes, compared to the 31 minutes reported here, and 60% of the respondents had no lateness tolerance at the workplace (it can be stated that Austin has experienced considerable growth in both population and traffic congestion in the intervening years). A detailed description of sample characteristics is presented in Chapter 5.

The subjects select their departure time (pre-trip) and routes (pre-trip and en-route) with the aid of ATIS information as described in Section 3.4.2. The prevailing conditions, information supplied, and user responses (route and departure time decisions under varying network conditions) are then recorded.

3.6 EXPERIMENTAL DESIGN AND TREATMENTS IN THE INFORMATION QUALITY EXPERIMENT

The second set of experiments focuses on the influence of information quality and ATIS information strategies on user decisions. Three experimental treatments concerning ATIS information quality are investigated in this set of experiments.

The first, pertaining to the nature of information, is aimed at studying the effect of alternative information provision formats on route switching. Two treatment levels are considered - descriptive and prescriptive information. Under the descriptive information level, the user is provided with trip times to the destination on alternative routes. Prescriptive information, on the other hand, simulates route guidance, by advising the user of the highway to follow next, and providing the user with the associated trip time.

The second factor investigated in this experiment is information type. The six levels considered here are designed to reflect a range of possible information quality and credibility that a user may encounter with real-world ATIS devices. The differences are primarily based on the accuracy, extent and timeliness of supplied information. The first level corresponds to prevailing information, where the travel time on the alternative paths from the current decision node are calculated based on prevailing travel times on downstream links. Prevailing travel times tend to be inaccurate as they project the future trip-times on the basis of currently prevalent conditions (Chen and Mahmassani, 1993). The second level, referred to as predicted information, is supplied on the basis of predicted travel times on downstream links. A mechanism to predict trip-time information on downstream links is implemented by means of virtual probe vehicles. These probe vehicles are emitted from each decision node over a wide range of departure times and the resulting trip times are recorded. Whenever a user reaches a decision location, he/she is supplied trip-time information experienced by the probe vehicle corresponding to his/her arrival time at the decision location. Compared to prevailing information, trip times calculated using a reliable prediction mechanism has been empirically shown to be more accurate (Mahmassani and Chen, 1991).

The next two levels of information type are intended to study the influence of partial information on choice behavior. Under both these levels, information is only provided on a subset of available paths. In both these levels, travel time information is not available to users on one of the three facilities (randomized each day). While in the third level the available information is supplied on the basis of prevailing trip times, under the fourth level, the differentially supplied information is based on predicted travel times instead.

The final two levels are designed to examine the effect of inaccurate and highly imperfect information, on choice behavior. Under the fifth level, perturbation of information is effected, by adding random error components drawn from a normal distribution to the predicted travel times. A coefficient of variation of 20% on the random errors ensures that the perturbation remains within a reasonable range. This level is intended to reflect field errors due to faulty traffic sensors and interference during transmission. In the final level, the ATIS supplies random information that is entirely independent of prevailing traffic conditions on the network. This level is designed to provide a benchmark in assessing user response to highly imperfect information.

The third factor, post-trip feedback supplied by the ATIS system, consists of three levels. Under the first level, the information system provides feedback on the user's own experience, including trip time on the chosen path, and arrival time at work. In the second level, in addition to this feedback on the path they chose, users also receive information on the path recommended by the ATIS and its associated trip time and arrival time. The recommended path is defined as the path obtained by selecting at each decision node the path with the least reported trip time or the path explicitly prescribed by the ATIS. Note that the recommended path here may not necessarily be the one with the actual minimum trip time. Trip statistics on the recommended path are also obtained using a traffic probing mechanism. Virtual cars are emitted on the recommended path at each decision node, and the corresponding trip performance is

tracked to obtain this information. This feedback level allows a user to assess the quality of information in relation to his/her travel experience.

Under the third level, the information system provides a user with feedback on the actual best path and its associated trip time and arrival time. To obtain this information, virtual probe vehicles are emitted into traffic on each of the three paths at each decision location starting at the user's departure time. The path and the trip time of the probe vehicle that reaches the destination first corresponds to the optimal (least trip-time ex-post facto) path for the chosen departure time. This feedback level enables the users to assess the quality of their decisions in relation to the optimal path corresponding to the chosen departure time.

In this experiment, an information strategy is defined as a combination of the various levels of these three factors. Of the 36 possible information strategies, 12 are discarded due to mutual inconsistency between factor levels and confounding effects. Examples of these include combinations of prescriptive information with levels of information quality such as random, perturbed, differential etc. The remaining 24 treatments are administered to 14 batches of 10 respondents each as depicted in Table 3.2. A sample size of about 140 respondents is chosen empirically to ensure roughly 30 observations for measuring each main factor effect.

These treatments are administered to respondents in the commuting context described in Section 3.4.1. In the experiment, the ATIS supplies information to each trip-maker, using three different information supply strategies (consisting of a combination of treatment levels). Each strategy is applied for four consecutive days. The strategies and the order in which they are administered are varied across different batches of users to ensure adequate observations (30+) for each treatment level. The information supplied to the user includes congestion indicated through color coding on network links, trip times on alternative paths, messages when the user is stuck in a queue, and feedback at the end of his/her trip. Note that the information is consistent with the treatment levels. For instance, the information elements in the random treatment are independent of the actual conditions. All the users' trip decisions, associated supply conditions, and the information provided by ATIS are recorded in the experiment.

The socio-demographics and commute characteristics of the respondents in this experiment are briefly described below. As explained previously, respondents with unrepresentative patterns such as students, and faculty are excluded from the sample. The selection process also ensured that the chosen participants regularly commuted to work (five or more days per week) predominantly by driving. The profile of sample respondents is roughly comparable to the profile of a larger sample obtained using travel diaries from the city of Austin in late eighties, with a few minor differences.

A majority of the subjects are between the ages of 20 to 60 (92%). The actual travel time to work for respondents in the sample has a mean of about 28 minutes and a standard deviation of about 15 minutes. The average work start time in this sample is 8:01 a.m. and the standard deviation is nearly 50 minutes. Approximately 47% of the participants report lateness tolerance of less than 15 minutes at the workplace. The respondents in this sample on an average prefer to arrive at the work place about two

TABLE 3.2

ADMINISTRATION OF ATIS INFORMATION STRATEGIES ACROSS BATCHES AND OVER TIME (EXPERIMENT 2)

	Experimental ATIS Information Strategy (Nature, Type, Feedback Levels)		
Batch #	Days 1-4	Days 5-8	Days 9-12
1	Prescriptive Predicted (r)	Descriptive Random(r)	Descriptive Prevailing (r)
2	Prescriptive Predicted (b)	Descriptive Differential Prevailing (b)	Descriptive Prevailing (b)
3	Descriptive Prevailing (o)	Prescriptive Predicted (o)	Descriptive Random (o)
4	Descriptive Prevailing (r)	Prescriptive Differential Predicted (b)	Descriptive Predicted (r)
5	Descriptive Random (b)	Descriptive Prevailing (b)	Prescriptive Predicted (r)
6	Descriptive Differential Prevailing (o)	Prescriptive Predicted (b)	Descriptive Prevailing (r)
7	Descriptive Prevailing (b)	Descriptive Differential Predicted (b)	Prescriptive Predicted (r)
8	Prescriptive Prevailing (r)	Descriptive Predicted (r)	Descriptive Differential Predicted (r)
9	Descriptive Predicted (b)	Prescriptive Prevailing (b)	Descriptive Perturbed (b)
10	Prescriptive Prevailing (o)	Descriptive Predicted (o)	Descriptive Perturbed (o)
11	Descriptive Differential Prevailing (b)	Descriptive Predicted (r)	Prescriptive Prevailing (b)
12	Descriptive Predicted (b)	Descriptive Differential Predicted (o)	Prescriptive Prevailing (r)
13	Prescriptive Prevailing (b)	Descriptive Perturbed (r)	Descriptive Predicted (r)
14	Descriptive Differential Prevailing (o)	Prescriptive Prevailing (r)	Descriptive Predicted (b)

Note: The letter in parenthesis denotes the level of feedback supplied by ATIS
o - feedback is provided only on own trip experience
r - feedback is provided on path recommended by ATIS
b - feedback is provided on actual best path (ex-post facto) for the user's departure time choice

minutes before work start time. The standard deviation of preferred arrival time is nearly 52 minutes. In a post-experiment questionnaire, a majority of respondents indicated a willingness to use ATIS information to assist in their route and departure time choice decisions. On the question of accuracy of information in the experiments, nearly 17% of the respondents felt that the ATIS information was very accurate, whereas 64% reported it as only reasonably accurate. A more elaborate description of sample characteristics is provided in Chapter 6.

3.7 SUMMARY

A review of existing approaches to observe trip-maker behavior under real-time information suggests that simulation-based approaches can provide an effective compromise between stated and revealed preference data collection methods. The approach devised for this study enables the observation of user behavior, along with supply conditions and information provision, at a temporal resolution that is appropriate for dynamic modeling purposes. The advantages of this approach include adequate experimental control over factors of interest, and moderate cost when compared to a full-scale field operational test. There is, however, a need to confirm the insights from simulator-based experiments with real-world data as ATIS usage becomes more prevalent.

This chapter describes the interactive travel behavior simulator used to measure user behavior dynamics. The essential components of the simulator include a graphical user interface, realistic task representation, ATIS information supply, and a dynamic traffic simulation model with path processing capabilities. The unique features of this simulator include multi-user capabilities, mutually consistent time-dependent interactions between user choices, network conditions, and information, and customized information provision. These features make it particularly well-suited to serve as an observational framework to measure user behavior dynamics.

Finally this chapter outlines the experimental design and procedures for two sets of interactive experiments using the simulator. The first is designed to examine the influence of congestion and network conditions on user behavior dynamics under ATIS information. The effect of variation in network load magnitudes and its day-to-day evolution are investigated. The second set of experiments is aimed at addressing the role of ATIS information quality and information strategies on user response. The information strategies considered in the experiment are defined on the basis of the nature of ATIS information (descriptive or prescriptive), type of information (prevailing, predicted, differential prevailing, differential predicted, perturbed, and random information), and post-trip feedback on trip performance (own experience only, feedback on ATIS recommended path, feedback on actual best path). A general framework is proposed in the following chapter to model the observed user behavior data from the experiments described here.

CHAPTER 4: MODELING FRAMEWORK FOR THE ANALYSIS OF COMMUTER BEHAVIOR DYNAMICS

4.1 INTRODUCTION

Continuing interest in analyzing and representing individual traveler behavior over time and space has resulted in an evolution of modeling efforts from fragmented cross-sectional analysis of independent travel decisions to longitudinal models of inter-related activity and travel patterns (Kitamura, 1990; Axhausen and Garling, 1992; Bhat, 1997; Mahmassani and Jou, 1998). Several conceptual, methodological and measurement challenges arise in connection with the analysis of behavioral dynamics as discussed in Section 1.4. Existing modeling frameworks are limited in their ability to satisfactorily address these challenges. In this chapter, a framework is proposed to model dynamics in discrete choice data by applying the kernel logit framework (Ben-Akiva and Bolduc, 1996; Revelt and Train, 1998). Furthermore, the theoretical and practical suitability of the proposed framework is also systematically investigated.

The multinomial logit (MNL) framework (see Ben-Akiva and Lerman, 1985, for a detailed presentation), though appealing in cross-sectional models due to its simplicity and closed-form likelihood function, imposes well-known and often untenable restrictions on the choice structure including independence from irrelevant alternatives (IIA) and homogeniety of response. However, consideration of the time element in many practical choice situations often necessitates modeling response heterogeneity, state-dependence, as well as contemporaneous and serial correlation effects. In such cases, MNL could lead to seriously inconsistent estimators and erroneous inferences.

A logical extension of the MNL framework, the Generalized Extreme Value (GEV) class of models, allows for the partial relaxation of the independence assumption. The error terms, in this case, are assumed to belong to type I extreme value error distribution (Domencich and McFadden, 1975; Ben-Akiva and Lerman, 1985). This class of models permits correlation across subsets of alternatives. The GEV class includes models ranging from the nested logit (NL) model requiring pre-specification of alternatives with shared unobservables to the paired combinatorial logit (PCL) model (Koppelman and Wen, 1996) that allows different correlations across alternatives. Note that the error terms, however, are identically distributed, thus, imposing response homogeneity in the choice context. With increasing number of alternatives this framework becomes increasingly cumbersome to calibrate (particularly the nested logit structure), as the number of possible nesting structures increases exponentially with the number of alternatives. Due to these considerations, the application of GEV class of models to dynamic choice situations has been limited (Roy et al., 1996).

The Multinomial Probit (MNP) framework accommodates a flexible covariance structure both across alternatives and over time through general multivariate normal error terms for the utility (Domencich and McFadden, 1975; Daganzo, 1980; Daganzo and Sheffi, 1982). Thus the MNP is capable of representing unobservables resulting from general dynamic and stochastic processes. While theoretically appealing, the MNP framework is admittedly computationally burdensome, as the likelihood

computation involves multi-dimensional integrals of the multivariate normal density function. For instance, in a cross-sectional discrete model with J alternatives, the likelihood computation for a single observation requires the evaluation of a (J-1)-dimensional multivariate integral. Longitudinal choice contexts with J alternatives and T time periods are essentially computationally equivalent to cross-sectional models with (J-1) x T alternatives (Daganzo and Sheffi, 1982). Dynamic models, thus, further increase the computational complexity in the MNP framework since the dimensionality of the integral increases by a factor of T. Furthermore, computational evidence suggests identification problems with MNP because of the possibility of flat log-likelihood functions, and instability of variance-covariance parameters (Horowitz, 1991; Lam and Mahmassani, 1991; Keane, 1992). Therefore, although the MNP is theoretically more suitable for dynamic modeling than preceding frameworks, it presents practical problems with large choice set dimensionality and general variance-covariance structures.

Application of the MNP model has been facilitated by increasing computing power. Monte-Carlo simulation techniques have emerged as the method of choice to evaluate the non-tractable integrals of multivariate normal density functions (Lam and Mahmassani, 1991; Mahmassani and Jou, 1998). Alternative simulation approaches have also been proposed to improve the efficiency of the estimation process (Bhat, 2000; Train, 2000). Monte-Carlo simulation also allows consideration of more general error structures which have encouraged the development and application of variants of the MNP model such as the generalized ordinal probit (Mahmassani, Yen, and Herman, 1994), and the space-time MNP application to freight demand proposed by Garrido and Mahmassani (2000).

One particularly attractive variant is the kernel logit model or the so-called 'mixed-logit model' (Ben-Akiva and Bolduc, 1996; Bhat, 1997; Revelt and Train, 1998). Revelt and Train (1998) use this formulation to capture heterogeneity in behavior across respondents when modeling recreational demand, whereas, Bhat (1999) models joint mode and departure time choice behavior using this formulation. This framework combines to a certain extent, the flexibility and realism of the probit structure with some of the computational simplicity of the logit model. In the kernel logit framework, a decomposable structure is assumed for the unobserved disturbance term for each alternative. The unobserved disturbance is the sum of two error terms - one that is multivariate normally distributed as in the MNP, and another that is Gumbel distributed as in the MNL framework. The Gumbel error terms are assumed to be independent and identical (over time and across alternatives) as in the MNL model, however, they only need be identically distributed across alternatives at a given time, unlike in the MNL model. The general variance-covariance structure among the normal error terms overcomes the well-known limitations of the i.i.d Gumbel term of the MNL. The Gumbel error terms contribute to the computational tractability of this model, because of the closed-form logit likelihood function, conditional on the MVN error terms. The unconditional likelihood may be obtained by integrating this conditional likelihood (in a logit form) over the MVN error terms, which can be readily accomplished in a Monte-Carlo simulation approach similar to the MNP model.

While the kernel logit model structure is not new, relatively few researchers have adopted this formulation to model discrete choice data. Most efforts till date, have focused almost exclusively on applying the kernel logit method to cross-sectional discrete choice models. Therefore, the primary objective in this chapter is to present dynamic kernel logit (DKL) formulations for ordered and unordered longitudinal discrete choice data. The latter formulation is modified suitably in Chapters 5 and 6, to model dynamic aspects in commuter behavior.

The few existing applications of the kernel logit model reported in the literature, focus on deriving insight primarily from cross-sectional discrete choice data. The theoretical suitability and properties of the kernel logit model, as applied to longitudinal data, have not been investigated. Therefore, the second objective, in this analysis, is to investigate the theoretical and econometric foundations of the dynamic kernel logit model. Toward this end, the generality of the DKL structure is assessed by investigating distributional convergence between DKL and MNP formulations. The calibration procedure, econometric properties of DKL estimators and identification issues are also discussed.

The third objective in this chapter is to systematically assess the performance of the dynamic kernel logit model from the perspectives of computational efficiency and estimate accuracy. To measure computational performance, the theoretical time-complexity of the DKL is compared to that of MNP. In addition, practical computational performance is analyzed through numerical experiments on synthetic data sets. Accuracy of estimates obtained from the two modeling approaches is also assessed through a set of numerical experiments using synthetic data sets.

The rest of this chapter is organized as follows. In the next section, the DKL formulation for modeling ordered and unordered response discrete choice data are presented, followed by a critical review of the assumptions involved. Section 4.3 discusses the calibration procedure, econometric properties of DKL estimators, and specification issues. In Section 4.4, performance of DKL is analyzed in relation to the MNP framework using numerical experiments, followed by a summary in Section 4.5.

4.2 DYNAMIC KERNEL LOGIT (DKL) MODEL FORMULATION FOR LONGITUDINAL ANALYSIS OF DISCRETE CHOICE DATA

First the choice context where the alternatives are unordered is considered, followed by an outline of the formulation for the ordered response case. For ease of exposition, and with no loss of generality, it is assumed in both cases that the choice set remains the same across individuals and over time.

4.2.1 Problem Definition

In the unordered response case, the problem can be stated as follows: Each individual n (in a sample of N decision-makers), faces the decision of selecting an alternative from a set of J (distinct) unordered alternatives, with this decision being repeated over T (T > 1) time periods. The modeling problem is motivated by the desire to represent and analyze users' choice propensities of various alternatives over time, and to forecast future choices as a function of user characteristics, attributes of the alternatives (static, and dynamic), and past choices.

The Random Utility Maximization (RUM) paradigm is commonly used to model choice behavior due its elegant micro-economic foundations and widespread acceptance in the modeling community (Domencich and McFadden, 1975; Ben-Akiva and Lerman, 1985). Furthermore, careful specification of the utility function can capture or approximate a wide array of behavioral phenomena and decision rules. Under this framework, it is assumed that at each time t, a decision-maker selects the alternative that maximizes his/her utility at that time. Note that by selecting an alternative that maximizes his/her local utility at each time, a decision-maker may not necessarily choose a sequence of alternatives that maximize his/her utility over the horizon of interest (t = 1,… T). According to standard RUM conventions, utility of an alternative consists of two components: a systematic component that is observable by the analyst (as a deterministic function of the attributes of the decision-maker and the alternatives), and a random component (which includes all unobservable effects influencing the choice). Assumptions on the functional form of the systematic component of the utility, and the distribution of unobservables are necessary to complete the specification in the modeling framework. The following notation is introduced for presenting the DKL formulation.

4.2.2 Dynamic Kernel Logit Formulation for Unordered Response Data Notation

Let t denote the time index, t = 1, ... ,T;

i - the alternative index, i = 1,.... J;

n - the index across individuals in a sample, n = 1, ...N;

C_n^t - the choice made by an individual n at time t;

U_n^{it} - the utility of alternative i at time t for individual n;

V_n^{it} - the deterministic term of the utility for individual n at time t for alternative i;

ε_n^{it} - the normal error term component of the utility of alternative i at time t for individual n;

τ_n^{it} - the Gumbel error term component of the utility of alternative i at time t for individual n;

$\boldsymbol{V_n^t}, \boldsymbol{V_n}$ - the vectors of deterministic terms of the utility for individual n (at time t and across all times respectively);

$\boldsymbol{\varepsilon_n^t}, \boldsymbol{\varepsilon_n}$ – the vectors of multivariate normal error terms for all alternatives for time period t and across different time periods respectively;

$\boldsymbol{\tau_n^t}, \boldsymbol{\tau_n}$ - the vector of multivariate normal error terms for all alternatives for time period t and across all time periods respectively.

P_n - the likelihood that individual n selects a sequence of choices C_n

The sequence of choices made by individual n can be represented by $C_n = \{C_n^1, C_n^2, \ldots\ldots C_n^T\}$;

According to the random utility maximization framework, the probability of observing a sequence of choices of individual n is given by

$P_n = Pr_n\{ C_n^1, C_n^2, \ldots\ldots, C_n^T \}$

$= Pr_n \{ U_n^{C\,t} \geq U_n^{it}, \forall\, i \neq C_n^t, \forall\, t = 1,\ldots\ldots,T\}$ (4.1).

The random utility U_n^{it} can be written as the sum of a deterministic term and a random term (without loss of generality). The differences between the probit and kernel logit specifications arise in the assumptions regarding the error term distributions. In the probit model the error terms are assumed to be multivariate normal, whereas, in the kernel logit model, a components of variance structure is considered with two error term components; one is multivariate normally distributed, and the other is Gumbel distributed. The Gumbel errors are also assumed to be independent across alternatives and over time. Furthermore, the normal errors and Gumbel errors are assumed to be independent. In addition, it is assumed that the Gumbel errors are identically distributed across alternatives for a given panel period.

Following Bhat's (1997) formulation of the cross-sectional kernel logit model, U_n^{it} can be expressed in the DKL formulation as

$U_n^{it} = V_n^{it} + \varepsilon_n^{it} + \tau_n^{it}$ (4.2),

where, V_n^{it} is the deterministic term of the utility

$\varepsilon_n \sim MVN(0,\Sigma_\varepsilon)$ (4.2a),

and, $\tau_n^{it} \sim$ independently Gumbel distributed with variance, $\sigma_t^2 = \pi^2/(6\mu_t^2)$, t= 1,…T,

where μ_t is the Gumbel scale parameter at time t and the location parameter is reset such that expected value of the Gumbel error term is zero.

Aggregating τ_n^{it} into a vector form, $\boldsymbol{\tau_n}$ may be expressed as

$\boldsymbol{\tau_n} \sim$ i.i.d. Gumbel$(0,\Sigma_g)$ (4.2b),

where Σ_g is a variance covariance matrix of size JT x JT, with variance of σ_t^2 for its diagonal terms, and zero for its covariances.

Note that the distributional assumption above does not necessarily assume independence across observations, but only over logit error terms, thus permitting contemporaneous correlations through the multivariate normal error terms ε_{in}^t.

Rewriting equation (4.1) by substituting (4.2) the following expression is obtained:

$Pr\{C_n^t, t = 1,\ldots T\} =$

$Pr\{(V_n^{C\,t} + \varepsilon_n^{C\,t} + \tau_n^{C\,t}) - (V_n^{i\,t} + \varepsilon_n^{i\,t} + \tau_n^{i\,t}) \geq 0, i \neq C_n^t, t = 1,\ldots\ldots,T\}$ (4.3).

By conditioning on $\boldsymbol{\varepsilon_n}$, equation (4.3) is rewritten as

$Pr\{C_n^t, t = 1,\ldots T\} = \int_{\boldsymbol{\varepsilon_n}} Pr\{C_n^t, t = 1,\ldots T \mid \boldsymbol{\varepsilon_n}\} f(\boldsymbol{\varepsilon_n}) d\boldsymbol{\varepsilon_n}$ (4.4),

where $f(\boldsymbol{\varepsilon_n})$ is the multivariate normal probability density function with parameters specified in (4.2a).

Combining equation (4.3) and (4.4) the likelihood of observing a given choice sequence is given by:

Pr{ C_n^t, t = 1,… T } =

$\int_{\varepsilon n}$Pr{ $(V_n^{Ct} + \varepsilon_n^{Ct} + \tau_n^{Ct})$ - $(V_n^{it} + \varepsilon_n^{it} + \tau_n^{it})$ ≥0, i≠ C_n^t, t = 1,...,T|ε_n}f(ε_n)dε (4.5).

Conditional on $\boldsymbol{\varepsilon}_n$, both ε_n^{it} and ε_n^{Ct} are known and can be treated as deterministic. For a given $\boldsymbol{\varepsilon}_n$, the conditional deterministic utility W_n^{it} is given by

$$W_n^{it} = V_n^{it} + \varepsilon_n^{it}$$

Simplifying (4.5) yields

Pr{ C_n^t, t = 1,… T } =

$\int_{\varepsilon n}$ Pr { $(W_n^{Ct} + \tau_n^{Ct})$-$(W_n^{it} + \tau_n^{it})$≥0, i≠ C_n^t, t = 1,...,T |ε_n}f(ε_n)dε_n (4.6).

The probability expression in the integrand in RHS of equation (4.6) can be rewritten as follows:

Pr { $(W_n^{Ct} + \tau_n^{Ct})$ - $(W_n^{it} + \tau_n^{it})$ ≥0, i ≠ C_n^t, t = 1,...,T |ε_n}

= $\Pi_{t=1}^{T}$ [Pr{$(W_n^{Ct} + \tau_n^{Ct})$-$(W_n^{it} + \tau_n^{it})$≥0, i≠ C_n^t ,| ε_n}] (4.7).

Equation (4.7) exploits the independence of Gumbel error terms over time and across alternatives. The probability expression on the RHS of (4.7) has a simple multinomial logit form as expressed in equation (4.8),

Pr{$(W_n^{Ct} + \tau_n^{Ct})$ - $(W_n^{it} + \tau_n^{it})$ ≥0, i ≠ C_n^t , | ε_n}=

$$\exp(\mu_t W_n^{Ct}) / \Sigma_i \exp(\mu_t W_n^{it}) \quad (4.8).$$

This follows from the independence of the error terms τ_n^{it} over time and across alternatives, and the assumption of identical distribution across alternatives for a given panel period (t).

Based on equations (4.7) and (4.8), and resubstituting for W_n^{it} the likelihood of observing the choice sequence C^t_n, t = 1,… T, for an individual n, may be expressed as:

Pr{ C_n^t, t = 1,… T }

=$\int_{\varepsilon n} \Pi_{t=1}^{T}$ { $\exp[\mu_t (V_n^{Ct} + \varepsilon_n^{Ct})] / \Sigma_i \exp[\mu_t (V_n^{it} + \varepsilon_n^{it})]$}f($\varepsilon_n$)d$\varepsilon_n$ (4.9).

In case the choice sequences are independent across observations, the log-likelihood can be given by:

LL = Σ_n log Pr{ C_n^t , t = 1,… T }

=$\Sigma_n$log($\int_{\varepsilon n} \Pi_{t=1}^{T}$ { $\exp[\mu_t (V_n^{Ct} + \varepsilon_n^{Ct})] / \Sigma_i \exp[\mu_t (V_n^{it} + \varepsilon_n^{it})]$}f($\varepsilon_n$)d$\varepsilon_n$ (4.10).

Note that the formulation above is subject to identification constraints, discussed in Section 4.3. For now, however, it may be noted that when the variance of the utility of alternative is split into two components as above, it will not be possible to identify both components uniquely, in the absence of further sources of identification. Second, the calibration procedure detailed in the next section, will exploit

the fact that the desired likelihood (P_n) may be written as an expectation of a kernel function h, that is, $P_n = E_\varepsilon [h(\varepsilon)]$. This follows from the fact that

$P_n = \int_\varepsilon h(V_n,\varepsilon_n) f(\varepsilon_n) d\varepsilon_n$ (4.11),

where $h(V_n,\varepsilon_n) = \Pi_{t=1}^{T} \{ \exp[\mu_t (V_n^{Ct} + \varepsilon_n^{Ct})] / \Sigma_i \exp[\mu_t (V_n^{it} + \varepsilon_n^{it})]\}$

Note that the formulation above can be used in cross-sectional models, by dropping all subscripts referring to time and considering only one panel period (T=1) in equation (4.10).

4.2.3 Review of DKL Assumptions

Three major assumptions are invoked in formulating the DKL model above. These are now reviewed critically in terms of the restrictions they impose, and possible extensions and relaxations. The first assumption is that the error term of the utility of an alternative can be decomposed into additive error components. This decomposability assumption imposes no loss of generality as any error term can be written as a sum of itself and zero (which can be represented mathematically as an error term with zero variance).

The second assumption relates to the distributional assumption on the error components. It is assumed that one of the error components is multivariate normally distributed, while the other is independently and identically (for a given time period) Gumbel distributed. To the extent that the unobservables of the utilities can be represented by a multivariate normal error term (often justified using the central limit theorem on unobservable factors), this assumption is not particularly restrictive. The mixed logit error structure converges in distribution to a corresponding MVN error structure as the Gumbel scale parameters increase asymptotically, as shown below using Moment Generating Functions.

Proposition: A random variable with the kernel logit error structure converges asymptotically in distribution to a multivariate normal error structure as $\mu_r \to \infty$, for r= 1,…T.

Proof: Consider the kernel logit error structure in the vector form,

$\zeta_n = \varepsilon_n + \tau_n$, $\varepsilon_n \sim MVN(0,\Sigma_\varepsilon)$, $\tau_n \sim$ independent Gumbel $(0,\Sigma_g)$,

where Σ_g also ensures identical Gumbel errors across alternatives for a given time t.

The Moment Generating Function (MGF) of ζ_n can be expressed as

$M_\zeta(K) = M_\varepsilon(K)\, M_\tau(K)$ (4.12),

by virtue of independence between ε_n and τ_n.

Under the assumptions, the MGF for the multivariate normal error vector ε_n and τ_n are respectively given by (Johnson and Kotz, 1970):

$M_\varepsilon(K) = \exp [½(K \Sigma_\varepsilon K')]$

$M_\tau(K) = \Pi_r \Gamma(1- k_r/\mu_r)$, r = 1,.... , JT,

where $\mu_r = \sqrt{\dfrac{\pi^2}{6\sigma_r^2}}$,

σ_r^2 represents the variance of the rth alternative (r = i*t for some alternative i at time t)

and $\Gamma(\alpha)$ is the standard Gamma function given by $\int_0^\infty e^{-x} x^{\alpha-1}dx$

Therefore the MGF of the kernel logit error structure is given by

$M_\zeta(K) = \exp\{½(K \Sigma_\varepsilon K')\} \Pi_r \Gamma(1- k_r/\mu_r)$, r = 1,.... , JT (4.13).

When the Gumbel variances σ_r^2 become asymptotically close to zero, the scale parameters $\mu_r \to\infty$, r = 1,…JT,

As $\mu_r \to\infty$, $(1- k_r/\mu_r)\to 1$, $\Gamma (1- k_r/\mu_r)\to 1$, then

$M_\zeta(K) \to \exp(K \Sigma_\varepsilon K'/2)$ (4.14),

Note that $M_\varepsilon(K) = \exp(K \Sigma_\varepsilon K'/2)$

Thus, asymptotically as the Gumbel variances become arbitrarily small, the DKL error structure converges in distribution to the MNP error structure.

Therefore asymptotically $M_\zeta(K) \xrightarrow{D} M_\varepsilon(K) \Rightarrow \zeta \xrightarrow{D} \varepsilon$ (4.15),

where the symbol $\xrightarrow{D}$ denotes asymptotic convergence in distribution.

The result in equation (4.14) implies that as μ increases (or the variance of the Gumbel term decreases) the mixed logit errors converge asymptotically in distribution to a corresponding multivariate normal error structure. However, there may exist special variance covariance structures Σ_ζ, that may be difficult to decompose in the additive form above. For instance, when the correlation between alternatives is very high, the independence assumption among the Gumbel error terms would not be particularly reasonable or practical. In such cases, to replicate nearly perfect correlation between alternatives, μ_r would need to be arbitrarily large. If μ is set to one due to scaling considerations, then it becomes necessary to rescale the normal variances (σ) to be much larger (close to ∞). As σ increases, without bound, it is possible that there may be some instability associated with parameter estimates and variance covariance structures.

Regarding the theoretical suitability of the 'mixed-logit' formulation, McFadden et al. (1998), demonstrated that under relatively mild regularity conditions, a discrete choice model derived using RUM principles, has a likelihood that can be approximated (arbitrarily closely) by some mixed-multinomial logit model (of the type discussed in this paper). The authors show that this can be achieved by approximating the true utility U* as the sum of the components - (U^{*k}) a polynomial approximation of the actual utility (arbitrarily close to the true utility), and an i.i.d error perturbation from a Gumbel distribution. While the authors specifically point out the result only for error components from the Gumbel distribution, it is noteworthy that any choice of error perturbation with finite and small variance is admissible for this error components scheme. A second interesting remark (which the authors do make) is that though the desired transformation U^{*k} exists for any U^* under mild regularity conditions, it is not known apriori in most cases even for a given choice of perturbation distribution.

The distributional result established in (4.15) is different from and stronger than the theoretical results in McFadden et al. (1998), in the following sense. While the previous result requires that the polynomial approximation be known apriori, the result (4.15) merely requires that the given discrete

choice situation be adequately captured by means of a true utility U* which is multivariate normally distributed. In such a case, (4.15) demonstrates that it is possible (with a few exceptions such as nearly perfect correlation between alternatives) to find a suitable DKL approximation such that the approximate likelihoods converge asymptotically in distribution to the distribution of the true utility U*. The exceptions refer to cases where it is not practical to model the multivariate normal utilities as the sum of a multivariate normal error component and an independent Gumbel error component.

The third assumption relates to the independence of the Gumbel error terms across alternatives and over time. The independence assumption is not particularly restrictive, as the independent component (namely Gumbel error terms) can be made arbitrarily small by choosing a sufficiently large scale parameter μ_t. However, the independence assumption may be problematic when some of the alternatives are perfectly correlated. The related assumption requiring that Gumbel error terms be identically distributed only applies across alternatives at a given time. The implications of this assumption are not quite clear. However, it is likely that this assumption too imposes little or no loss of generality, considering the fact that any differences in variances of utilities of alternatives may be accounted satisfactorily by the multivariate normal error structure.

The choice of Gumbel distribution for τ_n^{it} is purely out of convenience. Any other distribution with the following properties would have sufficed just as well. These components are to be independently distributed across alternatives and over time and identically distributed across alternatives for a given panel period. It is essential that $(\tau_n^{Ct} - \tau_n^{it})$ have a closed form cumulative distribution function (cdf). The distribution of τ^t_{in} must be closed under the maximization operation i.e., $(\max_k \tau_n^{kt}) \sim \tau_n^{it}$.

4.2.4 Dynamic Kernel Logit Formulation for Ordered Response Discrete Choice Data

The DKL formulation for modeling longitudinal discrete choice data when the alternatives are not ordered was presented in the previous section. This formulation may also be applied to model longitudinal discrete choice data, when the alternatives are ordered, as briefly outlined in this section. In this case, it is assumed that the user associates a utility with each choice situation t (and not with the alternatives). A pair of thresholds (lower and upper thresholds) is associated with each alternative. Further, the thresholds are assumed to be monotonically ordered across alternatives. The decision-maker is assumed to select an alternative k if his/her utility falls within the range of the corresponding thresholds. Let U^t_n represent the utility of alternative at time t to individual n, and ψ_{kt} and $\psi_{(k+1)t}$ represent the lower and upper thresholds for alternative k for individual n at time t. If C^t_n is the alternative chosen by individual n at time t, then the probability of observing the sequences of choices made by individual n may be expressed as follows:

$$\Pr\{ C^t_n, t = 1,\ldots T \}$$
$$= \Pr\{ \psi_{Ct} \le U^t_n \le \psi_{(C+1)t} , \psi_{it} \le \psi_{jt}, \forall\, i \le j , \forall\, t = 1,\ldots\ldots,T \}$$
$$= \Pr\{ U^t_n - \psi_{Ct} \ge 0, \psi_{(C+1)t} - U^t_n \ge 0, \psi_{it} \le \psi_{jt}, \forall\, i \le j , \forall\, t = 1,\ldots\ldots,T \} \qquad (4.16).$$

It is assumed that the thresholds and their associated error terms are multivariate normally distributed. Furthermore, it is assumed that the error term for the utility consists of two components: a multivariate normal error and a logistic error (in contrast to the Gumbel error term assumed in the unordered response case). The expression for the thresholds and the utility may be given as follows:

$\psi_{(C+1)t} = V_{(C+1)t} + \varepsilon_{(C+1)t}$

$\psi_{Ct} = V_{Ct} + \varepsilon_{Ct}$

$U^t_n = U^t_n + \varepsilon^t_n + \tau^t_n,$

where the ε^t_n denote the multivariate normal errors, and τ^t_n represent the logistic error terms. Under these assumptions, equation 4.16 can be rewritten as follows:

$Pr\{ C^t_n, t = 1,\ldots T \}$

$= Pr\{ U^t_n - \psi_{Ct} \geq 0, \psi_{(C+1)t} - U^t_n \geq 0 \mid \varepsilon, (\psi \in B)\} f(\varepsilon: (\psi \in B))d\varepsilon$ (4.17),

where B represents the set in which the ordering constraints on the thresholds are satisfied, and $f(\varepsilon: (\psi \in B))$ refers to the joint density of the normal error terms over this set B.

It can be shown that the conditional likelihood in equation 4.17, given the orderings of the threshold and the multivariate normal error terms, has a closed form probability. This closed form probability may be written as the difference between logit functions of the form: $F_L(V^t_{c+1} - V^t + \varepsilon^t_{c+1} - \varepsilon^t) - F_L(V^t_c - V^t + \varepsilon^t_c - \varepsilon^t)$ where $F_L(.)$ denotes the cumulative distribution function (cdf) of the logistic random variable evaluated at the operand. This conditional likelihood can be integrated over the multivariate normal terms in the desired domain to obtain the unconditional likelihood. The following section elaborates on the estimation procedure and examines the econometric properties of estimators and specification issues in relation to the more commonly used unordered-response case.

4.3 MODEL CALIBRATION AND ECONOMETRIC ISSUES IN DKL FORMULATION

4.3.1 Estimation Procedure

The log-likelihood in equation (4.11) involves the computation of a (J-1) x T dimensional multivariate normal integral in the unordered response case. The dimensionality reduction from JT to (J-1) x T follows from the fact that the choice likelihood depends only on the difference in utilities at each time. Hence the absolute location parameters of the utilities at each time (choice instance) are only unique up to a scale factor, and may be determined by setting the utility of an alternative to zero. In the ordered response case, the dimensionality of the likelihood integral is J x T as is clear from the following argument. There are (J+1) x T multivariate normal error terms associated with the thresholds for the J alternatives over T time periods. Of these, the lower threshold of the first alternative is set to zero and the upper threshold of the last alternative is set to infinity for each time, thus imposing 2T restrictions. In addition there are T error terms associated with the utility U corresponding to each choice situation, thus making the dimensionality of the integral to be JT.

In both cases the unconditional likelihood function generally does not have a closed form, and is calculated by Monte-Carlo simulation (Kohl's, 1972; Baumgartner et al., 1984; Rice, 1995). The desired likelihood p is the expected value of the kernel logit function $h(\varepsilon)$. This suggests that the likelihood

function may be simulated by a Monte-Carlo procedure where the kernel function is averaged over repeated draws from the MVN distribution. Such Monte-Carlo techniques are extensively used in the computation of higher dimensional integrals (Rice 1995). In the unordered case, both the DKL and MVN involve the computation of a (J-1) x T dimensional integral of the multivariate normal CDF. However, the difference between the two arises from the fact that the kernel function happens to be the Kronecker delta function (δ = 1, if ε is in the appropriate range, 0 otherwise) in the MNP model with a simple frequency simulator, whereas the kernel function is the function $h(\varepsilon)$ for the DKL, which can be evaluated over the entire range in closed form. This leads to the empirical expectation that a greater number of Monte-Carlo draws may be required for the MNP to have sufficient number of observations in the appropriate domain; The number of draws is intuitively (to be made precise later) of the order of (1/p) in the MNP, where p is the probability that the multivariate normal errors ε lie in the desired domain (Hajivassiliou et al., 1996; Bhat, 1997). This is particularly significant with larger number of time periods, as the joint likelihood of the sequence of choices roughly decreases exponentially with time (for a fixed probability of choice in each time). These observations are revisited more precisely when presenting the computational complexity of the two formulations in the following section.

The maximum likelihood technique is used for the calibration, in view of the desirable properties of its estimators, namely, consistency, asymptotic efficiency and asymptotic unbiasedness. Likelihood maximization is performed by embedding the likelihood computation above within a non-linear optimization framework as shown in Figure 4.1.

4.3.2 Econometric Properties of Estimators

The likelihood and its simulated estimates are given below:

Likelihood $L = \Pi_n P_n = \Pi_n \int_\varepsilon h(V_n,\varepsilon_n)\, f(\varepsilon_n) d\varepsilon_n$

Log-Likelihood LL = log(L), and,

Simulated Likelihood (with R draws), $\tilde{L}_R = \Pi_n \tilde{P}_n = \Pi_n (1/R) \Sigma_r h(V_n,\varepsilon_r)$ where ε_r is the vector of multivariate normal errors drawn on the rth realization of Monte-Carlo draws from the multivariate normal error distribution, and,

$h(V_n,\varepsilon_n) = \Pi_{t=1}^{T} \{ \exp[\mu_t (V_n^{Ct} + \varepsilon_n^{Ct})] / \Sigma_i \exp[\mu_t (V_n^{it} + \varepsilon_n^{it})]\}$

The simulated log-likelihood estimated using a total of R draws is given by:

$\tilde{LL}_R = \log(\tilde{L}_R)$,

Since the log-likelihood does not have a closed form, the simulated log-likelihood is only an approximation to the actual log-likelihood. So the estimation procedure maximizes the simulated log-likelihood ($\tilde{LL}$), instead of the actual log-likelihood (LL) which is unknown. The simulated likelihood function is an unbiased estimator of the actual likelihood since $E(\tilde{L}) = L$ (by an application of the Central

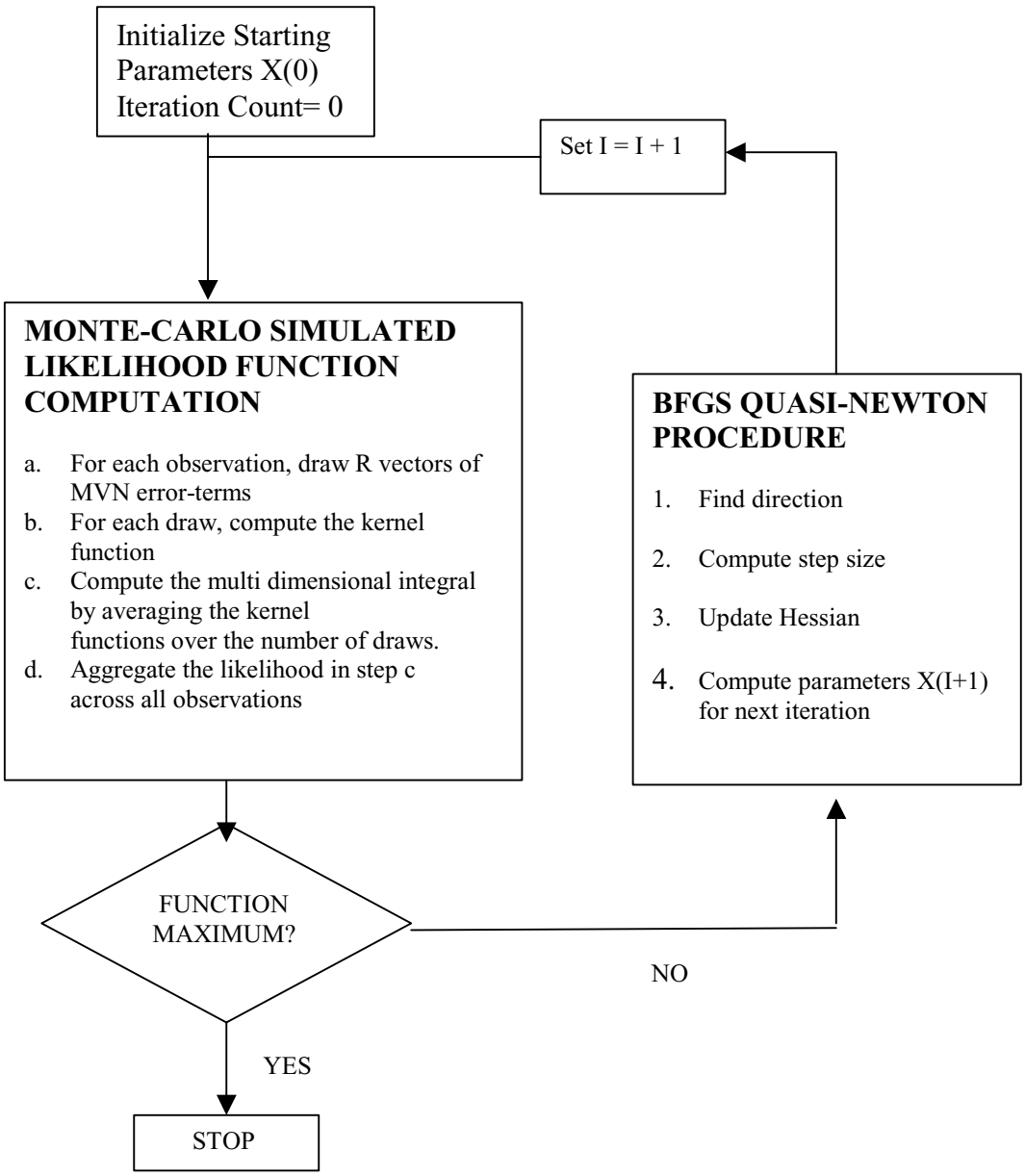

FIGURE 4.1
Schematic representation of the Dynamic Kernel Logit (DKL) calibration procedure.

Limit theorem). The simulated log-likelihood ($\tilde{LL}$) is, in general, a biased estimator of LL. However, this bias decreases asymptotically with increasing number of draws, specifically as, $R/\sqrt{T} \rightarrow \infty$ (Hajivassiliou et al., 1996), where R is the number of draws. Similarly, estimating (1/p) using the simulated log-likelihood estimator will also result in a biased estimate. However, it has been shown that such simulated log-likelihood estimators under rather mild regularity conditions are consistent, asymptotically efficient and asymptotically normally distributed (Hajivassiliou et al., 1996; Lee, 1992).

Note that the kernel logit function is a smooth and differentiable function of parameters and the variance of the simulated log-likelihood decreases with increasing number of draws. In contrast, the MNP (particularly acceptance/rejection simulator) log-likelihood function can exhibit discontinuity in parameters in some instances, leading to convergence problems during optimization. As with the MNP, the log-likelihood function in the DKL may not be globally concave with the consequence that there may be many local optima for the model parameters of interest (Liu and Mahmassani, 2000).

4.3.3 Identification Issues in DKL

Consider the following utility specification for the DKL formulation in equation (4.2).

$U^t_{in} = \beta X^t_{in} + \varepsilon^t_{in} + \tau^t_{in}$

Let $\tau^t_{in} \sim \text{Gumbel}(0, \pi^2/6\mu_t^2)$

Let $\varepsilon^t_{in} \sim \text{MVN}(0, \Sigma)$

Let X^t_{in} be a vector of K attributes and β represent the corresponding coefficient vector. Assuming that multi-collinearity is absent, up to k x (k+1)/2 parameter coefficients associated with β are estimable assuming normally distributed taste variations. The vector of parameters of this model is denoted as $[\beta, \Sigma, \lambda\mu_t]$.

Focusing on error terms, consider $\nu^t_{in} \sim \text{Gumbel}(0, \pi^2/6\lambda^2\mu_t^2)$ where λ is some positive scalar. Then it can be easily verified that the model with parameters $[\lambda\beta, \lambda\Sigma, \lambda\mu_t]$ produces an identical likelihood to the model with parameters $[\beta, \Sigma, \mu_t]$. Thus the scale of the Gumbel error term is indeterminate. This means that it is impossible to estimate the variance of both components (Normal and Gumbel) simultaneously without further restrictions. For convenience the Gumbel scale parameter is set to one (as the other coefficients (β, Σ) can be rescaled accordingly with a few exceptions). If this scale is adopted, a direct comparison of the DKL coefficients with MNP coefficients with the same multivariate normal covariance structure can be misleading, as the two formulations have different total variances for each alternative. Therefore, for comparison, it is necessary to rescale the coefficients in the DKL formulation to account for the differences in the total variance. While the total variance in the DKL is $\sigma_i^2 + \pi^2/6$, the corresponding variance in the MNP is simply σ_i^2.

The kernel logit error vector $\zeta = \{ \varsigma_n^{it}$, t = 1,.. T, i = 1, .. J} has a total of JT location parameters and a total of $\binom{JT}{2} + JT + T$ variance-covariance parameters. However, by setting the scale of Gumbel

parameters $\mu_t = 1$ for t=1,... T, the variance structure problem can be reduced to a corresponding MNP variance covariance structure. In this case, it has been shown that a maximum of (J-1)T location parameters (Alternative specific constants) and $\binom{(J-1)T}{2} + (J-1)T - 1$ variance covariance parameters can be estimated (Dansie, 1985; Bunch, 1991). The reduction in the number of variance-covariance parameters (by one) from the reduced matrix (with respect to a base alternative for each time) arises due to the indeterminacy of the scale parameter of the variances of normal error terms. In case, different scales are allowed for Gumbel parameters, the number of additional parameters that need to be estimated is T (one for each time period). In this case, at most $\binom{(J-1)T}{2} + (J-1)T - 1$-T parameters may be uniquely identified from the multivariate normal variance covariance matrix. In special cases, however, it may be possible to estimate more parameters in the variance-covariance matrix uniquely by exploiting the problem structure. For instance, if the absolute scale parameter is known (from apriori theoretical considerations for instance), an additional degree of freedom is obtained, for uniquely identifying one more parameter.

Panel data can also provide additional sources of identification compared to cross-sectional data. For example, the restriction of equality of coefficients across times enables the identification of a corresponding number of variance covariance parameters. General variance covariance patterns may also be represented and identified is through the imposition of a factor structure on the error terms. Consider, for instance an error components scheme as follows: ς_n^{it} = a^i + b^t + c_n^{it}, where the first two components are identically and independently normally distributed across decision-makers, and alternatives respectively, and the third component being Gumbel distributed. This error components scheme results in a covariance structure with at most $\binom{J}{2} + \binom{T}{2} + J + T - 1$ parameters which can be considerably smaller than $\binom{(J-1)T}{2} + (J-1)T - 1$ parameters in the general case. Thus imposing a factor structure could lead to a fairly general yet parsimonious and identifiable representation of the error structure, in both the DKL and MNP formulations.

It is possible that the choice probability of various alternatives may depend on the user's current state or choice(s). For instance, the likelihood of switching routes may be lower, immediately following a previous switching decision. State dependence has been shown to arise in a variety of empirical contexts, and has important implications for policy analysis and decision-making (Heckman and Borjas, 1980). Ignoring state dependence, when present, can cause serious specification errors and inaccurate forecasts and inferences. State dependence can be specified by representing the utility of an alternative at time t as a function of the choices at preceding times. Identification restrictions also apply for the number of state-dependence effects estimable in longitudinal data. It can be shown that for binary choice

situations (J=2) (with constant Gumbel scales over time), with three or more time periods (T ≥ 3), at least first order state-dependence effects can be captured. For multinomial choice situations (J ≥ 3), with (T ≥ 4), at least first order state dependence effects can be obtained (see Table 4.1). Increasing number of time periods enables the incorporation of richer state-dependence specifications. First order state-dependence effects in a J alternative choice context consists of J-1 coefficients representing transition probabilities.

TABLE 4.1
NUMBER OF STATE DEPENDENCE PARAMETERS ESTIMABLE IN LONGITUDINAL DISCRETE CHOICE MODELS

Number of longitudinal periods	Number of choice alternatives in each period	Dimension of reduced[1] covariance structure (a)	No. of structural parameters estimable (b)	No. of state-dependence parameters estimable
T	J	${}^{(J-1)T}C_2 + (J-1)T+J-2$	J^T-1	max(0, b-a)
2	2	3	3	0[2]
3	2	6	7	1
4	2	10	15	5
5	2	18	31	13
2	3	11	8	0
3	3	22	26	4
4	3	37	80	43
5	3	56	242	186
2	4	23	15	0
3	4	47	63	16
4	4	80	255	175
5	4	122	1023	901

Notes:
1. It is possible to estimate a state dependence if the variances are assumed equal when T=2, J=2.
2. The estimates in this table assume that error-terms have stationary location parameters over time.
3. The table shows that if J>4, state dependence effects may be estimated with at least 3 periods (T>=3).

4.4 COMPUTATIONAL PERFORMANCE OF DKL

The previous two sections establish that the DKL formulation is theoretically promising for the longitudinal analysis of discrete data. In this section, the computational performance characteristics of the DKL formulation are investigated in comparison to the MNP model. The MNP is chosen as the benchmark because it is the typical formulation used in dynamic models of discrete choice data. Computational performance is assessed by examining the computational efficiency of the estimation procedure and the accuracy of the calibrated estimates.

4.4.1 Computational Efficiency

In examining computational efficiency, both theoretical time-complexities and empirical calibration times of the DKL in numerical experiments are compared with those of the corresponding multinomial probit formulation. For comparison, the DKL coefficients are rescaled to reflect differences in total variances relative to the MNP.

For the purpose of determining the time-complexity of the likelihood computation in the two formulations, attention is initially restricted to a single decision-maker. The computation of the variance covariance matrix has a complexity of $O(JT)^2$ as its size is (J-1)T x (J-1)T. Similarly the complexity of the deterministic utility calculation is O(JT) for each decision-maker. Assuming that the likelihood computation for a given decision-maker requires R draws then, the total utility computation for a given observation involves the generation of O(RJT) random components. Thus for a given decision-maker, a single likelihood computation is of the order of O(RJT). By aggregating the computational time across all decision-makers in the sample (N), the total time complexity can be written as:
$O(J^2T^2 + NRJT)$. This time complexity is determined without explicit reference to MNP or DKL formulation and is applicable to both. The difference between the two formulations arises from the number of draws required for a likelihood computation. Under the frequency simulation in the MNP, each draw is checked to determine if it is in the desired domain for error terms (corresponding to the actually chosen sequence).

Let p be the probability of observing this sequence (desired likelihood). Then, over independent random draws of the vector of error terms from the MVN distribution, the number of trials until a draw in the desired domain is obtained is geometrically distributed with a parameter p. Thus the expected number of draws till a draw in the desired domain is obtained is 1/p (Hajivassiliou et al., 1996). With increasing J and T, $p = O(1/J^T)$ reflecting the fact that the probability of observing a given sequence is inversely proportional to the number of possible sequences (Geweke et al., 1997). Then the expected number of draws for the MNP, $R_{mnp} = O(J^T)$. Thus the average-case complexity of a likelihood computation in the MNP increases exponentially with increasing number of panel periods,

$$T_{mnp} = O(J^2T^2 + J^{T+1}T) \qquad (4.17).$$

Considering the number of draws required for the DKL, with R draws, the likelihood p for a given observation, is estimated by $\tilde{p}_R$ given by:

$$\tilde{p}_R = 1/R\ \Sigma_r\ h(r) \qquad (4.18),$$

where h(r) is the kernel function calculated at the rth draw. The calculation of the kernel function for a given draw involves the product of T logit functions. Each logit function in turn, involves the calculation of J utilities. Though one might expect a complexity of O(JT) for the kernel function computation, the actual complexity is somewhat higher. The increase can be attributed to the calculation of exponential function of utilities, which are often computed by power-series expansions of a finite order (k). Hence the actual time complexity for the kernel function computation is given by $O(J^kT)$ where k is a finite number greater than 1. Aggregating the computational time across R draws and N observations and including the time for utility and variance-covariance computations, the DKL can be given as:

$$T_{dkl} = O(J^2T^2 + NRJ^kT) \qquad (4.19).$$

An application of the Chebyshev inequality and the usage of central limit theorem on Equation (4.18) implies that the $\Pr\{ |\tilde{p}_R - p| \le \delta\} \ge \sigma^2/ R^2\delta^2$, where σ^2 represents the variance of the DKL likelihood

for a single draw of the (vector of) random error terms. For a given convergence level δ, and desired reliability level (α) = σ^2/ $R^2\delta^2$, the number of desired draws is given by

R = $\sqrt{\frac{\sigma^2}{\alpha\delta^2}}$. Now σ^2 is finite because the kernel function is bounded between 0 and 1. In fact it can be shown that σ^2 is strictly between 0 and p - p^2 where p is the likelihood of observing the chosen sequence for a given observation. Thus the number of draws is a polynomial function in p given a desired reliability level (α) and convergence level (δ), whereas the number of draws required in the MNP increases exponentially with the number of panel periods. Further, the DKL has a smaller estimator variance than MNP whose estimator variance is the Bernoulli variance p(1-p).

Considerable attention needs to be paid in the selection of the convergence criterion (δ). The selection of an unduly small convergence criterion (δ) can result in unnecessarily large number of draws and high computational costs for fewer alternatives and times. On the other hand, the choice of very large convergence criterion (δ) may adversely affect the accuracy of the estimates because of insufficient draws for likelihood computation. To avoid these problems, it may be desirable to decrease the convergence level c as a function of the number of alternatives J and times T, in a polynomial fashion, such that the polynomial time-complexity of the DKL is preserved.

The time complexity analysis implies that, asymptotically as J and T increase, the DKL is computationally superior to the MNP by more than an order of magnitude. This computational advantage stems from the lower variance of the DKL estimator relative to MNP frequency simulator and the exponential increase in the number of draws required in the MNP to achieve draws in the desired domain with increasing J and T. The time complexity above reflects asymptotic performance. To test the computational performance for smaller problems (in terms of J and T), and to empirically verify the results of the complexity analysis the following numerical experiments are conducted.

4.4.2 Numerical Experiments Comparing Computational Time for DKL and MNP Models

The numerical experiments are conducted using 16 synthetically generated data sets with varying number of alternatives per time period (M), and varying number of panel periods (T). Each data set consisted of 500 observations per time period. The number of alternatives J is varied from 2 to 5, whereas, the number of panel periods (T) is varied from two to eight in increments of two. The data sets are calibrated using both DKL and MNP formulations, and the times for likelihood computation are then compared between the two. The stochastic process generating the data sets can be represented as follows:

$U^{ijt} = \gamma^j + \beta_1 X_1^{ijt} + \beta_2 X_2^{ijt} + \varepsilon^{ijt}$ if $j \neq J$

$U^{ijt} = \beta_1 X_1^{ijt} + \beta_2 X_2^{ijt} + \varepsilon^{ijt}$ if $j = J$

where $\varepsilon = [\varepsilon^{ij1}, \ldots \varepsilon^{iJT}]' \sim MVN(0, \Sigma_\varepsilon)$ such that

$corr(\varepsilon^{ijt}, \varepsilon^{ij't}) = \rho_1, \; j \neq j'$

$corr(\varepsilon^{ijt}, \varepsilon^{ijt'}) = \rho_2, \; t \neq t'$

$corr(\varepsilon^{ijt}, \varepsilon^{i'j't'}) = 0, \; i \neq i'$

$var(\varepsilon^{ijt}) = \sigma^2$

In these expressions, the subscripts, i, j, and t refer to the decision-maker, alternatives, and panel period respectively, γ^j refers to the constant specific to the choice alternative j, and β_ι represents the coefficients of attribute I in the utility. The true parameters for the systematic utility and variance-covariance matrix generating the synthetic data sets are shown in Tables 4.2 and 4.3 respectively.

TABLE 4.2

DETERMINISTIC UTILITY PARAMETERS USED IN GENERATING SYNTHETIC DATA SETS

Actual Parameters	No. of alternatives per time period			
	J=2	J=3	J=4	J=5
$\gamma 1$	-2	-4	-3	-2.5
$\gamma 2$	n.a	-2	-1	-0.5
$\gamma 3$	n.a	n.a	1	1.5
$\gamma 4$	n.a	n.a	n.a	0.5
$\beta 1$	4	4	4	4
$\beta 2$	2	2	2	2

TABLE 4.3

COVARIANCE PARAMETERS USED IN NUMERICAL EXPERIMENT

Covariance Parameters	Covariance Structure	
	Σ_1	Σ_2
Variance of all alternatives - σ_1	2	4
Contemporary correlation across alternatives - ρ_1	0.08	0.4
Correlation over time of a given alternative - ρ_2	-0.12	0.5

In the computational performance experiments, the time taken to compute the likelihood for the entire sample is compared for the two formulations. To control for the effect of starting value on the likelihood computation, both MNP and DKL computations are conducted for the same set of parameter values (adjusted in the DKL to reflect the variance components), randomized across the different data sets. In this set of experiments, maximization of the simulated likelihood is not considered, whereas, the log-likelihood function is maximized in the next set of experiments focussing on empirical estimate accuracy.

The results of the computational time experiments are presented in Table 4.4. Contrary to prior expectations, the results indicate that for a given convergence criterion, and small values of J and T, the MNP likelihood computation is faster than the corresponding DKL (Figure 4.2). This finding can be attributed to the following reasons. First, with small dimensionality of J and T, the number of Monte-Carlo draws for MNP and DKL are roughly of the same order of magnitude. Second, for a fixed number of

Monte-Carlo draws in both models, the computational cost of DKL is higher than MNP. This is due to the higher cost incurred in computing exponential functions in DKL than that of frequency simulation in the MNP.

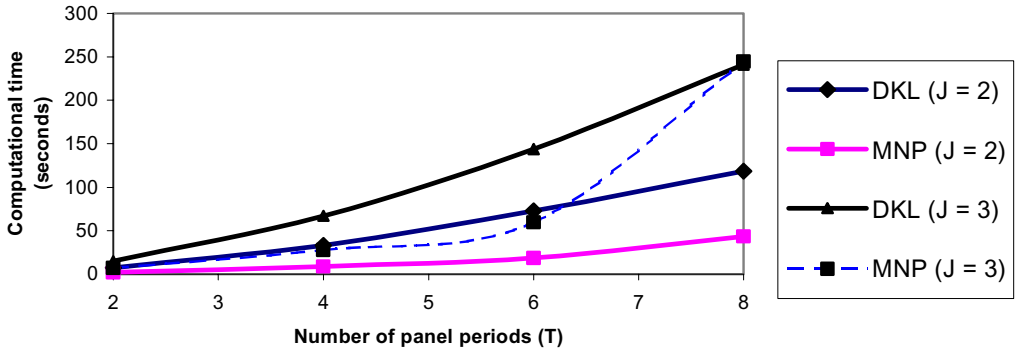

FIGURE 4.2
Computational time for DKL and MNP formulations
(for J = 2, 3 alternatives)

However, with increasing values of J, T or both, the experimental results clearly indicate the superiority of the DKL over MNP in terms of computational time (Figure 4.3). A logarithmic scale is used in Figure 4.3 to reflect the drastic increase in computational time with increasing number of alternatives, and more panel periods. The computational improvement in the DKL appears to be more than an order of magnitude with moderate J (5 alternatives at each choice instance) and large T (8 time periods) (JT > 30). The computational performance of the DKL relative to MNP appears to be the result of a trade-off between the number of Monte-Carlo draws required, and the computational cost of each draw. The results indicate that for lower values of J, T i.e. (JT < 25), MNP demonstrates superior performance due to a smaller computational cost per draw, whereas, for JT > 30, DKL outperforms the MNP. This finding has an interesting implication for cross-sectional discrete choice models (i.e., T = 1). With fewer than 25 alternatives, the results suggest that it is more advantageous to use the probit model (MNP) compared to the CKL.

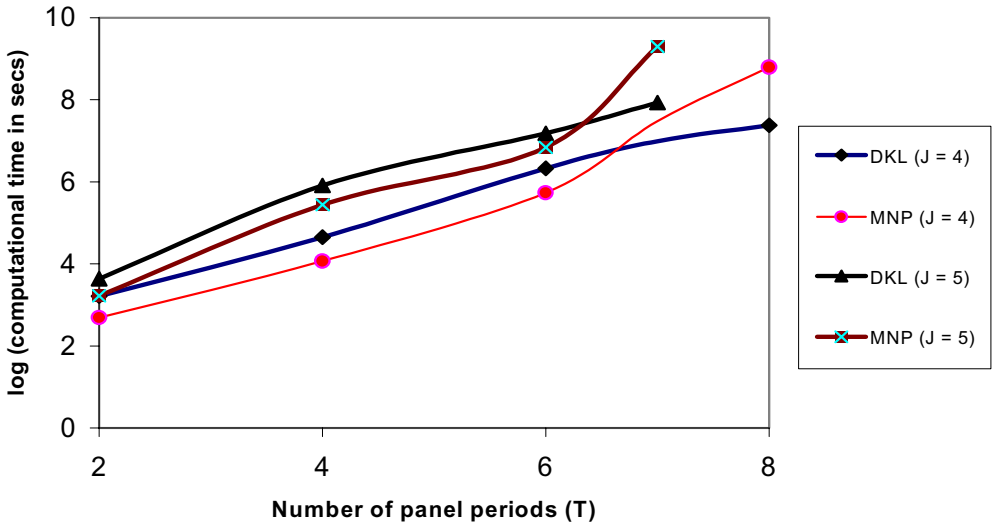

FIGURE 4.3
Computational time for DKL and MNP formulations
(for J = 4, 5 alternatives)

4.4.3 Estimate Accuracy

Next, the accuracy of estimates from DKL and MNP calibration procedures are examined. The following experiment is performed to investigate the accuracy of estimates using the two formulations, under varying number of alternatives (J), number of time periods (T) and the variance covariance structure (Σ).

The experiments on estimate accuracy use the same synthetic data sets as the computational time experiments. However, in this experiment the point estimates and the associated t-stats are calibrated from a starting value of zero for the deterministic utility parameters. An identity matrix is used as the initial variance covariance structure for the multivariate normal errors for both the MNP and the DKL formulations. A quasi-Newton (BFGS) optimization procedure is employed for maximizing the likelihood function in both formulations (Lam, 1991). The estimate accuracy of the two formulations are then compared on the basis of the following statistics: log-likelihood at convergence, parameter estimates at convergence, convergence behavior of the log-likelihood function. The log-likelihood convergence is intended to measure the discrepancy between the maximum likelihood of the MNP and DKL formulations. The parameter estimates are a measure of point-estimate accuracy in relation to the true parameters. The convergence behavior is likely to provide an indication of the nature of convergence in the DKL in relation to that in MNP.

TABLE 4.4

LIKELIHOOD COMPUTATION TIMES FROM NUMERICAL EXPERIMENTS FOR DKL AND MNP FORMULATIONS

Number of alternatives (J)	Number of nel periods	DKL Formulation		MNP Formulation	
		Time (sec)	No. of draws	Time (sec)	No. of draws
2	2	7.5	486	2.2	537
3	2	14.9	429	7.1	492
4	2	24.8	379	14.7	443
5	2	37.9	392	25.1	429
2	4	33.1	1588	8.8	1571
3	4	66.9	1486	27.7	1429
4	4	104.9	1142	58.5	1505
5	4	368.2	1074	231.1	1969
2	6	72.7	2133	18.5	1738
3	6	143.8	2110	59.6	1719
4	6	560.5	3099	308.9	4598
5	6	1319	2290	935.3	8244
2	8	118.5	2010	43.5	1453
3	8	241.1	2028	244.4	4170
4	8	1597.7	4474	6590	47330
5	7	2794.4	3146	10883	60854

Note: all computations were performed on a DEC computer with a 500 MHZ processor

Several noteworthy findings are observed in the numerical experiments. First, the log-likelihood at convergence is comparable across the two formulations, indicating that the kernel logit model reasonably approximates the MNP log-likelihood function (Table 4.5). The average discrepancy in log-likelihoods between the two formulations was about 1.6% whereas, the maximum discrepancy was about 4%. This result, however, is not entirely unexpected given the distributional convergence result presented previously. Second, to study the relative accuracy of the two formulations, the average root mean squared deviation (RMS) from the true parameters is computed. The RMS errors for the two formulations are displayed in Tables 4.6 and 4.7. It is observed that the estimate accuracy in the DKL tends to increase progressively as the number of panel periods (T) is increased while the number of alternatives (M) is held fixed. However, the MNP formulation does not exhibit any regular decrease in estimate accuracy with increasing number of panel observations per decision-maker. Another interesting observation is that the relative accuracy of the two formulations appears to depend on the variance-covariance structure. It is observed that the DKL produced a consistently lower RMS deviation from the true parameters when the correlation coefficients were relatively high and positive (for e.g. when the number of alternatives was 3 or 4). However, the calibrated MNP formulation is more accurate than the corresponding DKL formulation, when the covariance parameters are relatively small and includes negative components. However, even in these cases, the relative superiority in accuracy of the MNP over the DKL formulations tends to diminish with increasing number of panel periods (for e.g. when t=8).

Investigating the convergence behavior of the log-likelihood it is found the DKL and MNP exhibited similar convergence patterns both in terms of the number of iterations to converge, and step-sizes in each non-linear search iteration. This may be expected since both procedures involve the maximization of a non-linear likelihood function involving a multivariate normal density function. In the general case, it can be expected that the non-linear likelihood function is likely to be non-concave in parameters, thus suggesting the possibility of multiple optima. Empirically, it was observed that the estimator values at convergence depended on the starting values, though the log-likelihood at convergence was robust across different starting values. Thus flat likelihood functions and unstable parameter estimates, which have often been associated with the MNP model may also be expected in the DKL formulation.

TABLE 4.5

LIKELIHOOD AT CONVERGENCE FOR SYNTHETIC DATA SETS USING DKL AND MNP FORMULATIONS

Number of alternatives (J)	Number of panel periods (T)	DKL	MNP
2	2	-351.89	-345.91
2	4	-735.46	-728.6
2	6	-1144.72	-1150.46
2	8	-1522.53	-1547.29
3	2	-761.77	-742.26
3	4	-1372.67	-1346.28
3	6	-1866.97	-1792.74
3	8	-2390.67	-2384.15
4	2	-979.61	-960.69
4	4	-1752.42	-1704.19
4	6	-2432.03	-2355
4	8	-3179.17	-3122.5
5	2	-802.23	-802.37
5	4	-1684.77	-1678.59
5	6	-2536.78	-2554.53
5	7	-2849.48	N/A

TABLE 4.6
RMS ERROR OF ESTIMATES FROM THE MNP MODEL RELATIVE TO THE TRUE PARAMETERS

Number of alternatives (J)	Number of panel periods			
	2	4	6	8
2	0.464	0.187	0.252	0.084
3	0.168	0.315	0.291	0.317
4	0.454	0.289	0.247	0.340
5	0.408	0.138	0.216	

TABLE 4.7
RMS ERROR OF ESTIMATES FROM THE DKL MODEL RELATIVE TO THE TRUE PARAMETERS

Number of alternatives(J)	Number of panel periods			
	2	4	6	8
2	0.701	0.514	0.369	0.245
3	0.124	0.036	0.032	0.034
4	0.193	0.182	0.106	0.030
5	0.159	0.156	0.124	0.112

4.5 SUMMARY

In this chapter, Dynamic Kernel Logit formulation is presented to model dynamics in discrete choice data, for both the ordered and unordered response choice contexts. The Dynamic Kernel Logit (DKL) formulation presents a methodological alternative to the MNP framework to model dynamic discrete choice. Distributional results presented and the review of theoretical assumptions establish the theoretical suitability of the proposed formulation to model dynamic discrete choice data. The estimation procedure, econometric properties of estimators and specification issues associated with the DKL formulation are also discussed.

The DKL formulation can be applied (with a few exceptions) to model dynamic discrete choice behavior in a wide range of decision contexts. Examples in the travel behavior area include mode, route departure time, destination and activity-travel patterns. The formulation can also be generalized to model joint choice of various discrete dimensions over time. Further, this formulation would also lend itself well to other domains of panel data analysis with discrete choices including econometrics, marketing research, information search, portfolio selection etc.

Distributional results presented here together with numerical results from computational experiments reveal that the two frameworks are comparable in so far as coefficient estimates are concerned. However, with increasing dimensionality of the number of alternatives and/or time periods, the DKL is computationally superior to the MNP model (based on frequency simulation) by more than an order of magnitude. This gain in computationally efficiency arises mainly from the reduction in the number of Monte-Carlo draws required to evaluate the kernel logit function (h) above, and the smaller simulator

variance of the DKL likelihood estimator. With fewer alternatives and/or time periods, it is observed that the MNP is computationally faster than the DKL formulation. There appears to be little advantage in applying the kernel logit formulation relative to the MNP to cross-sectional data with a small number of alternatives.

In summary, the Dynamic Kernel Logit (DKL) models proposed here appear to be suitable (with a few exceptions) for modeling longitudinal discrete choice data with a large number of alternatives per time (M) and large number of time periods (T). The DKL formulation presented here, however, is not suitable in modeling discrete choice contexts where some of the alternatives are nearly perfectly correlated. The following chapters present the application of this generic formulation to model dynamics in various choice dimensions in commuter behavior. Specifically, the DKL formulation is used in Chapter 5 to model route and departure time switching behavior under information. In Chapter 6, this formulation is used to analyze the compliance behavior of trip-makers.

CHAPTER 5: THE ROLE OF CONGESTION AND INFORMATION ON TRIP-MAKERS' ROUTE AND DEPARTURE TIME SWITCHING BEHAVIOR

5.1 INTRODUCTION

While several researchers have investigated on the effect of user-behavior (in the presence of information) on network performance and congestion (Mahmassani and Jayakrishnan, 1991; Mahmassani and Peeta, 1993; Emmerink et al., 1995; Hu et al., 1997), relatively few studies examine the role of varying network congestion levels (from day-to-day) on trip-makers' route and departure time choice behavior. In addition, the role of information in driver decision-making processes under varying degrees of congestion in the traffic system also needs to be investigated. In this context, this chapter addresses these substantive questions, through the following objectives.

The first objective is to examine whether and how drivers respond to experienced congestion under information, with particular attention paid to the key variables influencing route and departure time switching decisions. Specifically, two related issues are investigated: (1) the effect of travel demand in the network on driver behavior under ATIS is examined by modeling the influence of increasing network loads on driver behavior; and, (2) the influence of dynamic system evolution on driver behavior – in particular, the influence of day-to-day variation in network loads on user behavior is examined.

The second objective relates to the role of information in behavior under varying degrees of congestion in the system. Several issues need to be addressed in this regard. For instance, what is the influence of information quality on trip-maker behavior? What role does information play in perception formation and updating regarding future traffic conditions? Do behavioral mechanisms exist that may be influenced by information, and if so, how and to what extent? And, how is the role of information on behavior influenced by the level of congestion and its day-to-day evolution?

The third objective pertains to the role of experience in user behavior under ATIS. The primary interest here is to quantify the nature of dependency between drivers' route and departure time choice behavior and their past experience in the traffic system. This has meaningful implications for ATIS information provision strategies and the assessment of ATIS impacts. These objectives are investigated using the data from experiment one (described in Chapter 3), where the magnitude and day-to-day evolution of network loads are varied as part of the experimental treatments.

Understanding trip-maker behavior processes under varying network conditions is important for: (1) Traffic system modeling and network state prediction, because trip-makers' route and departure time choices collectively determine traffic evolution within the system, both within-day and day-to-day; and (2) impacts assessment and evaluation of alternative congestion alleviation strategies.

In addressing the above mentioned objectives, this chapter presents models of departure time and route switching decisions based on data from the first set of interactive experiments, (described in Chapter 3, Section 3.5). These experiments are directed towards investigating the effect of network congestion and its day-to-day evolution on trip-maker behavior. The departure time switching decisions are modeled using the multinomial probit formulation, in view of the smaller number of alternatives (11).

Route switching decisions are modeled based on the DKL formulation (by suitably modifying the model presented in Section 4.2).

The rest of this chapter is organized as follows. The next section presents the profile of respondents from the first set of interactive experiments, and an exploratory analysis of the effect of congestion levels on route and departure time switching decisions. The modeling framework for departure time switching decisions, based on the Multinomial Probit (MNP) formulation is briefly outlined, followed by a discussion of substantive results in Section 5.3. Section 5.4 presents a DKL formulation, obtained by suitably modifying the generic DKL formulation presented in Section 4.2, to model route switching decisions in the presence of information. The substantive results from the route switching models and their implications are also discussed in Section 5.4, followed by a summary in the next section.

5.2 EXPLORATORY ANALYSIS

Information is elicited from each respondent regarding his/her socio-demographic attributes, commute characteristics, information use propensity, and factors influencing switching decisions, using a questionnaire. These characteristics are summarized in the sections that follow.

5.2.1 Socio-Demographic Characteristics

Socio-demographic attributes of the respondents in the sample, particularly regarding age, gender, and occupation of the participants, are reported in Table 5.1. The sample consists of 63% females and 37% males. A survey of commuters in Dallas and Austin reported that 63% of respondents were males (Mahmassani et al., 1993). Since females are over-represented in the sample, in relation to the population, caution will be exercised in making gender-related inferences from this sample. The age distribution reveals that about 35% respondents are younger than 40 years, 48% between 40-60, and 17% over the age of 60%. Thus the sample is adequately represented in the younger, middle, and older age categories, and is perhaps slightly skewed towards middle-aged respondents. This is comparable to the age distribution of 9, 56, 30 and 5% respectively in the categories 18-29, 30-44, 45–59, 60 and above in the aforementioned commuter survey. The occupation statistics indicate that 14% are technical specialists, 27% are clerical staff, 26% hold administrative/research responsibilities, and about 33% are employed in other capacities. Care is taken to exclude university faculty from the sample, in view of their flexible schedules and possibly unrepresentative commute patterns.

TABLE 5.1

SOCIO-DEMOGRAPHIC PROFILE OF EXPERIMENTAL RESPONDENTS IN EXPERIMENT ONE (NETWORK LOADING FACTORS)

Socio -Demographic Attributes					
Gender	Male	Female			
Percentage (%)	37	63			
Age	20-29	30-39	40-49	50-59	60+
Percentage (%)	6	29	35	13	17
Occupation	Technical	Clerical	Admin.	Other	
Percentage (%)	14.00	27.00	26.00	33.00	
	Mean	Std. Devn.			
Commute days per week	4.94	0.31			
	Mean	Std. Devn.			
Number of days of driving to work/ week	4.47	1.29			
	Mean	Std. Devn.			
Commute time minutes (one-way)	30.93	18.19			
	Mean	Std. Devn.			
Work Start Time (a.m.)	8:01	32.17			
	Mean	Std. Devn.			
Preferred arrival time at workplace (a.m.)	7.56	43.02			
Lateness tolerance at work	< 5min	5 - 15	15 - 30 mi	30 - 60	> 60
Percentage (%)	10.00	32.00	16.00	14.00	28.00

5.2.2 Commute Characteristics

Respondents were also requested to provide information regarding their actual commute characteristics. This information may provide valuable information about prior propensities in commuting behavior (which may be transferred to the experiment) and attitudes towards lateness. The mean number of commuting days per week is about 4.94 days suggesting that on an average the respondent commutes to work about five days a week, thus being representative of the user group of interest. More than 85% of the respondents commuted to work by the auto mode as compared to about 90% reported in the commuter diary survey.

The average commute time for the respondents in this sample was nearly 31 minutes and the corresponding standard deviation was 18.19 minutes. The average trip time is higher than the 22 minutes reported in the commuter survey in Austin in 1989. It may be noted that the population and the traffic in the city of Austin have increased considerably in the intervening years. The mean work start time (actual) of the participants was 8:01 a.m. Therefore choice of a work start time of 8:00 a.m. for the simulated

commute is reasonable. The average preferred arrival time in the sample is 7:56 a.m. However, there appears to be considerable variability in preferred arrival times among sample respondents, as reflected in the relatively high standard deviation of 43 minutes. The sample also exhibits significant variation in lateness tolerance across individuals. Forty-two percent of the respondents in the sample report a permissible lateness tolerance of fifteen minutes or less, compared to 58% reporting no lateness tolerance in the 1988 survey. At the other extreme, 28% report flexible working arrangements in this sample, as compared to 10% in the earlier survey.

5.2.3 Attributes Related to ATIS Information

Following the experiments, responses to questions on willingness to acquire pre-trip and en-route ATIS information indicated that about 90% of the respondents were (definitely or probably) willing to acquire both types of information. Respondents were also asked to rate the accuracy of information on a five point Likert scale (see Table 5.2). While eight percent of the respondents rated the information as very accurate, a majority (53%) found it to be somewhat accurate, and two percent rated the information as very inaccurate. When asked about additional information that they desired from the ATIS (in addition to travel time and congestion-related information in the experiments), 82% preferred information about incidents, accidents etc., 63% sought route guidance information, while 40% of the respondents were interested in parking information. Questions on the possible use of ATIS revealed that 47% of the respondents were definitely likely to switch routes following ATIS information, and 35% were definitely inclined to switch departure times.

These responses indicate willingness on the part of many of the respondents to acquire and use ATIS information. For comparison purposes, it may be noted that of the 638 commuters surveyed in 1988, about 55% and 51% adjusted departure times and routes respectively, on the basis of radio traffic reports (Mahmassani et al. 1993).

5.2.4 Factors Influencing Switching Propensity

The subjects were asked to rate the factors influencing route and departure switching propensity on an importance scale (Table 5.3). Trip time savings of more than fifteen minutes appears to be a very significant influence on route switching for a majority of respondents (82%). While 43% consider a five to 15 minute savings worthwhile (very important) in influencing switching, this proportion drops to a mere 13% for trip time savings of less than five minutes. This suggests the existence of trip-time saving thresholds in route switching behavior. Route switching

decisions also appear to be influenced by incidents (81% rate this information as very important), congestion on current route (68%), and late arrival by following current path (55%). In contrast, departure time switching appears to be substantially motivated by lateness avoidance (61% rating as very important), congestion (59%) and trip time savings (58%). Another interesting influence on departure time switching is the need to perform other activities in conjunction with the commute (46% respondents rate this as very important)

TABLE 5.2
USERS' RATING OF ATIS INFORMATION ACCURACY AND STATED USAGE INTENTION.

Rating of ATIS in experiment Percentage (%)	Very Acc. 8.00	Accurate 53.00	Somewhat Acc. 37.00	Inaccurate 0.00	Very Inaccurate 2
Willingness to Use ATIS (pre-trip) Percentage (%)	Definitely 46.00	Probably 44.00	Not decided 0.00	Probably not 2.00	Definitely not 0.00
Willingness to Use ATIS (en-route) Percentage (%)	Definitely 48.00	Probably 51.00	Not decided 1.00	Probably not 0.00	Definitely not 0.00
Additional Information Desired Percentage (%)	Incidents 82	Route guidance 63	Parking 40	None 6	Other 14
Switching Intention based on ATIS info Route Switching (%)	Definitely 47	Probably 34.00	Not decided 9.00	Probably not 8.00	Definitely not 2
Departure Switching Percentage (%)	Definitely 35.00	Probably 45.00	Not decided 7.00	Probably not 13	Definitely not 0

TABLE 5.3

USER'S RESPONSES TO ATTITUDINAL QUESTIONS ON IMPORTANCE OF FACTORS INFLUENCING SWITCHING DECISIONS

Importance Rating	Percentage of Respondents Rating Factor as			
Attribute Description	Very Important	Somewhat Important	Not very Important	Not at all Important
Route Switching Factors				
Trip time savings (less than 5 min)	13.3	28.3	50.0	8.3
Trip time savings (5-15 min)	42.6	49.2	6.6	1.6
Trip time savings (15-30 min)	81.7	10.0	5.0	3.3
Trip time savings (more than 30 min)	83.1	5.1	3.4	8.5
Congestion on original route	67.7	30.6	1.6	0.0
Incidents on original route	80.6	19.4	0.0	0.0
Arrival time constraints	41.0	39.3	19.7	0.0
Familiarity with alternative routes	25.8	66.1	8.1	0.0
Late arrival upon following orig. route	54.8	37.1	6.5	1.6
Avoiding early arrival	6.5	14.5	29.0	50.0
Departure Time Switching Factors				
Trip time savings (less than 5 min)	8.3	28.3	45.0	18.3
Trip time savings (5-15 min)	40.3	37.1	16.1	6.5
Trip time savings (15-30 min)	58.3	26.7	11.7	3.3
Congestion avoidance	58.1	33.9	6.5	1.6
Lateness avoidance	61.3	29.0	9.7	0.0
Earliness avoidance	8.2	16.4	34.4	41.0
Perform activities en-route	46.2	34.6	11.5	7.7

5.2.5 Departure Time Switching

To explore possible differences in departure time switching behavior between the systematic and random treatments, a plot of departure time switching rate and associated cumulative proportion of users is shown in Figure 5.1. The departure time switching rate is determined for each user as the ratio of the number of departure time switches to the total number of departure time switching opportunities. The cumulative proportion of users corresponding to a given switching rate is calculated by determining the proportion of total users with a switching rate smaller than the given rate. Trends of cumulative proportion appear to be similar between the random and sequential treatments, particularly at lower switching rates (0-20%). Nearly 55% of the users are observed to switch departure times at moderate rates of between 20-40% in the random treatment, compared to about 70% in this bracket in the systematic treatment. In contrast, a greater proportion of respondents, about 25%, are observed to switch between 40-60% in the random treatment, compared to 10% observed in the systematic treatment.

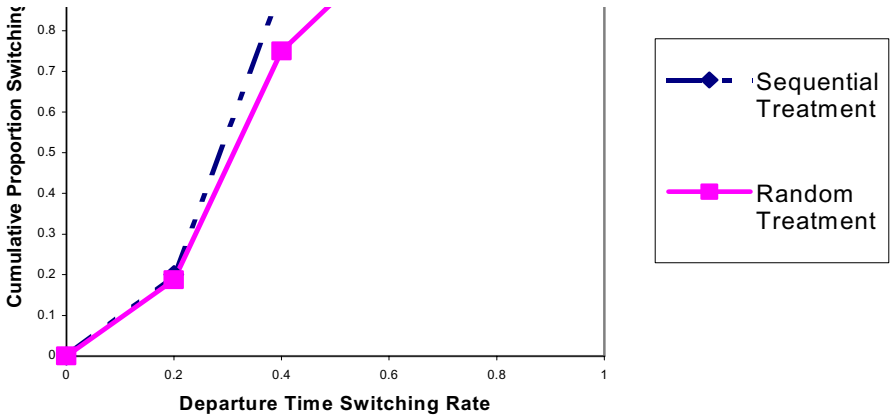

FIGURE 5.1
Departure time switching distribution under random and sequential treatments

The effect of congestion on departure time switching behavior is illustrated by plotting the average proportion of departure switches against the level of network loads encountered on the previous day (Figure 5.2). Early (late) side schedule delay corresponds to arrival before (after) one's preferred arrival time. When the day-to-day evolution of traffic conditions follows the systematic pattern (defined in the experimental design), the departure time switching rate decreases as the loading level increases from low to moderate, but increases slightly from moderate to severe congestion. Furthermore, it was found that the time departure switching on the late side is lower than the early side. In contrast, when traffic conditions fluctuate randomly from day-to-day, the overall departure time switching rate appears to decrease with increasing congestion levels. Further analysis indicated an asymmetry between the early and late sides. The departure time switching rate is found to decrease on the early side with increasing congestion levels. On the late side, however, the switching rate increases with increasing congestion. These exploratory findings suggest that under the systematic evolution, drivers are more tolerant of both early and late schedule delays, whereas when traffic evolution is random, greater congestion is accompanied by increased late-side and dampened early-side departure time switching.

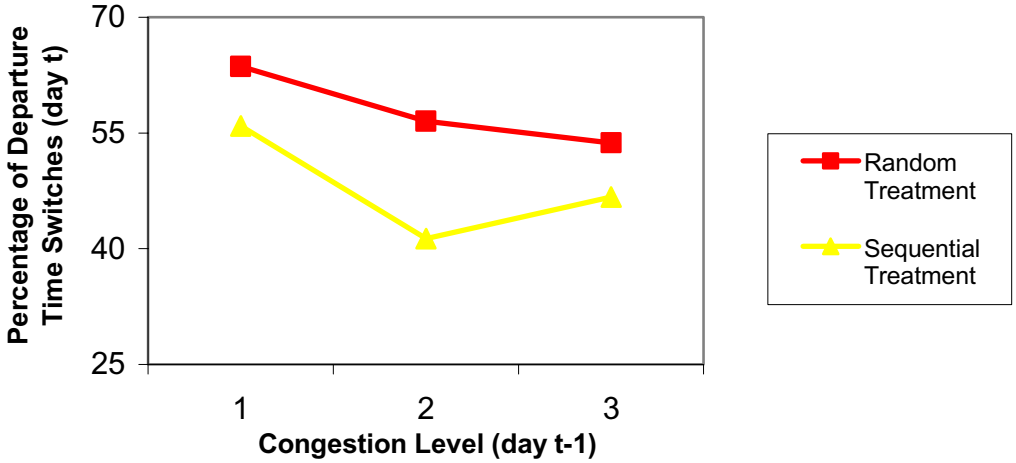

FIGURE 5.2
Effect of varying congestion levels on departure time switching percentages

5.2.6 Route Switching

Plots of aggregate route switching behavior are presented for both systematic and random treatments in Figure 5.3. Route switching rates and cumulative proportion are defined in a manner analogous to the definition of departure switching rates. The distribution of users at various route switching rates appears to be remarkably similar between the random and systematic day-to-day evolution in network loads. Note that this similarity may be the result of aggregation of switching rates over different loading levels.

The effect of network loading levels on route switching behavior is illustrated by plotting the proportion of route switches against the network loading levels (Figure 5.4). Pre-trip route switching is defined relative to one's route on the preceding day, such that the current day's route, pre-trip, is a switch from the previous day if it differs from the previous day's initial route. An en-route path switch occurs when the route chosen to the destination at the current decision point (excluding pre-trip) is different from the route chosen at the previous decision node. In the random treatment level, it is observed that pre-trip route switching is high for light loading (level A), and considerably lower when the loading level is moderate or severe. On the other hand, en-route switching exhibits less variation across different congestion levels.

In contrast, in the systematic treatment, pre-trip route switching appears to decrease as network loads increase from low to moderate congestion and increases as the magnitude of network loading increases from moderate congestion to high congestion. En-route switching proportion is higher than the baseline (mild congestion) for both moderate and severe congestion levels. Thus there appears to be increased switching for higher congestion levels in the systematic treatment, but only a relatively small effect of congestion on en-route switching in the random treatment.

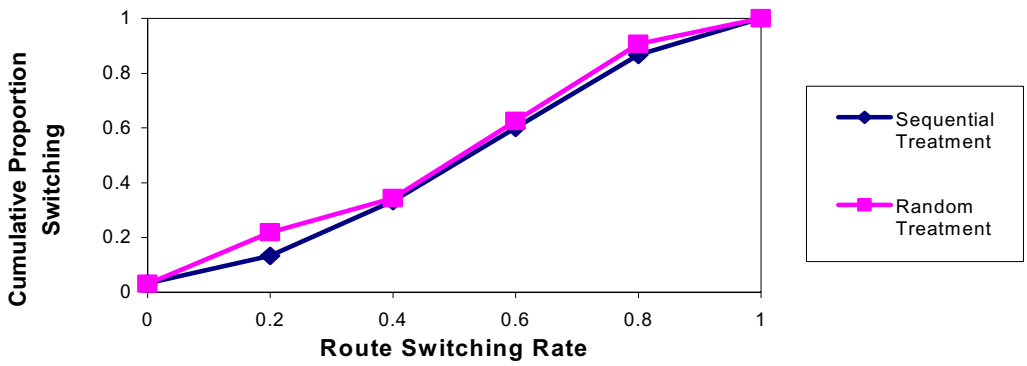

FIGURE 5.3
Route switching distribution under random and sequential treatments

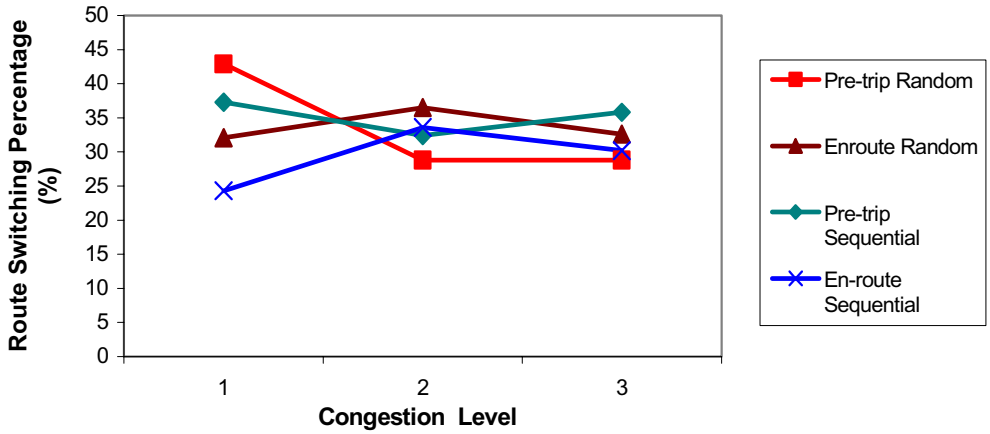

FIGURE 5.4
Effect of varying congestion levels on route switching percentages

5.3 DEPARTURE TIME SWITCHING BEHAVIOR

In this section, a framework is proposed for modeling departure time switching behavior under real-time information. This framework is used to analyze the influence of congestion, information and experience on departure time switching decisions of users. The influence of each of these factors is contrasted between the systematic and random treatments.

5.3.1 Departure Switching Model Formulation

Notation

Let i be the subscript to denote the individual trip-maker, i = 1,.... I;

t - the time index, t = 1, ... ,T;

U_{it} - utility of departure switching for individual i at time t;

$g^e(X_i, Z_{it}, \Theta_{it})$ - deterministic component of U_{it} on the early side;

$g^l(X_i, Z_{it}, \Theta_{it})$ - deterministic component of U_{it} on the late side;

Z_i - relevant attributes of trip-maker i;

X_{it} - traffic experience, information, and other variables of influence for user i at time t;

Θ_{it} - parameters for the deterministic component of the utility;

γ_{it} - departure time switching binary indicator;

γ_{it} = 1, if driver i switches on day t with respect to departure time on day t-1,

γ_{it} =0 otherwise;

$ESD_{i,t-1}$ - early schedule delay for driver i on day t-1;

$LSD_{i,t-1}$ - late schedule delay for driver i on day t-1;

$PAT_{i,t}$ - preferred arrival time at workplace for driver i on day t;

$AT_{i,t}$ - actual arrival time of driver at workplace i on day t;

$ESD_{i,t-1} = \max(PAT_{i,t-1} - AT_{i,t-1}, 0)$;

$LSD_{i,t-1} = \max(AT_{i,t-1} - PAT_{i,t-1}, 0)$;

$IBE_{i,t}$ - Early indifference band for driver i on day t;

$IBL_{i,t}$ - Late indifference band for driver i on day t;

$w^e_{i,t-1}$ = 1, if individual i arrived on time or early w.r.t PAT on day t-1,

= 0 otherwise.

$w^l_{i,t-1}$ = 1, if individual i arrived late w.r.t PAT on day t-1,

= 0 otherwise.

Note $w^l_{it} = 1 - w^e_{it}$

ε^e_{it} - early side normal error term component of the utility U_{it};

ε^λ_{it} - late side normal error term component of the utility U_{it};

ε - vector of ε_{it} for all t;

5.3.1.1 Behavioral Framework. The analysis methodology and the framework for modeling departure switching decision are now briefly outlined. Drivers are assumed to be boundedly rational decision-makers whose behavior follows the satisficing principle (Simon, 1955). Drivers are postulated to accept an alternative if it is both sufficient and satisfactory. A plausible satisficing mechanism, used extensively in earlier work and validated by travel diary data, is the notion of indifference bands of schedule delay (Mahmassani and Stephan, 1988). The departure time decision is premised to be anchored on a preferred arrival time at the workplace with indifference bands (early and late) on either side to reflect tolerable earliness and lateness. According to this satisficing mechanism, a departure time leading to an arrival within the corresponding indifference band is considered acceptable, whereas an arrival outside the indifference interval would induce switching.

5.3.1.2 Modeling Framework. The boundedly rational framework is operationalized as follows:

$U_{it} = ESD_{i,t-1} - IBE_{i,t}$, if user i arrived earlier than PAT on day t-1

$U_{it} = LSD_{i,t-1} - IBL_{i,t}$, if user i arrived later than PAT on day t-1

Then $U_{it} = w^e_{i,t-1}(ESD_{i,t-1} - IBE_{i,t}) + w^l_{i,t-1}(LSD_{i,t-1} - IBL_{i,t})$.

The behavioral framework above can be operationalized as follows:

$\gamma_{it} = 1$ iff $U_{i,t} \geq 0$, and $\gamma_{it} = 0$ otherwise.

This can be written as: $(2\gamma_{it} - 1)U_{i,t} \geq 0$

5.3.1.3 Utility Specification. The indifference bands are modeled as latent random variables with mean values varying systematically with drivers' experience and learning in the system. The following specification for the indifference bands are assumed:

$(ESD_{i,t-1} - IBE_{i,t}) = g^e(Z_i,X_{it},\Theta_{it}) + \varepsilon^e_{it}$,

$(LSD_{i,t-1} - IBL_{i,t}) = g^l(Z_i,X_{it},\Theta_{it}) + \varepsilon^l_{it}$,

Let $\boldsymbol{\varepsilon} = (\varepsilon^e_{i1}, \varepsilon^l_{i1}, \ldots\ldots\ldots, \varepsilon^e_{it}, \varepsilon^l_{it}, \ldots\ldots\ldots\ldots, \varepsilon^e_{iT}, \varepsilon^l_{iT})$.

Assuming $\boldsymbol{\varepsilon}' \sim MVN(0,\Sigma_\varepsilon)$ the utility U_{it} can be written as:

$$
\begin{aligned}
U_{it} &= w^e_{i,t-1}(ESD_{i,t-1} - IBE_{i,t}) + w^l_{i,t-1}(LSD_{i,t-1} - IBL_{i,t}) \\
&= w^e_{i,t-1}(g^e(Z_i,X_{it},\Theta_{it}) + \varepsilon^e_{it}) + w^l_{i,t-1}(g^l(Z_i,X_{it},\Theta_{it}) + \varepsilon^l_{it}) \\
&= w^e_{i,t-1}\, g^e(Z_i,X_{it},\Theta_{it}) + w^l_{i,t-1}\, g^l(Z_i,X_{it},\Theta_{it}) + w^e_{i,t-1}\varepsilon^e_{it} + w^l_{i,t-1}\varepsilon^l_{it} \\
&= V_{it} + \varepsilon_{it}, \text{ where,}
\end{aligned}
$$

$V_{it} = w^e_{i,t-1}\, g^e(Z_i,X_{it},\Theta_{it}) + w^l_{i,t-1}\, g^l(Z_i,X_{it},\Theta_{it})$,and,

$\varepsilon_{it} = w^e_{i,t-1}\, \varepsilon^e_{it} + w^l_{i,t-1}\, \varepsilon^l_{it}$.

Since ε^e_{it}, and ε^l_{it} are errors from a multivariate normal distribution, the error vector $\boldsymbol{\varepsilon}$ is also multivariate normally distributed.

The sequences of choices made by individual i can be represented by $C_i = \{\gamma_{it}, t = 1,\ldots,T\}$. Using the framework above, the probability of observing a sequence of departure time switching decisions of individual i is given by

$$Pr\{\gamma_{it}, t=1,..,T\} = Pr\{(2\gamma_{it} - 1)\, U_{it} \geq 0,\ t = 1,\ldots\ldots,T\} \qquad (5.1).$$

This may be rewritten as follows:

$$Pr\{\gamma_{it}, t= 1,.. ,T\} = Pr\{(2\gamma_{it} - 1)(V_{it} + \varepsilon_{it}) \geq 0, t= 1,.. ,T\} \qquad (5.2).$$

Under the assumption of multivariate normal error terms the likelihood in (5.2) is a multinomial probit model of dimension T+1. This can be seen by constructing an auxiliary choice model with the following pseudo-utilities: alternative 1 has a utility set at zero. Alternative k corresponds to departure time switching on day k-1 and has a corresponding utility of $(2\gamma_{ik} - 1)(V_{ik} + \varepsilon_{ik})$. The likelihood in (5.2) can then be viewed as a discrete "choice" among T+1 pseudo-alternatives, such that alternative 1 is always "chosen." Since the utilities of the pseudo-alternatives are multivariate normal, the likelihood corresponds

to a multinomial probit function. The calibration results of this departure time switching model for the random and sequential day-to-day evolution are presented in Tables 5.4 and 5.5 respectively.

5.3.2 Modeling Results

The influence of congestion on departure time switching behavior is investigated by examining three relevant threads. First, the effect of systematic and random congestion evolution on the mean indifference bands for schedule delay is considered. Note that the mean indifference bands refer to the alternative specific constant corresponding to the threshold specifications, and must be interpreted, as the mean indifference band when the other variables in the specification are held fixed at their baseline levels. When congestion levels fluctuate randomly from day-to-day, the mean early indifference band is 10.81 min., and the late indifference band is 5.97 minutes. In the systematic treatment, the mean early schedule delay band is 9.46 min., and the late side band is 4.88 min. (when other factors are held at the baseline levels). This implies that an early arrival of up to about 10 min., and a late arrival of up to about 5 min., will not induce switching.

Two interesting observations can be made based on these results. First, drivers tend to increase their indifference bands, on the late side by about 1.5 minutes, in response to increased uncertainty in the random treatment, as compared to the systematic treatment. Second, these results further corroborate the strong asymmetry between late and early schedule delays reported in the literature (Chang and Mahmassani, 1988; Mahmassani and Liu, 1997). The early indifference band is about twice as large as the late side band - a reflection of the effect of arrival time constraint on the departure time decision of drivers.

Next, the influence of network loads on drivers' departure time switching behavior is examined. The lowest level of congestion (A) is taken as the baseline, and the other two levels are included as binary indicator variables in the specification of the systematic indifference bands. In response to increasing congestion levels in the random treatment, drivers increase their early side indifference band by about 1.4-2.1 minutes. Upon being late, however, drivers respond to increasing loads by decreasing their late side indifference bands (by 1.67-2.13 min.), resulting in greater switching on the late side. In contrast, when the congestion levels increase in the systematic treatment, drivers are willing to accommodate an additional schedule delay of about one to two minutes on both early and late sides in response. In other words, when the traffic conditions fluctuate dramatically from day-to-day, drivers exhibit more risk-averse departure time behavior – being more tolerant of early arrivals, and less so of late arrivals.

To investigate the role of information on departure time switching behavior, we examine the influence of information quality on driver behavior. When the reported information is inaccurate and it contributes to schedule delay, drivers respond by switching more often. For example, when the ATIS overestimates trip times on the early side (reported trip time exceeds experienced trip time) or underreports trip times associated with late arrival, greater departure time switching propensity is observed for both the random and systematic treatments (Tables 5.4 and 5.5). This increased switching

may be the result of trip-makers basing their switching decision on the perceived trip time rather than on the reported trip time. Perceived trip time, in turn, may be estimated based on the magnitude of the discrepancy between the reported and experienced trip times.

TABLE 5.4

CALIBRATION RESULTS FOR DEPARTURE TIME SWITCHING INDIFFERENCE BANDS UNDER THE RANDOM TREATMENT

Variable Definitions	Random Evolution			
	Late Side		Early Side	
	Coefficients	t-stats	Coefficients	t-stats
Mean Indifference Band (min.)	5.97	7.89	10.81	4.00
Information Quality				
Information Overestimation Error (%)	-0.16	-2.02	-0.06	-2.77
Information Underestimation Error (%)	-0.03	-2.81	-4.25	-2.42
Congestion Level				
Moderate Congestion (B)	-1.67	-3.23	2.11	3.35
Severe Congestion (C)	-2.13	-3.75	1.37	2.91
Experience				
Cumulative Number of Dep. Time Switche	0.11	2.16	1.58	2.30
Stuck (= 1, if driver was stuck in traffic on previous day, 0 otherwise)	-2.25	-1.96	2.98	2.25
Variance (late side)	28.10	6.37		
Variance (early side)	27.90	5.98		
Correlation (late to late)	-0.23	-1.75		
Correlation (early to early)	0.097	4.91		
Correlation (late to early)	-0.0031	-0.184		
Correlation (early to late)	-0.08	-2.84		
LL	-82.97			
LL(0)	-110.90			
ρ2	0.25			

TABLE 5.5

CALIBRATION RESULTS FOR DEPARTURE TIME SWITCHING INDIFFERENCE BANDS UNDER THE SEQUENTIAL TREATMENT

Variable Definitions	Late Side		Early Side	
	Coefficients	t-stats	Coefficients	t-stats
Mean Indifference Band (min.)	4.88	4.11	9.46	5.24
Information Quality				
Relative Overestimation Error (%)	-2.27	-3.15	-4.72	-5.96
Relative Underestimation Error (%)	-1.42	-2.27	-3.08	-3.48
Congestion Level				
Moderate Congestion (B)	1.11	3.06	2.02	2.89
Severe Congestion (C)	2.10	2.82	1.86	8.70
Experience				
Cumulative Number of Dep. Time Switche	0.77	3.61	0.61	2.25
Stuck (= 1, if driver was stuck) in traffic on previous day, 0 otherwise)	-1.05	-2.88	0.93	1.80
Variance (late side)	22.69	4.09		
Variance (early side)	22.68	4.13		
Correlation (late to late)	0.22	1.78		
Correlation (early to early)	-0.2	-1.49		
Correlation (late to early)	-0.01	-0.37		
Correlation (early to late)	-0.11	-1.01		
LL	-171.87			
LL(0)	-205.86			
ρ2	0.17			

The influence of experience – both short-term and longer-term, on drivers' departure switching behavior is now considered. Short-term experience is captured by an indicator variable reflecting the driver's traffic experience on the previous day, namely, whether he/she was stuck in a queue on some segment. The coefficient of this variable is negative on the late side (-1.05 and –2.25 min. for the sequential and random treatments respectively) and positive on the early side (0.93 and 2.98 min.), and is significant. Being stuck in traffic on the previous day induces greater departure time switching if the driver was late on the previous day, and less switching if he/she was early. Thus recent negative experiences associated with late arrivals are weighted heavily by drivers in the decision to switch departure times. The longer-term experience is modeled by the cumulative number of departure time switches on previous days. This variable represents the cumulative unsuccessful attempts at meeting the desired arrival time. The variable of this form representing cumulative past experience can be shown to represent a Polya stochastic process (Heckman, 1981; Mahmassani and Chang, 1988). Drivers with greater number of switches on preceding days are found to increase their indifference bands on both sides for the

systematic and random treatments. This is indicative of an adjustment process that tends to moderate one's aspiration level regarding arrival time, in relation to his/her traffic experience. Even though the longer-term experience is represented here for a period of about two weeks, the duration of learning and adjustment in the system could occur over a much longer duration, perhaps on the order of months.

In addition to the temporal dependency captured through systematic experience variables as above, another form of temporal dependency is also noted in departure time switching. It is found that the unobservables influencing this behavior are serially correlated from day-to-day. In the sequential treatment, the calibrated serial correlation coefficients between late indifference bands on successive days is significant with a value of 0.22, whereas, the corresponding correlation between early indifference bands is -0.20. The data also indicates moderate though insignificant correlations between early and late indifference bands (and vice-versa) on successive days in the sequential treatment. The respective variances of early and late indifference bands are nearly equal in the sequential treatment (22.7 minutes^2). In contrast, in the random treatment, the late indifference bands on successive days are serially correlated with a coefficient of 0.23.

The corresponding correlation between early indifference bands is mildly positive (0.10). These correlations suggest significant unobservables in users' departure time switching decisions from one day to the next. The variances of early and late indifference bands in the random treatment were estimated to be higher under the sequential treatment (28.10 minutes^2).

To summarize these findings, congestion, both in terms of its magnitude and its day-to-day evolution, significantly influences departure time switching behavior. It is noteworthy that the influence of network loads, and users' past experience in traffic have differing impacts depending on departure time switching decision, depending on whether network conditions change from day-to-day in a random or systematic manner. Random changes are reflective of incident-induced congestion in actual traffic networks. In the sequential treatment, drivers are observed to increase their indifference bands to accommodate increasing congestion. In contrast, in the random treatment, drivers are more tolerant of earliness, and less so of lateness. The results also indicate that providing inaccurate information results in higher switching rates, especially if it contributes to the schedule delay. The short-term and longer-term traffic experiences also significantly influence drivers' switching behavior.

5.4 ROUTE SWITCHING BEHAVIOR

This section presents the behavioral framework, model structure and specification, as well as parameter estimation results, for dynamic models of commuters' route switching decisions. The model results highlight the influence of congestion, information and experience on route switching decisions of users, both within-day and day-to-day.

5.4.1 Route Switching Models

Notation

Let i be the subscript to denote the individual trip-maker , i = 1,.... I;

j - the decision location, j = 1,.... J, j=1 is an origin (pre-trip location);

t - the day index, t = 1, ... ,T;

U_{ijt} *- the utility of switching for individual i at decision node j at time t;*

δ_{ijt} *- route switching binary indicator;*

δ_{ijt} *= 1, if driver i switches route at decision node j on day t;*

= 0 otherwise;

TTC_{ijt} *- trip time along the current path from decision point j to the destination for user i on day t;*

TTB_{ijt} *- trip time along the reported best path from decision point j to the destination for user i on day t;*

TTS_{ijt} *- trip time savings upon switching to the best path, to individual i at decision node j on day t;*

$TTS_{ijt} = TTC_{ijt} - TTB_{ijt}$;

$TTSP_{ijt}$ *- perceived trip time savings for individual i at decision node j at time t;*

ε^s_{ijt} *- normal error term component of the perceived travel time saving$_t$;*

τ_{ijt} *- logistic error term component of $TTSP_{ijt}$;*

IBR_{ijt} *- indifference band for individual i at decision location j on day t;*

$IBRR_{ijt}$ *- relative indifference band for individual i at decision location j on day t;*

$IBRM_{ijt}$ *- minimum indifference band for individual i at decision location j on day t;*

η_{ijt}, π_{ijt} *relative and minimum trip time savings thresholds for driver i at decision node j on day t;*

$g^r(Z_i, X_{ijt}, \Theta_{ijt})$ *- deterministic component of the relative indifference band;*

ε^r_{ijt} *- normal error term component of the relative indifference band;*

$g^m(Z_i, X_{ijt}, \Theta_{ijt})$ *- deterministic component of the minimum indifference band;*

ε^m_{ijt} *- normal error term component of the minimum indifference band;*

Z_i *- socio-demographic attributes of user i*

X_{ijt} *- traffic and other relevant of variables of influence for user i at decision node j and day t;*

Θ_{ijt} *- parameters of the deterministic component of the utility;*

$IBRR_{ijt} = TTC_{ijt}(\eta_{ijt}) = TTC_{ijt}(g^r(Z_i, X_{ijt}, \Theta_{ijt}) + \varepsilon^r_{ijt})$

$IBRM_{ijt} = \pi_{ijt} = g^m(Z_i, X_{ijt}, \Theta_{ijt}) + \varepsilon^m_{ijt}$

$IBR_{ijt} = \max(IBRR_{ijt}, IBRM_{ijt})$

$\boldsymbol{\varepsilon_t}$ *- vector of ε^r_{ijt}, ε^m_{ijt}, ε^s_{ijt}, for all j, t;*

$\boldsymbol{\tau_i}$ *- vector of τ_{ijt} for all j, t;*

V^r_{ijt} *- conditional deterministic term of the relative indifference band given $\boldsymbol{\varepsilon_t}$;*

V^m_{ijt} *- conditional deterministic term of the minimum indifference band given $\boldsymbol{\varepsilon_t}$;*

V^s_{ijt} *- conditional deterministic term of the perceived trip time saving, $TTSP_{ijt}$, given $\boldsymbol{\varepsilon_t}$;*

V^r_{ijt}*- conditional deterministic term of switching utility , U_{ijt}, given $\boldsymbol{\varepsilon_t}$;*

The utility of switching is defined as:

$U_{ijt} = TTSP_{ijt} - IBR_{ijt}$.

5.4.1.1 Behavioral Framework. Experimental evidence presented by Mahmassani and Stephan (1988) suggests that commuters exhibit boundedly rational behavior in switching routes. Following Mahmassani

and Jayakrishnan (1991), the driver is assumed to continue on his/her current path unless there is sufficient incentive in the form of trip time saving relative to the trip time on the current path. Furthermore, the driver is presumed to continue on his/her current route if the trip time saving that accrues by switching is less than a minimum savings threshold. The driver is unlikely to switch if the absolute trip time saving does not exceed some minimum threshold even if the relative trip time saving exceeds the relative threshold. This framework can be translated into the following route switching model.

$$\delta_{ijt} = 1 \text{ if } TTSP_{ijt} > IBR_{ijt} = \max[\eta_{ijt} TTC_{ijt}, \pi_{ijt}],$$
$$= 0 \text{ otherwise.}$$

5.4.1.2 Modeling Framework. Both the relative and minimum thresholds can be expected to vary across individuals, as well as within an individual from day-to-day, in response to experience and learning that occurs in the commuting system. These thresholds are latent random variables with mean values varying systematically with drivers' experience and learning in the system. They are expressed as:

$\eta_{ijt} TTC_{ijt} = g^r(Z_i, X_{ijt}, \Theta_{ijt}) + \varepsilon^r_{ijt}$,

$\pi_{ijt} = g^m(Z_i, X_{ijt}, \Theta_{ijt}) + \varepsilon^m_{ijt}$,

$IBR_{ijt} = \max(\eta_{ijt} TTC_{ijt}, \pi_{ijt})$,

$IBR_{ijt} = \max(g^r(X_i, Z_{ijt}, \Theta_{ijt}) + \varepsilon^r_{ijt}, g^m(X_i, Z_{ijt}, \Theta_{ijt}) + \varepsilon^m_{ijt})$.

Further it is assumed that the perceived trip time saving has the reported trip time saving as its mean, and the unobservables can be written as the sum of two random error terms as given below.

$TTSP_{ijt} = TTS_{ijt} + \varepsilon^s_{ijt} + \tau^s_{ijt}$.

Let $\varepsilon = (\varepsilon^r_{i11}, \varepsilon^m_{i11}, \varepsilon^s_{i11}, \ldots\ldots\ldots, \varepsilon^r_{ijt}, \varepsilon^m_{ijt}, \varepsilon^s_{ijt}, \ldots\ldots\ldots\ldots, \varepsilon^r_{iJT}, \varepsilon^m_{iJT}, \varepsilon^s_{iJT})$.

Let $\tau = (\tau^s_{i11}, \ldots\ldots\ldots, \tau^s_{ijt}, \ldots\ldots\ldots\ldots, \tau^s_{iJT})$.

Assuming, $\varepsilon' \sim MVN(0, \Sigma_\varepsilon)$, and $\tau' \sim$ i.i.d logistic, $(0, \sigma_g^2 I)$,

where $\sigma_g^2 = \pi^2/(3\mu^2)$, I is JT dimensional unit matrix and μ is the logit scale parameter. Further, it is assumed that the logistic error vector τ' is independent of the multivariate normal error vector ε'.

In the absence of an error term in the perception of trip time saving, the model above would lead to a dynamic probit-based model of route switching of dimension 2JT (a model of this type has been implemented by Liu and Mahmassani, 1998). This would imply that the users' perceptions of trip time saving coincide with the trip times reported by ATIS, which is not likely to hold. An assumption of only multivariate normal error term on perception would also lead to a dynamic probit model as before, but with a variance covariance matrix of dimension (3JT x 3JT). This framework is computationally more expensive to estimate with a large number of decision situations than the previous model. The route choice model in the systematic treatment consists of 55 choice situations (11 days with five decision nodes) leading to an equivalent probit choice probability with 56 alternatives. Probit estimation results have not been reported for data with such large dimensionality.

The need for an alternative framework that retains the flexibility of general variance covariance structures of probit but exploits to some extent the computational tractability of the logit model is necessitated by the computational cost of the probit model. By introducing a simple logistic error term to

the perceived trip time savings, the conditional model given the normal error terms results in a logit form of the type discussed in Chapter 4. This closed form evaluation of the conditional likelihood greatly simplifies the computation of the unconditional model. The resulting model belongs to the class of dynamic logit kernel models discussed in Chapter 4. Earlier it was shown in Section 4.4.3, that the kernel logit and corresponding multinomial probit models yield very comparable results in so far as coefficient estimates are concerned.

The boundedly rational behavioral rules described previously can be operationalized on the basis of the following observation. A user would switch routes from current path if the perceived travel time savings exceeds the indifference band threshold for route switching. Therefore, the utility of switching can be written as the difference between the perceived trip time savings and the route switching indifference band. Thus, $U_{ijt} = TTSP_{ijt} - IBR_{ijt}$ represents the utility of switching for individual i at decision node j at time t. A user would switch from her current path iff the corresponding utility exceeds 0. Thus,

$\delta^{sw}_{ijt} = 1$ iff $U_{ijt} \geq 0$,

$= 0$ otherwise;

Equivalently, $(2\delta^{sw}_{ijt} - 1)\, U_{ijt} \geq 0$.

Now, τ' is independent of ε'. Therefore, given ε', U_{it} is independent of $U_{it'}$. This follows by virtue of the i.i.d assumption on τ'. The probability of observing a sequence of choices of individual n is given by

$Pr_n\{C_{ijt}, j = 1,..J, t = 1,..T\} =$

$$Pr_n\{(2\delta^{sw}_{ijt} - 1)\, U_{ijt} \geq 0, j = 1,..,J, \; t = 1,.....,T\} \qquad (5.3).$$

Since U_{ijt} is a function of ε, conditioning (5.10) on $\boldsymbol{\varepsilon}$

$Pr\{C_{ijt}, j = 1,..J, t=1,..,T\} =$

$$\int_{\varepsilon} Pr\{2\delta^{sw}_{ijt} - 1)\, U_{ijt} \geq 0, j=1,.. J, t = 1,.....,T \mid \boldsymbol{\varepsilon}\}\, f(\boldsymbol{\varepsilon})d\boldsymbol{\varepsilon} \qquad (5.4).$$

Using the fact that conditional on the multivariate normal error vector ε, U_{ijt} is independent of $U_{ij't'}$ equation (5.11) can be rewritten as:

$Pr\{2\delta^{sw}_{ijt} - 1)\, U_{ijt} \geq 0, j=1,.. J, \; t = 1,.....,T \mid \boldsymbol{\varepsilon}\}$

$$= \Pi_{t=1}^{T} \Pi_{j=1}^{J} Pr\{2\delta^{sw}_{ijt} - 1)\, U_{ijt} \geq 0 \mid \boldsymbol{\varepsilon}\} \qquad (5.5).$$

The above equation follows from the conditional independence of IBR_{ijt} across j and t given $\boldsymbol{\varepsilon}$. Conditional on $\boldsymbol{\varepsilon}$, the indifference bands are deterministic, since they only depend on ε

$$\eta_{ijt}\, TTC_{ijt} \mid \boldsymbol{\varepsilon} = V^{r}_{ijt} = g^{r}(X_i, Z_{ijt}, \Theta_{ijt}) + \varepsilon^{r}_{ijt} \qquad (5.6).$$

$$\pi_{ijt} \mid \boldsymbol{\varepsilon} = V^{m}_{ijt} = g^{m}(X_i, Z_{ijt}, \Theta_{ijt}) + \varepsilon^{m}_{ijt} \qquad (5.7).$$

$$IBR_{ijt} \mid \boldsymbol{\varepsilon} = \max(\eta_{ijt} TTC_{ijt}, \pi_{ijt} \mid \varepsilon) = \max(V^{r}_{ijt}, V^{m}_{ijt}) \qquad (5.8).$$

$$TTSP_{ijt} \mid \boldsymbol{\varepsilon} = V^{s}_{ijt} + \tau^{s}_{ijt} \text{ where } V^{s}_{ijt} = TTS_{ijt} + \varepsilon^{s}_{ijt} \qquad (5.9).$$

For a given user i, decision location j, and day t, two route switching outcomes are possible. First, the outcome corresponding to a route switch is considered in case 1, followed by a non-switching decision in case 2.

Case 1: The user i switches at node j at time t or $\delta^{sw}_{ijt} = 1$,

$$\Pr\{(2\delta^{sw}_{ijt} - 1)\, U_{ijt} \geq 0 \;\; | \boldsymbol{\varepsilon}\} = \Pr\{U_{ijt} \geq 0 \;\; | \boldsymbol{\varepsilon}\}$$
$$= \Pr(TTSP_{ijt} - IBR_{ijt} \geq 0 \;\; | \boldsymbol{\varepsilon})$$
$$= \Pr\{V^s_{ijt} + \tau^s_{ijt} - \max(V^r_{ijt}, V^m_{ijt}) \geq 0 \;\; | \boldsymbol{\varepsilon}\}$$
$$= \Pr\{V_{ijt} + \tau^s_{ijt} \geq 0 \mid \boldsymbol{\varepsilon}\}$$
$$= \exp(\mu V_{ijt}) / [1 + \exp(\mu V_{ijt})] \qquad (5.10).$$

where,

$V_{ijt} = V^s_{ijt} - \max(V^r_{ijt}, V^m_{ijt})$ and the R.H.S of (5.10) follows from the cumulative distribution of the logistic error terms.

Case 2: The user i does not switch at node j at time t, $\delta^{sw}_{ijt} = 0$,

$$\Pr\{U_{ijt} < 0 \;\; | \boldsymbol{\varepsilon}\} = \Pr(TTSP_{ijt} - IBR_{ijt} < 0 \;\; | \boldsymbol{\varepsilon})$$
$$= \Pr\{V^s_{ijt} + \tau^s_{ijt} - \max(V^r_{ijt}, V^m_{ijt}) < 0 \;\; | \boldsymbol{\varepsilon}\}$$
$$= \Pr\{V_{ijt} + \tau^s_{ijt} < 0 \;\; | \boldsymbol{\varepsilon}\} = 1 / [1 + \exp(\mu V_{ijt})] \qquad (5.11).$$

Rewriting the two cases (5.10) and (5.11) succinctly, the following expression is obtained:

$$\Pr\{U_{iCt} - U_{ijt} \geq 0,\ \forall\, i \neq C_{ijt} \mid \boldsymbol{\varepsilon}\} = 1 / [1 + \exp(\mu(2\delta^{sw}_{ijt} - 1)V_{ijt})] \qquad (5.12)$$

Since the likelihood in equation 5.12 is conditional on the multivariate normal error vector ε, it is unconditioned as follows to obtain the unconditional likelihood,

$$\Pr\{C_{ijt}, j=1,..J, t = 1,\ldots T\}$$
$$= \int_{\varepsilon} \Pi_{j=1}^{J} \Pi_{t=1}^{T} \{1 / [1 + \exp(\mu(1 - 2\delta^{sw}_{ijt})V_{ijt})]\}\, f(\boldsymbol{\varepsilon})d\boldsymbol{\varepsilon} \qquad (5.13).$$

Equation (5.13) represents the likelihood of observing a sequence of route switching decisions for a given user i. The likelihood of observing the sequence of route switching decisions by a sample consisting of I independent decision-makers can then be given by:

$$L = \Pi_i \Pr\{C_{ijt}, j= 1,\ldots J, t = 1,\ldots T\} \qquad (5.14).$$

The log-likelihood of the sequence of route switching decisions observed for the sample can be given as:

$$LL = \log(L) = \Sigma_i \log \Pr\{C_{ijt}, j= 1,\ldots J, t = 1,\ldots T\}$$
$$\Sigma_i \log [\int_{\varepsilon} \Pi_{j=1}^{J} \Pi_{t=1}^{T} \{1 / [1 + \exp(\mu(1 - 2\delta^{sw}_{ijt})V_{ijt})]\}\, f(\boldsymbol{\varepsilon})d\boldsymbol{\varepsilon}] \qquad (5.15).$$

The likelihood function in (5.15) is calibrated using the maximum likelihood estimation technique in view of its desirable asymptotic properties. The objective of model calibration is to obtain the vector of parameters ($\boldsymbol{B}$) corresponding to the deterministic utility V_{ijt}, and the vector of parameters ($\boldsymbol{\Theta}$) corresponding to the variance covariance of the multivariate normal error terms ($\boldsymbol{\varepsilon}$). These parameters are determined by a non-linear optimization procedure that maximizes the log-likelihood function in (5.15). The calibration procedure broadly follows the generic procedure outlined in Chapter 4.

In calibrating the route switching model, the deterministic utility is chosen to be a linear function of parameters for both the relative and minimum indifference bands. While it is possible to calibrate very general variance covariance structures with this formulation, the following simplifying assumptions are introduced in the interest of parsimony in parameters, and computational efficiency. The unobservables associated with the relative and minimum indifference bands are assumed to be correlated both within-

day and from day-to-day as shown in Tables 5.6 and 5.7 respectively. Table 5.6 describes the within-day covariance structure, whereas the day-to-day covariance structure is shown in Table 5.7 Note that the error terms associated with the relative band (η) are assumed to be uncorrelated with the unobservables associated with the minimum indifference band (π). Furthermore, the minimum and relative indifference bands are assumed to be correlated for a given decision node over days, and uncorrelated across

TABLE 5.6

WITHIN-DAY COVARIANCE STRUCTURE FOR ROUTE SWITCHING INDIFFERENCE BANDS

Variances	
Relative indifference band Variance pre-trip = $E[\varepsilon^r_{i1t}{}^2]$	$\sigma_1{}^2$
Relative indifference band Variance en-route = $E[\varepsilon^r_{ijt}{}^2]$, (j = 2,…5)	$\sigma_2{}^2$
Minimum indifference band Variance pre-trip = $E[\varepsilon^m_{i1t}{}^2]$	$\sigma_3{}^2$
Minimum indifference band Variance en-route = $E[\varepsilon^m_{i1t}{}^2]$, (j = 2,…5)	$\sigma_4{}^2$
Within-Day Covariances (t = t')	
Pre-trip and en-route relative indifference bands $E[\varepsilon^r_{i1t}, \varepsilon^r_{ijt}]$, j = 2,…, 5	$\rho_{r1r}\sigma_1\sigma_2$
En-route relative indifference bands $E[\varepsilon^r_{ijt}, \varepsilon^r_{ij't}]$, j, j' = 2,…, 5, ($j \neq j'$)	$\rho_{r2r}\sigma_2{}^2$
Pre-trip and en-route minimum Indifference bands $E[\varepsilon^m_{i1t}, \varepsilon^m_{ijt}]$, j = 2,…, 5	$\rho_{m1m}\sigma_3\sigma_4$
En-route minimum indifference bands $E[\varepsilon^m_{ijt}, \varepsilon^m_{ij't}]$, j, j' = 2,…, 5, ($j \neq j'$)	$\rho_{m2m}\sigma_4{}^2$

different decision nodes on different days. A third simplifying assumption, is that the perception errors can be captured entirely by logistically distributed error terms that are independent across decision locations and days. These simplifying assumptions greatly reduce the dimensionality of numerical integration in the likelihood computation from 165 (three MVN errors for 11 days and five decision locations) to 55. Some of

the restrictions imposed on the error-structure in this analysis are relaxed later in Chapter 7. The route switching indifference band model calibration results are presented next.

TABLE 5.7

DAY-TO-DAY COVARIANCE STRUCTURE FOR ROUTE SWITCHING INDIFFERENCE BANDS

Day-to-day Covariances ($t \neq t'$)	
Pre-trip relative indifference bands $E[\varepsilon^r_{i1t}, \varepsilon^r_{i1t'}], t \neq t'$	$\rho_{r3r}\sigma_1^2$
En-route relative indifference bands $E[\varepsilon^r_{ijt}, \varepsilon^r_{ijt'}], t \neq t', j = 2,\ldots,5$	$\rho_{r4r}\sigma_2^2$
En-route relative indifference bands $E[\varepsilon^r_{ijt}, \varepsilon^r_{ij't'}], t \neq t', j,j' = 2,\ldots,5, j \neq j'$	0
Pre-trip minimum indifference bands $E[\varepsilon^m_{i1t}, \varepsilon^m_{i1t'}], t \neq t'$	$\rho_{m3m}\sigma_3^2$
En-route minimum indifference bands $E[\varepsilon^m_{ijt}, \varepsilon^m_{ijt'}], t \neq t', j = 2,\ldots,5$	$\rho_{m4m}\sigma_4^2$
En-route minimum indifference bands $E[\varepsilon^m_{ijt}, \varepsilon^m_{ij't'}], t \neq t', j,j' = 2,\ldots,5, j \neq j'$	0
Other Relative and Minimum Indifference Bands $E[\varepsilon^r_{ijt}, \varepsilon^m_{ij't'}]$	0

5.4.2 Route Switching Results

The results from the route switching indifference band model calibration are displayed in Tables 5.8 and 5.9 respectively for the random and sequential treatment. The influence of congestion, information, and experience on route switching decisions of users from day-to-day are analyzed based on these results. The influence of congestion on route switching is analyzed by examining the mean indifference bands (corresponding to baseline levels of other variables) for relative and minimum trip time savings.

In addition, the effect of network loading levels are compared between the systematic and random treatment levels. In the systematic treatment, the mean relative indifference band is 25% and the minimum indifference band is about 2.51 minutes with other factors at their baseline levels. In other words, drivers expect a trip time saving of about 25% over their current path before they switch routes, and that this trip time saving should be about two to three minutes. In the random treatment level, the relative indifference band is marginally lower, with the relative savings threshold at about 15%, whereas the minimum threshold is slightly larger at 2.83 minutes (Tables 5.8 and 5.9). The notion of minimum trip-

time saving necessary to induce switching is also consistent with the findings from the post-experiment questionnaire, where only 13% of the respondents indicated a willingness to switch with a trip-time savings of less than five minutes.

Next, the effect of network loads on route switching is considered. The lowest network loading level is treated as baseline and the others are reflected through corresponding binary indicator variables in the specification of thresholds. When the traffic evolution is random, there is no significant effect of network loads on en-route switching. On the other hand, pre-trip route switching is found to be higher in response to very high congestion on the previous day, and lower for moderate congestion. In contrast, when the day-to-day evolution is systematic, there appears to be a discernible effect of network loads on switching behavior. In pre-trip decisions, the highest switching probability occurs at the highest loading level, whereas there are no significant differences between the other two levels. In en-route switching decisions, the switching rates at both moderate and severe congestion levels are significantly higher than the baseline. Thus, when the traffic evolution is sequential, the drivers switch routes more frequently in response to increasing network loads.

The role of anticipated traffic conditions in route switching behavior is explored next. The effect of expected congestion is modeled by including the indifference band specification; variables that capture the color-coded visual congestion information provided to the users. On each link, the congestion is displayed as one of the following levels – light (1), moderate (2), heavy (3), and severe (4), depending on traffic concentrations prevailing on the link. Four look-ahead levels were considered for this variable: next link, next segment, next two segments, and entire downstream segment. The congestion levels on the current path and best path are averaged over the look-ahead segment. The results are presented here only for the next segment look-ahead level, as it was found to be the most influential in log-likelihood terms. For both the systematic and random treatments, it is observed that a greater congestion level on the current path induces more route switching, whereas a greater congestion level on the best path inhibits route switching. These findings can be explained by the desire of drivers to avoid congested conditions on the current route. However, when the best path itself is congested, switching is reduced since the rerouting opportunities in the network are likely very limited. Furthermore, it is observed that expected congestion on the current path has a greater effect in the random case than in the systematic case (reflected in larger coefficients, and scale being fixed in both models since the coefficient of trip time saving is one naturally). Taken in conjunction with the fact that network loads did not have a significant impact on route switching, it appears that the expectations of traffic conditions and congestion appear to play a dominant role over past experience in the random case. In the systematic case, though, the drivers appear to be influenced both by the network loads, and the expected congestion. Thus the process of adjustment appears to be based on both experience and expectations when the traffic evolution is systematic.

TABLE 5.8
CALIBRATION RESULTS FOR ROUTE SWITCHING INDIFFERENCE BANDS FOR RANDOM TREATMENT

Variable Definition	Random Treatment			
	Relative Indifference Threshold		Minimum Indifference Threshold	
	Coefficient	t-stats	Coefficient	t-stats
Mean Relative Indifference Band	0.15	3.71	2.83	2.97
Effect of Congestion Levels				
En-Route				
Moderate (B)	*0.03*	*0.87*	*0.01*	*0.69*
Severe (C)	*0.004*	*0.27*	*0.00*	*0.20*
Pre-Trip				
Moderate (B)	0.09	1.71	3.99	1.69
Severe (C)	-0.14	-1.67	-4.33	-1.65
Expected Congestion				
On Current Path	-0.15	-4.92	-5.17	-4.59
On Best Path	0.03	2.12	1.17	1.81
Experience Effects				
Cumulative No. Of Dep. Time Switches to the Early Side	*0.01*	*0.90*	*0.50*	*0.81*
Cumulative No. Of Dep. Time Switches to the Late Side	0.06	2.51	2.27	2.34
Information-Inertia Effect				
Inert (=1, if current path = best path, 0 otherwise)	0.25	3.29	11.83	5.98
Log-Likelihood	-406.4			
Log-Likelihood(0)	-530.95			
ρ2	0.235			

Note: Variables not significant at 10% are shown in italics for comparison purposes
The corresponding variance-covariance parameters are displayed in Table 5.10

The influence of expectations regarding arrival time on route switching is examined by considering the effect of potential early and late schedule delays that would be experienced by following the current path. This variable was not significant. Two plausible explanations may be advanced in this regard. First, it is likely that visual information can be processed more easily than information about reported trip-times and schedule delays that involve computations on the part of users. Second, it is also possible that route switching decisions under real-time information are motivated more by congestion avoidance than schedule delay considerations. This can be contrasted to previous findings without real-time information where schedule delay dominated day-to-day switching behavior (Mahmassani, 1990).

To model the effect of recent experience on route switching, the binary indicator variable -"stuck" is included in the specification of the indifference bands. For en-route switching decisions, this variable indicates whether a user was stuck in traffic on the previous network segment for en-route decisions, as

well as whether a user was stuck in traffic on the previous day, for pre-trip route switching decisions. Contrary to expectations, this variable did not significantly influence either the relative or minimum thresholds for both treatments, and hence it is not included in models shown in Tables 5.8 and 5.9. One possible explanation is that a significant number of drivers may have been stuck even on the best path due to congestion, and therefore have learned not to switch in response to being stuck. Longer-term experience is modeled by the cumulative number of departure switches to earlier departure times and the cumulative number of departure switches to later departure times. In the random treatment, it is found that, a greater number of switches to later departure times is consistent with a reduced probability of route switching. In the systematic case, it is observed that drivers with a greater number of switches to earlier departure times are more likely to switch routes. Greater number of switches to earlier departure times presumably occur due to too many unacceptably late arrivals or to avoid congested conditions. In response, drivers are more likely to switch both route and departure time. In the case of too frequent early arrivals, drivers tend to merely switch departure time but not route, confirming previous findings without real-time information (Mahmassani and Herman, 1990).

The role of information on route switching behavior is examined next. Information quality, represented by overestimation and underestimation errors, does not appear to significantly influence route switching behavior and is not shown in the final model specification. Overestimation error, it may be recalled, refers to the discrepancy between trip time reported by ATIS and experienced trip time, when the former overestimates the latter. Underestimation errors are defined analogously when the information supplied by ATIS underestimates experienced trip time. This finding is surprising as previous studies report that poor information quality results in greater switching activity (Liu and Mahmassani, 1998). The previous studies, however, assume that the network loadings do not vary from day-to-day. In this experiment, commuters might have attributed the difference between reported and experienced trip times to the traffic evolution in the commuting system instead of attributing it to poor information quality. Pending further experiments and investigation, these results regarding the effect of information quality may be taken as tentative. The results also indicate that information can strengthen the inertial tendency of trip-makers, particularly, if the current path coincidentally happens to be the best path reported by ATIS. The users, in this case, are observed to be considerably less likely to switch routes than when the current path is not the best path. Strong information-inertia interaction is observed in route switching decisions for both systematic and random treatment levels. The effect of information quality on route and departure time switching decisions is examined in more depth in Chapter 7, based on data from the second set of interactive experiments described in Section 3.6.

TABLE 5.9

CALIBRATION RESULTS FOR ROUTE SWITCHING INDIFFERENCE BANDS FOR SEQUENTIAL TREATMENT

Mean Relative Indifference Band	0.25	3.71	2.51	1.88
Effect of Congestion Levels				
En-Route				
Moderate (B)	-0.10	-2.97	-1.77	-3.35
Severe (C)	-0.10	-3.78	-2.39	-3.63
Pre-Trip				
Moderate (B)	*-0.09*	*-1.58*	*-0.29*	*-1.47*
Severe (C)	-0.16	-3.91	-2.06	-3.24
Expected Congestion				
On Current Path	-0.03	-2.61	-0.53	-4.45
On Best Path	0.02	2.07	1.63	2.50
Experience Effects				
Cumulative No. Of Dep. Time Switches to the Early Side	-0.06	-2.91	-0.47	-2.84
Cumulative No. Of Dep. Time Switches to the Late Side	*0.02*	*0.95*	*0.24*	*1.03*
Information-Inertia Effect				
Inert (=1, if current path = best path, 0 otherwise)	0.21	5.91	2.36	9.58
Log-Likelihood	-760.45			
Log-Likelihood(0)	-1030.97			
ρ2	0.262			

Note: Variables not significant at 10% are shown in italics for comparison purposes
The corresponding variance-covariance parameters are displayed in Table 5.11

Finally, modeling results indicate that the dynamic route switching decisions of trip-makers are serially correlated. The calibration results indicate some significant within-day and day-to-day correlations among the error terms associated with the minimum and relative indifference bands (Tables 5.10 and 5.11). The serial correlation could result from persistent unobserved error terms due to repeated measurements, and possible time lags between experience and adjustment of behavior. In the random treatment, the pre-trip variance is slightly larger (not significantly, though) than the en-route variance for both relative and minimum thresholds.

TABLE 5.10

VARIANCE-COVARIANCE PARAMETERS OF ROUTE SWITCHING INDIFFERENCE BAND FOR THE RANDOM TREATMENT

Parameter Description	Relative Threshold Parameter	Relative Threshold t-statistics	Minimum Threshold Parameter	Minimum Threshold t-statistics
Pre-trip Variance	σ_1^2 = 1.75	2.05	σ_3^2 =1.71	1.97
En-Route Variance	σ_2^2 = 1.64	1.87	σ_4^2 =1.63	2.53
Within-day correlation (pre-trip, en-route)	ρ_{r1r} = 0.022	0.064	ρ_{m1m} = 0.021	0.06
Within-day correlation (en-route, en-route)	ρ_{r2r} = 0.101	1.137	ρ_{m2m} = 0.008	0.02
Day-to-day correlation (pre-trip, pre-trip)	ρ_{r3r} = 0.09	1.141	ρ_{m3m} = 0.072	1.14
Day-to-day correlation (en-route, en-route)	ρ_{r4r} = 0.162	1.15	ρ_{m4m} = 0.04	0.11

In contrast, in the sequential treatment, the pre-trip variance for the relative indifference band is considerably (significantly) larger than the corresponding en-route variance, whereas the pre-trip and en-route variances for the minimum indifference band are nearly equal. A plausible explanation for the greater pre-trip variance for the relative indifference band is that the trip times encountered may depend on departure time choices that could vary across pre-trip decisions on different days. In both treatments, it is observed that within-day and day-to-day correlations are not significant for the minimum indifference bands. One plausible explanation is that the persistent effects in this threshold can be captured reasonably by the specification of the systematic utility. Furthermore, in the sequential treatment, within-day correlations between the relative indifference band errors are not significant. However, the day-to-day correlations between these errors are significant and positive for both pre-trip and en-route decisions. In the random treatment, however, the correlations for the relative indifference band errors are not significant.

The day-to-day correlations are significant for the relative threshold in the sequential case, but not for the random treatment. This suggests that the sequential treatment affords a greater opportunity for users to learn about the network, conditions and respond accordingly, resulting in a persistence of unobservables over time. The lack of significance of within-day correlations in the sequential treatment suggests that users may review and adjust thresholds dynamically, not after each trip segment, but after the completion of the trip.

TABLE 5.11

VARIANCE-COVARIANCE PARAMETERS OF ROUTE SWITCHING INDIFFERENCE BAND FOR THE SYSTEMATIC TREATMENT

Parameter Description	Relative Threshold Parameter	Relative Threshold t-statistics	Minimum Threshold Parameter	Minimum Threshold t-statistics
Pre-trip Variance	$\sigma_1^2 = 6.01$	1.98	$\sigma_3^2 = 1.64$	3.09
En-Route Variance	$\sigma_2^2 = 2.09$	10.10	$\sigma_4^2 = 1.67$	2.74
Within-day correlation (pre-trip, en-route)	$\rho_{r1r} = 0.02$	0.17	$\rho_{m1m} = 0.10$	0.21
Within-day correlation (en-route, en-route)	$\rho_{r2r} = 0.098$	0.22	$\rho_{m2m} = 0.093$	0.08
Day-to-day correlation (pre-trip, pre-trip)	$\rho_{r3r} = 0.28$	1.52	$\rho_{m3m} = 0.05$	0.01
Day-to-day correlation (en-route, en-route)	$\rho_{r4r} = 0.35$	4.32	$\rho_{m4m} = 0.052$	0.03

While route switching behavior is influenced by congestion, the nature of influence varies depending on whether the evolution of traffic from day-to-day is random or systematic. Under the systematic treatment, both the network loads and the expectation of congestion strongly influence switching behavior. In contrast, the role of congestion expectation is more dominant than the influence of network loading levels in the random treatment. It may be noted that random day-to-day changes are reflective of incident-induced congestion in the real-world traffic networks. This suggests that ATIS can play a significant role in mitigating uncertainty about traffic conditions under drastically varying network conditions. Congestion levels, displayed visually, on both the current path and the best path significantly influence switching behavior, more than supplied information regarding trip times. Furthermore, there appears to be an asymmetric relationship between departure time switching and route switching behavior: route switching propensity increases with switches to earlier departure times, presumably in response to late arrivals, whereas switches to later departure times appear to be accompanied by reduced route switching propensity. One of the mechanisms operating in route switching behavior, inertia, is significantly influenced by the information provision. Whenever the information supports retaining the current path, reduced route switching propensity is observed. Under drastically varying congestion conditions, when information is provided to users on the basis of currently prevailing traffic conditions, it is possible that the users are unable to distinguish between deterioration in information quality and variation in traffic conditions.

5.5 SUMMARY

Commuters' route and departure time switching behavior, in the presence of ATIS information under varying degrees of congestion, are investigated in this chapter. User behavior dynamics are

observed under mutually consistent and time-dependent interactions between network conditions, congestion evolution, and ATIS information in the first set of interactive simulator-based experiments described in Section 3.5.

Route and departure switching decisions are analyzed based on a well-established boundedly rational behavioral framework (Chang et al., 1988; Jou et al., 1998). The dynamics here refers primarily to the real-time dynamics that results from the interaction between real-time information and users' decisions on a given day. The day-to-day dynamics is captured by the influence of the longer-term experience on switching behavior and through the specification of a serially correlated error structure. The indifference bands for departure time and route switching decisions vary dynamically in response to experienced and anticipated congestion. Substantially differences in behavioral patterns are noted in switching behavior under random and systematic treatments. Random treatment represents drastic fluctuations in traffic conditions from day-to-day, whereas, systematic treatment reflects a more gradual evolution of network flows over time. Drivers are observed to increase their mean indifference band for schedule delays to accommodate the uncertainty in the random treatment levels. For the systematic treatment, drivers are found to tolerate early schedule delays of about 10 minutes, and a late schedule delay of about five minutes from their preferred arrival time. In response to increased network loads, the drivers are observed to increase their indifference band on both the early and late sides under systematic traffic variations from day-to-day. Under the random treatment, however, drivers tend to tolerate smaller late schedule delays, and larger early schedule delays.

Congestion also significantly influences route switching behavior in both treatments. Under the random day-to-day evolution, increasing loads appear to have little effect on indifference bands. In contrast, under the systematic evolution, the indifference bands for route switching increase with increasing network loads. The mean relative indifference bands for the random and systematic treatments are about 15% and 25% respectively. The mean minimum trip time savings required for switching is of the order of 2.5-2.83 minutes respectively for the systematic and random day-to-day variation. Anticipated congestion on the downstream segment also plays a significant role in the route switching decision. This factor exerts a greater influence when traffic conditions fluctuate randomly than when the variation is systematic. These findings, regarding the effect of congestion on behavior, have important implications for the evaluation of congestion relief measures, and for dynamic network traffic assignment.

Driver behavior is also strongly influenced by information provision. Poor information quality contributing to schedule delay results in a greater propensity to switch departure times. Under some conditions, information may support behavioral inertia of drivers to retain their current path, while it may support the switching decision in other cases. These results emphasize the need for ATIS to provide information based on a reliable predictive mechanism that incorporates driver behavior and compliance with ATIS information.

Both short-term and longer-term experience of drivers in the commuting system is found to influence route and departure time decisions. Though user behavior for about a two-week period is

modeled in this set of experiments, the duration of adjustment in user behavior may last for considerably longer duration of the order of months. It is hoped that these empirical results regarding the role of experience will lead to more detailed investigations on the role of experiential factors in driver decision-making. Though user behavior over a period of nearly two weeks is modeled in this experiment, the duration of adjustment could be considerably longer, perhaps, of the order of months.

The limitations of this study can be classified into the following two categories. The first set of limitations relates to the observational framework and differences in behavior between the simulated observational basis and the real-world traffic environment. For instance, the simplified network structure adopted in this study to capture commuters' switching behavior, where, a majority of trip-makers select a major facility to commute to a central work location, may not be particularly suitable for modeling suburb to suburb commuting decisions. It is also possible that the cost of switching in real-life networks may be higher than in the simulated corridor due to the presence of one-way streets, left turns, traffic signals etc. In such a case, the actual rate of switching could be lower, and will likely be reflected by a larger route switching indifference bands. Several other factors not examined here, could also influence route switching including geometrics, scenery on alternative routes, urban plight, traffic control and accessibility near destination etc. Nevertheless, it is suspected that these factors are not likely to influence dynamic behavior, since they are generally fixed components of the transportation system.

The second set of limitations relates to the assumptions and restrictions associated with the route and departure time switching models calibrated in this chapter. The models in this chapter calibrate route and departure time switching dimensions separately, due to the large number of parameters that need to be estimated in a joint model. This restriction is relaxed in Chapter 7, where the two decisions are modeled jointly using data from the second set of experiments presented in Chapter 3. The models presented here also assume response homogeneity across decision-makers. This restriction is also relaxed in Section 7.3.1, where heterogeneity in route and departure time switching is modeled at the observed and unobserved levels. The switching models presented here are based on the assumption that dynamics in these decisions can be satisfactorily represented by including time-dependent variables in the systematic utility of switching. Temporal correlations are captured to a limited extent by the specification of error terms. A more general variance covariance structure is specified and calibrated later in Chapter 7. In view of these assumptions and limitations, the results presented here should be interpreted with caution given the relatively moderate sample size and the nature of experiments and associated conditions. Nevertheless, the results provide preliminary insight on the role of congestion and information on driver behavior under accurate prevailing information. The insights obtained from these experiments need to be validated further based on other empirical studies and field data.

Preliminary insights into the dynamic aspects in behavior are obtained here by modeling the effect of time-dependent variables such as experience (short and longer-term), congestion, trip-time on alternative facilities etc, at the observed level. At the unobserved level, time-dependence is represented by the correlation of error terms across choice situations. Users' departure time and route choice

decisions appear to be the result of cognitive processes that include learning about traffic conditions and assessing the quality of information supplied by ATIS. In the experiments analyzed in this chapter, the ATIS supplied accurate prevailing information, whereas, the next chapter examines the related dimension of users' compliance with ATIS information.

CHAPTER 6: DYNAMIC COMPLIANCE DECISIONS OF COMMUTERS WITH ATIS

6.1 INTRODUCTION

The previous chapter examines the influence of network congestion levels on commuters' route and departure time switching decisions based on the first set of interactive experiments described in Section 3.5. In this chapter, another important dimension of behavioral response to ATIS information, namely, compliance with the information is examined. Compliance behavior has received very limited research attention, even though it is a key measure of credibility and effectiveness of ATIS (Chen and Jovanis, 1997; Bonsall, 1991). Studying compliance behavior is important for: 1) designing ATIS products and services and information provision strategies, and 2) assessment of impacts and evaluation of investment into ATIS and other ITS elements.

Compliance with ATIS is defined in a straightforward manner when the ATIS provides route guidance or prescribes a path. A trip-maker is then said to comply with information if he/she follows the prescribed path. This definition of compliance is generalized to include in its scope other ATIS information strategies as follows. A user is said to comply with the information if he/she follows the path, which is the 'best' among the alternative paths reported by the information system. While the information system may not explicitly recognize or recommend a best path, the 'best' path may be inferred based on some underlying criteria, that is presumed to be applied by all users. The least trip time path among the alternatives is selected as the criterion for the 'inferred' best path in the rest of this chapter. This definition is chosen to ensure an objective measurement of compliance behavior across various decision situations, and to gauge the impact of various ATIS strategies. It is quite possible that the best path as perceived by users may be based on more than one criteria. Furthermore, the criteria and perceptions upon which the best path is defined may vary across users. However, these more general definitions introduce considerable complexity in measuring and identifying compliance, especially in the absence of well-developed supporting cognitive notions. Therefore, attention is restricted here to compliance as defined above, solely anchored on information about traffic supply conditions as reported by the ATIS.

In this chapter, commuters' compliance behavior is analyzed under various ATIS information strategies. These strategies encompass a range of information provision formats and information quality. Three principal objectives are investigated in this set of experiments. The first objective is to model the dynamics of compliance behavior. Under this objective it is of interest to examine the effect of past experience on current behavior. A related task in this regard is to assess whether there are differences in perception of information quality, and how they are manifested in choice behavior.

The second objective is to ascertain the key factors influencing compliance behavior. The effect of trip-maker characteristics, trip characteristics and traffic conditions, short and long-term experience and attributes of information supplied by ATIS are examined in this context. These have important applications in predicting compliance behavior, designing information provision strategies, and simulating user behavior in dynamic traffic assignment models.

The third objective is to investigate the influence of ATIS information strategies on commuters' compliance decisions. Specifically, the influence of the following treatments and levels of ATIS strategies are considered:

1. Nature of information: prescriptive and descriptive
2. Information type: (trip time information based on) reliable prediction, prevailing traffic condition, differential information (both prevailing and predicted), perturbed predicted, and random information
3. Feedback: own trip experience, feedback on recommended path, and feedback on actual best path

The experimental design and procedures were described in considerable detail in Sections 3.4 and 3.6. This chapter emphasizes model formulation and results. Section 6.2 describes the profile of respondents and discusses the findings from the exploratory data analysis. The next section presents the behavioral and modeling frameworks and the results from dynamic compliance behavior models calibrated using data from experiment 2 (see Section 3.6). Finally, concluding comments are presented in Section 6.4.

6.2 EXPLORATORY ANALYSIS (EXPERIMENT 2)

Data regarding respondents' socio-demographic and commute characteristics as well as attitudes towards information and switching are obtained in this experiment. In addition, the subjects are asked to rate the accuracy of ATIS information at the end of each strategy (four days of simulated commute). The profile of the respondents in terms of their socio-demographic characteristics, commute characteristics, information use propensity, and factors influencing switching decisions is displayed in Tables 6.1 - 6.3, and summarized below.

6.2.1 Socio-Demographic Characteristics

The sample consists of about 63% females and 37% males (Table 6.1). Females are over-represented in the sample relative to the population. The age distribution reveals that about 30% respondents are younger than 40 years, 62% between 40-60, and 8% over the age of 60%. This sample appears to be close in age distribution to the commuter surveys in Austin and Dallas (Mahmassani et al., 1993). The occupation statistics indicate that 17% are technical specialists, 25% are clerical staff, 23% hold administrative/ research jobs, and 30% are employed in other capacities. Faculty members and students at the University of Texas were excluded from the sample, as their commute patterns may not be typically representative of the population.

6.2.2 Commute Characteristics

More than 87% of the respondents commute to work by the auto mode. The average actual commute time of the respondents in the sample was 27.54 minutes and the standard deviation was 15.34 minutes. The mean work start time of the respondents in the sample was 8:01 a.m, close to the work start time of 8:00 a.m. in the experimental scenarios. The average actual preferred arrival time in the sample is 7:59 a.m. The considerable variability in preferred arrival times across respondents is evident from the

relatively large standard deviation of 52 minutes. It may be recalled that the average work start time for the respondents in the first experiment was about 8:01, but the corresponding standard deviation was smaller at 32 minutes. The average commuting time (31 minutes) and preferred arrival times (7:56 a.m.) are also comparable between the two samples.

The participants were also asked to supply a preferred arrival time for the simulated experiments. The average preferred arrival time in the experiments was 7:49 a.m. The difference, though marginal, most likely reflects a margin of safety for unfamiliarity with the simulated network conditions. The sample also exhibits significant variation in lateness tolerance across individuals. Forty-seven percent of the respondents report a permissible lateness tolerance of 15 minutes or less. On the other extreme 27% report flexible working arrangements.

TABLE 6.1

SOCIO-DEMOGRAPHIC PROFILE OF RESPONDENTS IN EXPERIMENT 2

Socio-Demographic Attributes					
Gender Percentage (%)	Male 37.00	Female 63.00			
Age	20-29 12	30-39 18	40-49 37	50-59 25	60+ 8
Occupation Percentage (%)	Technical 17.00	Clerical 25.00	Admin 23.00	Other 35.00	
Commute days per week	Mean 4.99	Std. Devn. 0.59			
Number of days of driving to work/week	Mean 4.36	Std. Devn. 0.62			
Commute time minutes (one-way)	Mean 27.54	Std. Devn. 15.34			
Work Start Time (a.m.)	Mean 8:01	Std. Devn. 49.98			
Preferred arrival time at workplace (a.m.)	Mean 7.59	Std. Devn. 52.53			
Lateness tolerance at work (minutes) Percentage (%)	<5 11:00	5-15 36.00	5-30 19.00	30-60 5.00	>60 30.00

6.2.3 ATIS Information-Related Attributes

Approximately 87% of the respondents indicated a strong willingness to acquire both pre-trip and en-route information from ATIS (Table 6.2). Respondents were also asked to rate the accuracy of information on a five point Likert scale. While 17% of the respondents rated the information as very accurate, a majority (64%) found it to be somewhat accurate, and only about one percent rated the information to be very inaccurate. Compared to the previous set of experiments, a marginal increase in the accuracy rating of the ATIS by the respondents was noted. This difference may be attributable to the possible confounding between information quality of ATIS and day-to-day traffic variation referenced in the previous chapter. In addition to travel time and congestion-related information in the experiments, users also desired the following additional information from the ATIS. Nearly three out of four respondents

(76%) preferred information about incidents, accidents etc., whereas half the participants (50%) sought route guidance information. Forty two percent of the respondents desired parking information. The prioritization of additional ATIS information in this experiment is consistent with that observed with a different set of participants in the previous experiment. On the possible use of ATIS, 38% of the respondents were very likely to switch routes following ATIS information, and 27% were strongly inclined to switch departure times. These responses indicate a definite willingness on the part of many respondents to acquire and use ATIS information for assisting them with route and departure time decisions.

6.2.4 Factors Influencing Switching Propensity

Attitudinal questions (Table 6.3) indicate that (as in the previous experiment), trip time saving of more than fifteen minutes appears to be a very significant influence on route switching for the majority of respondents (78%). While 44% consider a five to 15 minute savings worthwhile (very important) in influencing switching, this proportion drops to a meager 15% for a trip time saving of less than five minutes. Incidents (69% of the participants rate this piece of information as a very important factor influencing switching), congestion on current route (58%), and late arrival by following current path (52%) are the other most important factors cited as influencing route switching decisions. Departure time switching appears to be influenced by lateness avoidance (60% rating as very important), trip time savings (59%), and congestion (55%). Interestingly, nearly 40% of the respondents indicated that departure time switching decisions are motivated by the need to perform other activities during the commute.

TABLE 6.2

USERS' RATINGS OF ATIS INFORMATION ACCURACY AND STATED USAGE INTENTIONS

Rating of ATIS in experiment Percentage (%)	Very Acc. 17.00	Accurate 64.00	Somewhat Acc. 18.00	Inaccurate 0.00	Very Inaccurate 1
Willingness to Use ATIS (pre-trip) Percentage (%)	Definitely 38.00	Probably 50.00	Not decided 7.00	Probably not 4.00	Definitely not 1.00
Willingness to Use ATIS (en-route) Percentage (%)	Definitely 43.00	Probably 44.00	Not decided 6.00	Probably not 6.00	Definitely not 1.00
Additional Information Desired Percentage (%)	Incidents 76.00	Route guidance 50.00	Parking 41.00	None 4.00	Other 11.00
Switching Intention based on ATIS info Route Switching (%)	Definitely 39	Probably 48.00	Not decided 8.00	Probably not 5.00	Definitely not 0
Departure Switching Percentage (%)	Definitely 27.00	Probably 50.00	Not decided 9.00	Probably not 14.00	Definitely not 0

TABLE 6.3

USER'S RESPONSES TO ATTITUDINAL QUESTIONS ON IMPORTANCE OF FACTORS INFLUENCING SWITCHING DECISIONS

Importance Rating	Percentage of Respondents Rating Factor as			
Attribute Description	Very Important	Somewhat Important	Not very Important	Not at all Important
Route Switching Factors				
Trip time savings (less than 5 min)	14.6	33.1	36.9	15.4
Trip time savings (5-15 min)	43.8	42.2	8.6	5.5
Trip time savings (15-30 min)	78.0	14.2	3.1	4.7
Trip time savings (more than 30 min)	84.8	8.0	0.8	6.4
Congestion on original route	58.5	36.9	0.8	3.8
Incidents on original route	69.2	22.3	2.3	6.2
Arrival time constraints	50.4	36.4	9.3	3.9
Familiarity with alternative routes	33.8	50.8	8.5	6.9
Late arrival upon following orig. route	51.5	37.7	5.4	5.4
Avoiding early arrival	1.5	18.5	40.0	40.0
Departure Time Switching Factors				
Trip time savings (less than 5 min)	7.2	27.2	44.0	21.6
Trip time savings (5-15 min)	35.9	37.4	21.4	5.3
Trip time savings (15-30 min)	59.4	29.7	7.8	3.1
Congestion avoidance	55.0	34.4	5.3	5.3
Lateness avoidance	60.6	31.8	2.3	5.3
Earliness avoidance	3.8	27.7	35.4	33.1
Perform activities en-route	40.5	26.7	16.8	16.0

6.2.5 Compliance Behavior

At an exploratory level, the aggregate compliance behavior is examined as depicted in Figure 6.1. The compliance rate for each user is determined as the ratio of the number of instances of compliance to the total number of route choice decisions; compliance opportunities available made by the user. The cumulative proportion of users corresponding to a given compliance rate is calculated by determining the proportion of total users with a compliance rate smaller than the given rate. The plot illustrates that a relatively large proportion of users display high compliance; nearly 80% of respondents display between 60 to 100% compliance rates and less than five percent of users exhibit compliance rates lower than 20%. The plot also shows that en-route compliance is closer to the overall compliance rate distribution across respondents. There appears to be a slight decrease in pre-trip compliance rates relative to the overall compliance rate. In pre-trip route choices, only about 65% of respondents exhibit a compliance rate of 60% or more.

The effect of information strategies on compliance behavior is analyzed at an exploratory level by plotting the average compliance rate (across all users) for various levels of the information strategies. When the ATIS provides users with prescriptive information a higher compliance rate of nearly 80% is observed, as compared to nearly 69% compliance with descriptive information (Figure 6.2). A range of

compliance rates is observed when the information type is varied (Figure 6.3). For this factor, the highest compliance corresponds to the supply of predicted or prevailing information with nearly 80% compliance rate, followed by about 70% compliance with predicted perturbed information. The compliance rate is reduced to about 60% when the ATIS supplies partial / differential information. The lowest compliance propensity of nearly 50% is observed when the ATIS provides random information to users. Feedback on the recommended path or on the best path considerably improves compliance with information (by as much as 10-12 %) as compared to the baseline level of feedback only on used path (Figure 6.4).

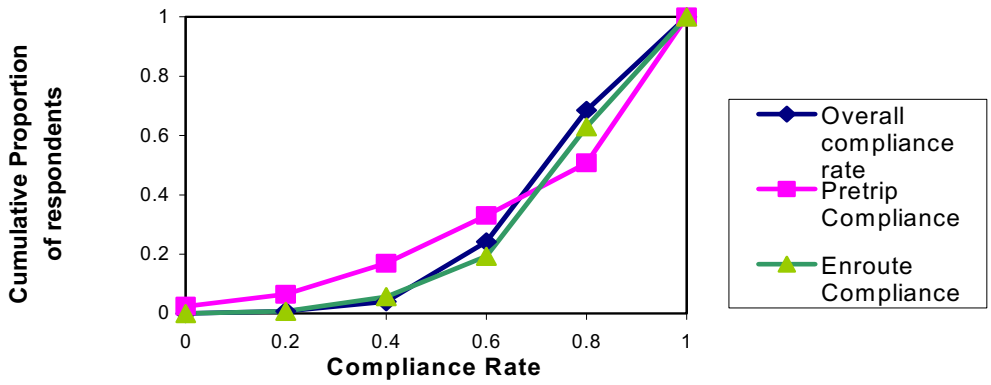

FIGURE 6.1
Cumulative distribution of compliance rates

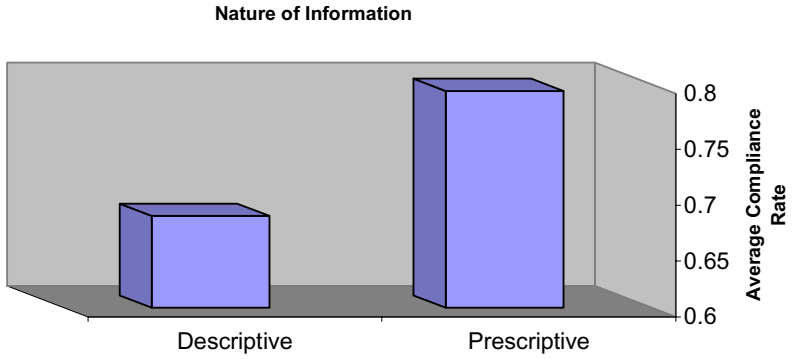

FIGURE 6.2
Effect of nature of information on mean compliance rate

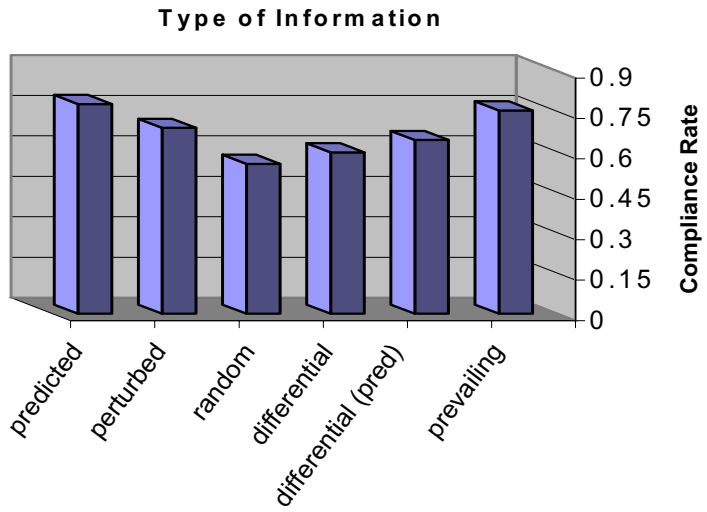

FIGURE 6.3
Effect of information type on mean compliance rate

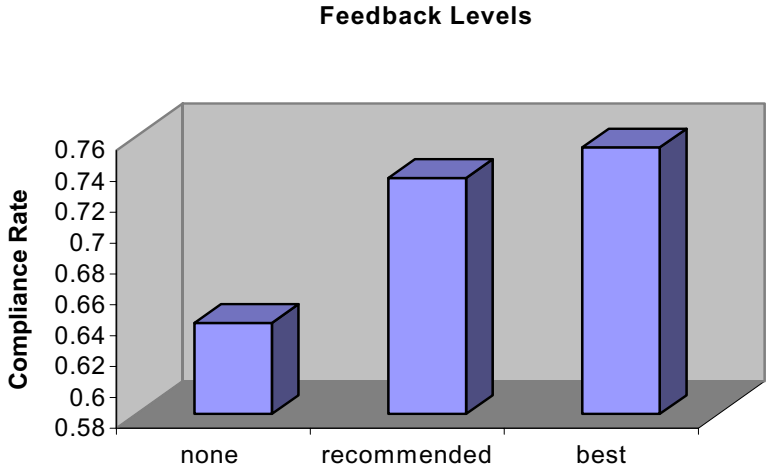

FIGURE 6.4
Effect of feedback on mean compliance rate

6.3 USER COMPLIANCE MODEL: BEHAVIORAL FRAMEWORK, MODELING METHODOLOGY, AND RESULTS

This section presents the analysis of compliance at a disaggregate level by modeling the compliance decisions of individual users at each decision node. The purpose of this analysis is to obtain empirical insight into how users combine information from ATIS with past experience in the system and the resulting influence on compliance behavior. It may be recalled that each commuter faces the discrete

choice of whether or not to comply with the advice or the implicit best path (least trip time path) provided by the ATIS at each decision node. As noted earlier, compliance is defined *vis-a-vis* a directly prescribed path for prescriptive information and on an inferred best path (minimum trip time) for the descriptive information.

Notation

Let i be the subscript to denote the individual trip-maker, i = 1,.... I

Let j represent the decision node, j = 1,.... J

Let t be the time index, t = 1, ... ,T.

Let $\delta^{c}ijt$ *represent the compliance decision made by individual i at decision node j at time t*

$\delta^{c}ijt$ *= 1, if individual i complies at decision node j at time t,*

= 0, otherwise.

Let U_{ijt} represent the corresponding utility of compliance for individual i at decision node j at time t

$g^{c}(Z_i, X_{ijt}, \Theta_{ijt})$ *is the deterministic component of* U_{ijt}

Z_i *represent the socio-demographic attributes of user i*

X_{ijt} *represent the traffic and other relevant variables of influence for user i on decision node j at time t.*

Θ_{ijt} *is the set of parameters for the deterministic component of the utility.*

ε_{ijt} *represents the normal error term component of the utility* U_{ijt}

τ_{ijt} *represents the logistic error term component of the utility* U_{ijt}

ε *is the vector of* ε_{ijt} *for all j, t*

τ *is the vector of* τ_{ijt} *for all j, t*

V^{c}_{ijt} *represents the deterministic term of the conditional utility for individual i at decision node j at time t given the vector of multivariate normal error terms*

6.3.1 Behavioral Framework

It is assumed that the compliance behavior is consistent with the standard random utility maximization (RUM) paradigm. Furthermore, it is assumed that the utility of not complying at each decision situation is zero for all users, with no loss of generality. Then the decision rule for compliance may be stated as:

δ^{c}_{ijt} = 1 if $U_{ijt} > 0$,

= 0 otherwise.

Succinctly, this is equivalent to $(2\square^{c}_{ijt} - 1)\, U_{ijt} \geq 0$.

Alternatively, the behavioral process could be viewed as the outcome of a latent propensity variable crossing a threshold.

6.3.2 Modeling Framework

If the repeated decisions of each individual over all decision nodes were indeed independent of each other, a simple binary logit model would suffice. In general, though, the persistence of unobservables of a given individual across different decision instances may introduce serial correlation.

When ignored, serial correlation may result in seriously inaccurate and biased coefficient estimates and erroneous inferences. To account for this, a general error structure is proposed to analyze the data. The choice process is modeled as a latent variable crossing a threshold as discussed in the behavioral framework. The utility of compliance is treated as a random variable with a mean that is a function of user characteristics, traffic experiences, and ATIS information attributes.

Under the random utility assumptions above the utility of compliance associated with the decision made by user i at decision location j at time t can be written as:

$U_{ijt} = g^c(Z_i, X_{ijt}, \Theta_{ijt}) + \varepsilon^c_{ijt} + \tau^c_{ijt}$

Let $\varepsilon = (\varepsilon^c_{i11}, \varepsilon^c_{i21}, \ldots\ldots\ldots, \varepsilon^c_{ijt}, \ldots\ldots\ldots\ldots, \varepsilon^c_{iJT})$

Let $\tau = (\tau^c_{i11}, \ldots\ldots\ldots \tau^c_{ijt}, \ldots\ldots\ldots\ldots \tau^c_{iJT})$

Assuming, $\varepsilon' \sim MVN(0, \Sigma_\varepsilon)$, and $\tau' \sim$ i.i.d logistic, $(0, \sigma_g^2 I)$,

where $\sigma_g^2 = \pi^2/(3\mu^2)$, I is JT dimensional unit matrix and μ is the standard logit scale parameter. Further it is assumed that the logistic error vector τ'' is independent of the multivariate normal error vector ε'.

Under these assumptions the likelihood formulation broadly parallels the DKL formulation in Section 4.2. Therefore, in presenting the model formulation, only the salient differences between this model and the formulation in Section 4.2 are highlighted. Analogous to the generic DKL formulation presented in Section 4.2, the utility of compliance at each decision instance (decision location j, and day t) is assumed to consist of two error terms. The first error component is assumed to be multivariate normally distributed across decision locations and over time (as in Section 4.2). However, the second error component is assumed to be identically and independently logistically distributed across decision instances and over time (from day-to-day) in this formulation, in contrast to the i.i.d Gumbel errors assumed in Section 4.2. Note that one may view the utility of non-compliance to be zero, with no loss of generality. Then the difference between the utility of the alternatives (compliance and non-compliance) conditional on the normal errors is logistically distributed, as with the previous formulation in Section 4.2. Another minor notational difference is that a decision instance is characterized here by two subscripts, one corresponding to the decision location j, and the second corresponding to the commute day t, whereas, each decision instance in the formulation in Section 4.2 is only represented by the time index t. Accounting for these differences, and following the presentation in Section 4.2, the corresponding log-likelihood can be expressed as:

$LL = \log(L)$

$= \Sigma_i \log \Pr\{\delta^c_{ijt}, j = 1,.. J, t = 1,\ldots T \}$

$= \Sigma_i \log [\int_\varepsilon (\Pi_{t=1}^{T} \Pi_{j=1}^{J} \{1 / [1 + \exp(\mu(1-2\delta^c_{ijt})V^c_{ijt})]\}) f(\varepsilon)d\varepsilon]$ (6.1)

The likelihood function in (6.1) is calibrated using the maximum likelihood estimation technique, discussed in Section 4.3.1, in view of its desirable asymptotic properties. The objective of model calibration is to obtain the vector of parameters (B) corresponding to the deterministic utility V^c_{ijt}, and the vector of parameters (Θ) corresponding to the variance covariance of the multivariate normal error terms (ε). These

vectors of parameters are determined by a non-linear search procedure with an objective of maximizing the log-likelihood function in (6.1). The calibration procedure broadly follows the generic procedure outlined in Chapter 4. In calibrating the compliance model, the deterministic utility is chosen to be a linear function of parameters. The error terms are assumed to have identical variances across decision locations and over days. Further, it is assumed that the contemporaneous correlation between compliance decisions made on a given day is ρ_1. The compliance decisions at a given location on different days is assumed to be first-order auto-correlated with a correlation coefficient ρ_2. Correlation between compliance decisions at different locations and made on different days is assumed to be zero.

The compliance model calibration results are presented in the following sub-section. A linear-in-parameter specification of the utility V^c_{ijt} is assumed, and the explanatory variables included in the model specification are displayed in Table 6.4 and the results discussed in the following section.

6.3.3 Modeling Results

The influence of the following factors on the compliance behavior are examined - information quality, experience in traffic, inertia, and ATIS information strategies. First, the nature and extent of influence of information quality on compliance decisions are examined. Accuracy and reliability have often been used to represent the effect of information quality. Unfortunately, both measures continue to be used interchangeably and without systematic definitions by several researchers leading to inconsistent terminology. In the interest of clarity, two separate measures are defined below to distinguish the two, while recognizing the inter-relationship between them.

TABLE 6.4

CALIBRATION RESULTS OF COMPLIANCE BEHAVIOR UNDER VARIOUS INFORMATION STRATEGIES

Variable Definitions	Coefficient	t-stat
Constant	2.31	5.40
Feedback Effect		
On own experience	-0.62	-5.91
On recommended Path	*-0.14*	*-1.44*
Nature of Information		
Prescriptive Information	0.27	3.95
Type of Information		
Prevailing	*-0.05*	*-1.11*
Predicted Perturbed	*-0.16*	*-1.18*
Differential Predicted	-0.33	-2.52
Differential Prevailing	-0.30	-2.27
Random	-0.47	-4.18
Information Quality		
Over Estimation Errors	-0.31	-2.96
Under Estimation Errors	*-0.05*	*-1.56*
Reliability (30% threshold)	0.10	3.72
Information - Inertia Interaction		
Inertia supported by information (dummy =1, if current path = recommended path)	0.59	4.78
Compliance Benefits (Relative trip time savings)	1.96	5.26
Switching Cost (Additional distance to be traveled to comply)	-1.68	-4.39
Experience Variables		
Pre-trip Effects		
Number of Switches to later dep. Times	0.03	2.37
Standard deviation of trip times till previous day	-0.04	-3.24
Early Schedule Delay (previous day)	0.04	2.63
Late Schedule Delay (previous day)	*0.01*	*0.67*
Stuck (previous day)	-0.61	-3.17
En-Route Effects		
Stuck (en-route)	-0.84	-5.28
Early schedule delay on 'presc' path	-0.02	-5.61
Late schedule delay on 'presc' path	-0.001	-1.44

Note: Italicized Coefficients indicate variables not significant at 10% level.

Log-Likelihood	-2612.52
Log-Likelihood(0)	-3754.82

Accuracy is measured by the discrepancy between information reported by the ATIS and users' experience in the traffic system (for instance, the difference between reported and experience travel times). Thus the greater the discrepancy, the lower is the accuracy of information. Of particular interest is the effect of overestimation – when the reported travel time exceeds the experienced trip time, and underestimation – when the reported information underestimates the actual trip time. Two measures of accuracy are considered. Relative error is the ratio of deviation of reported-to-actual trip time with respect to actual trip time, as defined in the previous section. Absolute error is the difference between reported and actual trip times. It is found that while, both significantly influenced compliance, the relative error specification added much more explanatory power to the model in terms of log-likelihood than the absolute error specification. Overestimation errors are found to significantly reduce the likelihood of compliance. Even though underestimation errors may be expected to have a greater negative effect on compliance due to the possibility of late arrival, the estimated coefficient for this variable was negative but not significantly different from zero. One possible explanation is that this effect might have been captured better in this specification by an experience variable – indicating whether the user was stuck in traffic in the segment preceding the decision node. The influence of information inaccuracy further confirms the results from frequency count models of compliance based on the same data (Chen, 1998) and corroborate earlier results on the effect of these errors on route switching behavior observed in a different set of experiments (Mahmassani and Liu, 1997).

A related measure of information quality is reliability. Following standard convention in probability, reliability is defined here as the probability that the accuracy exceeds a threshold.
Reliability measures are calculated at each decision node for each user as the fraction of prior experiences with absolute value of relative error falling below a threshold. For instance, the reliability at a 10% threshold for relative error is calculated as number of previous experiences for the user where the absolute value of relative error was below 10%, divided by the total number of previous experiences. Using this definition, reliability variables associated with relative error thresholds of 10, 20, 30, 40, and 50% are computed. With increasing reliability of information, a higher compliance propensity is observed. Furthermore, it was found that the specification with threshold of 30% resulted in a better model fit than other thresholds. Thus compliance depends not only on how accurate the ATIS information is but also on how frequently it is accurate. These results further substantiate the effect of reliability on compliance behavior reported by Bonsall et al. (1991) and Vaughn et al. (1995), though in these cases the reliability levels were preset. In contrast in the experiments analyzed here, the reliability of information is a consequence of both the information strategy (e.g. prevailing, predicted, random) as well as the choices made by all trip-makers on the network.

Next, the role of experience in compliance behavior is examined. First, the influence of recency and frequency of experiences is considered. There is substantial evidence from the cognitive behavior literature indicating that recent events are subject to quicker and more accurate recall than events in the distant past. In order to test the effect of recent events on compliance behavior, a binary indicator variable

- '*stuck'* (defined in Section 5.4), representing whether a user was stuck in traffic on the segment immediately preceding the decision node for en-route decisions. For pre-trip decisions, this variable indicates if a user was stuck in traffic on the previous (simulated) day. Providing strong evidence of impact of recent adverse experience in traffic, this variable is very significant and negative, indicating a lower compliance.

The effect of cumulative experiences is tested by including the cumulative number of departure time switches on the preceding days as an explanatory variable. It is presumed here that departure time switches occur when aspiration levels regarding arrival time have not been met during previous commutes. It is found that this variable is very significant and positive. Greater number of switches to later departure times (presumably occurring due to unacceptable early arrivals) is consistent with a higher compliance. A similar behavioral phenomenon was also observed in switching behavior by Liu and Mahmassani (1998).

The second aspect of the effect of experience relates to the decision node under consideration. Of particular interest are possible differences in the influence of experience between pre-trip decisions and en-route decisions. Differences in the role of experience variables between pre-trip and en-route may be expected due to differences in the amount of time available for decision-making, recall time-lags (one day for pre-trip compared to minutes for en-route), and validation of ATIS information with current experience. The effect of being stuck has almost the same effect on users' pre-trip and compliance decisions. Thus there appears to be no significant difference in the effect of being stuck between pre-trip and en-route compliance decisions. However, other experience variables only influence the pre-trip decision and not en-route compliance. For instance, an early arrival with respect to the preferred arrival time results in higher compliance pre-trip, with virtually no effect on en-route compliance. Similarly, with increasing variability encountered by a user (represented by the standard deviation of the trip times experienced up to the previous day), a lower pre-trip compliance is observed, but no effects are observed in en-route compliance behavior. In this context, Abdel-Aty et al. (1995), based on commuter survey data from Southern California, observed that increased trip time variability associated with a path adversely affects the corresponding choice probability. Differences in the role of experience variables, between pre-trip and en-route compliance behavior, is apparent.

The role of information, behavior and supply interaction are investigated next in light of the relationship between compliance and switching behavior. Two variables are tested in the model specification. Findings are that the cost of switching, reflected by the distance required to switch between current path and the prescribed path, significantly reduced compliance. Thus, users are more likely to comply when the current path is also the prescribed / 'best' path, suggesting an interaction between information and behavioral inertia to switching. On the flip side, the benefit of complying is also a significant determinant of compliance, especially, when it involves switching. To reflect potential benefits from complying, the relative trip time saving (the relative trip time saving by complying with the best path reported by the ATIS as compared to continuing on the current path) is included as an explanatory

variable. Increasing benefits of compliance lead to greater compliance with information. Thus, compliance behavior appears to be based on a trade-off between costs incurred (physical and cognitive) in switching to the best path and the anticipated benefits.

To model the role of ATIS experimental factors, binary indicator variables corresponding to the various treatment levels of information strategy are introduced in the model specification. The baseline case consists of the ATIS supplying descriptive predicted information with feedback provided on the best path in addition to user's chosen path at the end of each commuting trip. Several interesting results on the effect of ATIS information strategies are observed. First, prescriptive information is found to induce greater compliance than descriptive information. Second, there appears to be a hierarchy of compliance rates corresponding to the various types of information. The greatest compliance rate is associated with reliable predicted information, whereas the least compliance propensity occurs when random information is supplied to users. Between these two extremes, the compliance rate increases from partial information (no information on one facility) to complete, but somewhat imperfect, information (predicted perturbed, and prevailing information). Feedback on the recommended path or best path (ex-post facto) appears to enhance the credibility of the information system by allowing the user to compare personal experience with reported information/ optimal path choice, in contrast to supplying feedback only on the user's chosen path.

As with the route switching models, the variance of pre-trip residuals (of the compliance utility) are found to be larger than en-route variances (Table 6.5). The pre-trip variance is estimated to be around 2.01, whereas the corresponding variance for en-route compliance decisions was 1.33. The contemporaneous and day-to-day correlations are also significant. The contemporaneous correlation between pre-trip and en-route compliance decisions made on the same day is 0.012 but significant, while the correlation between en-route compliance decisions on a given day is about four times smaller (0.003). The within-day correlations are relatively small in magnitude, yet significant. In contrast, the day-to-day correlation between pre-trip compliance decisions is higher and negative (-0.314), whereas the correlation between en-route compliance decisions on successive days is also negative but much smaller (-0.048). The larger correlation observed between pre-trip decisions on successive days might indicate periodic review of information quality at the end of each day's commute. One plausible explanation for the significance of serial correlation term is due to dynamic experience effects unaccounted for in the systematic utility and the persistence of unobservables from repeated measurements. A possible reason for the significance of contemporaneous correlation is the unobserved influence of departure time choice on the compliance decisions on a given day.

TABLE 6.5

ESTIMATED VARIANCE-COVARIANCE PARAMETERS FOR THE COMPLIANCE MODEL

Parameter	Coefficient	t-statistics
Variance (pre-trip)	4.028	5.58
Variance (en-route)	1.782	6.61
Correlation within-day (pre-trip, en-route)	0.012	4.49
Correlation within-day (en-route, en-route)	0.003	3.88
Correlation day-to-day (pre-trip, pre-trip)	-0.314	-4.78
Correlation day-to-day (en-route, en-route)	-0.048	-2.27

6.4 SUMMARY

In this chapter a framework is proposed to model compliance behavior by suitably adapting the general DKL framework presented in Chapter 4. The results from the model enable the identification of the following major factors affecting users' compliance with ATIS information strategies and time-dependent traffic conditions.

The results presented in this chapter indicate that the quality of real-time information strongly influences commuters' compliance decisions. Not surprisingly, commuters show a marked disinclination towards complying with real-time information that is either inaccurate and/or unreliable. Further, a hierarchical range of compliance levels is observed with ATIS information strategies of varying information quality, timeliness and scope. In this hierarchy, commuters tend to comply the most with predicted and prevailing information. A lower compliance is observed with perturbed information and partial information strategies. The lowest compliance propensity is observed when the ATIS supplies random information that is independent of the traffic conditions.

In addition to the type of information, ATIS information strategies strongly influence compliance rates, based on the nature of information provision and feedback supplied to users on their traffic experience and quality of information. A higher compliance rate may be achieved when prescriptive or normative information is provided than if descriptive information is supplied. The type of post-trip feedback also influences compliance behavior. ATIS systems providing feedback on either the recommended path or the actual best path are more likely to result in a higher rate of user compliance than systems that supply feedback solely on the user's chosen path. Trip-makers receiving feedback with the actual best path tend to comply more than those receiving feedback with the path recommended by the system.

The compliance behavior appears to be a consequence of a trade-off between the cost and benefits of complying with ATIS information. Commuters tend to comply more with real-time information when no switching is required, i.e., when the current path is indeed the path suggested/recommended by

the system. A substantially lower level of compliance is likely to be achieved in situations where compliance involves switching from the current path. This aversion to switching, when instrumented as a "cost" of switching, is found to be a particularly influential factor. Greater benefits (in the form of trip-time savings) encourage increased compliance behavior.

Compliance is also affected by the traffic conditions experienced by users. A lower rate of compliance is likely to be achieved if commuters recently experienced significant congestion, such as getting stuck in traffic (especially in the preceding highway segment). Following early schedule delays, or when experiencing high variability in trip times, commuters tend to comply more with the pre-trip information. These experiences have little or no influence on commuters' en-route compliance decisions. Commuters' short-term and long-term experiences are also significant determinants of compliance behavior. Commuters are more inclined to comply with information following more frequent departure time switches to later departure times.

Given the relatively moderate sample size and the nature of the experiments and associated conditions, caution must be exercised in interpreting and generalizing the results presented here. Comparison of user behavior under varying network conditions and various types of ATIS information strategies indicates considerable similarity in compliance behavior and relatively stable factors influencing it. The results provide preliminary insight into the role of ATIS information quality and strategies on dynamic compliance behavior of drivers. The analyses presented in this and the previous chapter focus on modeling three important user choice dimensions: route switching, departure time switching, and compliance. In these analyses, the dynamics in user behavior are captured mainly by time-dependent explanatory variables and through the correlation of unobservables over time. Due to the focus on substantive questions related to ATIS and network conditions, these analyses have assumed the absence of other structural dynamic effects in choice behavior, and independence between the choice dimensions. The next chapter relaxes these assumptions, to investigate more general structural effects in the interdependent dimensions of route and departure time switching. The inter-relationship between-route switching and compliance is examined in Chapter 9.

CHAPTER 7: MODELING HETEROGENEITY AND STRUCTURAL EFFECTS IN COMMUTER BEHAVIOR DYNAMICS UNDER ATIS

7.1 INTRODUCTION

The two preceding chapters present the modeling framework and analyses of commuter responses to variations in network conditions and ATIS information strategies respectively. The first analysis was centered on the substantive issues of how network loads and its evolution over time influenced route and departure switching behavior. The second analysis focused on compliance behavior of commuters in response to differences in ATIS information format, quality, type, and feedback. In the previous two chapters, it was assumed implicitly that the dynamics of commuter behavior is almost entirely accounted for by the specification of the systematic component of the utility. In other words, the observed dynamics in user behavior can be represented entirely by the experienced supply condition dynamics (as determined in the traffic simulator). Dynamical trends in user behavior were incorporated to a limited extent by the serial correlation of error terms across repeated decisions made by a given individual. The previous models also assume response homogeneity across individuals. These assumptions are neither insignificant, nor inconsequential, and have substantial implications that are discussed subsequently. In spite of the lack of adequate theoretical or empirical support, these assumptions continue to be extensively used in empirical travel behavior literature, both in cross-sectional and longitudinal analyses, driven mainly by the ease of calibration, and data limitations (Bonsall et al., 1991; Koutsopoulos et al., 1994; Abdel-Aty et al., 1995). It is possible to relax these assumptions, aided mainly by the flexibility of the proposed analytical framework, and the measurement of dynamic user behavior at an adequate temporal resolution in this study, and to explicitly investigate the presence of heterogeneity and other structural effects in this behavior. Relaxing these assumptions not only enables the specification of behaviorally richer and more accurate models, but is also important for ATIS design and evaluation as discussed in Chapter 1.

The first objective in this chapter is to formulate a modeling framework that can incorporate the effects of repeated measurements, heterogeneity, within-day and day-to-day correlations, and state-dependence effects. The dynamic kernel logit model proposed in Chapter 4 is modified to explicitly accommodate these effects.

In the analysis of network supply conditions on user behavior, the decisions of route and departure time switching were modeled separately. This modeling approach implicitly assumes that the two decisions are independent of each other. Previous models, in fact, provide evidence to the contrary (for example, see Liu and Mahmassani, 1998). Therefore, the second goal in this chapter is to model the two dimensions of route and departure time switching as inter-dependent decisions. The effect of trip-maker characteristics, trip characteristics and traffic conditions, experiences in traffic, and attributes of ATIS information on these choice dimensions are examined.

The data from the second set of experiments (described in Section 3.6) are used to calibrate the models in this chapter. This data set is used in the analysis here mainly because of its larger sample size. Further, it enables studying the influence of ATIS information strategies on route and departure time switching behavior, with significant implications for the design and deployment of ATIS products and services. Furthermore, calibrating the route and departure switching models on a different data set (from the data set in Chapter 5) will enable the validation and assessment of robustness of model results. The previously proposed route and departure time switching models were based on boundedly rational behavior rules. In contrast, the joint route and departure time switching model proposed in this chapter is based on the utility maximization framework. This framework is chosen because of the large number of parameters in the joint route and departure time switching model. The total number of parameters to be estimated in the joint model based on a boundedly rational framework would exceed 200, therefore making interpretation difficult and forecasting tedious. Furthermore, the development of models based on alternative behavioral frameworks allows for the comparative assessment of the robustness of the findings.

A third, but related, objective is to investigate heterogeneity effects in route switching behavior. In general, differences may be expected in route switching propensities (intrinsic biases or preference heterogeneity) as also the sensitivity to level-of-service measures and other independent variables, across decision-makers. Though it is preferable to account for these effects through systematic specification, it is nearly impossible to ensure this in practice. Therefore, it is desirable to account for the presence of both observed and unobserved heterogeneity effects. Ignoring heterogeneity when present can lead to inconsistent and biased parameter estimates (Chamberlain, 1980). While some travel behavior studies account for observed heterogeneity, albeit only preference heterogeneity (Hatcher and Mahmassani, 1992; Abdel-Aty et al., 1994; Mannering et al., 1994), others ignore heterogeneity both observed and unobserved (Polydoropolou, 1996). A few studies account for heterogeneity entirely through unobserved effects (Ben-Akiva et al. 1993, Revelt and Train 1998) which could lead to an over-reliance of the model on the sample characteristics and a low transferability of parameters across data sets. In this chapter, observed heterogeneity is modeled in the form of both preference and response heterogeneity. Unobserved preference heterogeneity is accommodated in this analysis through individual-specific error terms. Unobserved response heterogeneity is modeled through random effects associated with the utility coefficients. Modeling heterogeneity has important applications in identifying market segments for information and evaluation of alternative policy measures.

Finally, time-dependent effects in route and departure time switching behavior are examined. In addition to the time-dependent variables examined in Chapters 5 and 6, it is also necessary to investigate more general dynamic effects at both the observed and unobserved levels. At the unobserved level, time dependent effects are analyzed in this chapter by specifying suitable variance components. The variance covariance structures are tested for the presence of temporal correlation (both within-day, day-to-day), in addition to serial correlation (due to repeated measurements). The variance covariance structure tested in

this chapter is more general than those tested in Chapters 5 and 6, and at the same time is also more parsimonious. At the observed level, the effect of past choices on current decisions is incorporated through state-dependence coefficients in the utility specification. In addition, at the systematic level, the influence of past experiences on current behavior is also assessed.

The next section provides an overview of the framework for a joint route and departure time switching model. Model specification aspects including heterogeneity, state-dependence, covariance structure, and habit persistence are elaborated in Section 3. In Section 4, the modeling results are presented. The last section discusses the implications of the results followed by some concluding comments.

7.2 JOINT ROUTE AND DEPARTURE TIME SWITCHING MODEL

This section presents the framework for jointly modeling route switching and departure time switching dimensions in commuter behavior. Route switching, it may be recalled, is defined with respect to the current path. The current path is defined in a straightforward manner for en-route decisions, and as the actual pre-trip path chosen on the previous day for pre-trip route switching. Departure time switching is defined relative to the departure time chosen on the preceding day.

<u>Notation</u>

Let i denote the individual trip-maker, i = 1,.... I;

j - the decision location or node, j = 1,.... J;

j=1 denotes departure time switching decision location;

j=2 represents a pre-trip route switching decision location;

j>2 refers to en-route switching decision location;

t - the day index, t = 1, ... ,T;

$\delta^r ijt$ *- switching decision indicator for individual i at decision node j on day t;*

$\delta^r ijt$ *= 1, if user i switches route if decision node j corresponds to route switching at time t;*

$\delta^r ijt$ *= 1, if user i switches departure time if decision node j corresponds to departure time switching at time t; = 0, otherwise.*

U_{ijt} *- utility of switching for individual i at decision node j on day t;*

$g^r(Z_i, X_{ijt}, \Theta_{ijt})$ *- deterministic component of* U_{ijt}*;*

X_i *- the socio-demographic attributes of user i;*

Z_{ijt} *- traffic and other relevant variables for user i on decision node j on day t;*

Θ_{ijt} *- vector of parameters for the deterministic component of the utility;*

ε_{ijt}*,- multivariate normal error term component of utility* U_{ijt}*;*

ε_t *- vector of* ε_{ijt}*, over all j = 1,.. J, and t = 1,.. T for individual i;*

τ_{ijt} *- multivariate normal error term component of utility* U_{ijt}*;*

τ_t *- vector of* τ_{ijt} *over all j = 1,.. J, and t = 1,.. T for individual i;*

V^c_{ijt} *- conditional deterministic utility of switching given* ε_t*.*

This notation is slightly different from Chapter 4. Here J refers to the total number of decision nodes, whereas, previously J referred to the number of alternatives at each time.

7.2.1 Behavioral Framework

The framework adopted here assumes that a trip-maker will switch (route /departure time) if the corresponding utility exceeds a threshold. This threshold for switching is taken as zero with no loss of generality. The decision rule for switching may then be stated as: $(2\delta^r_{ijt} - 1)\ U_{ijt} \geq 0$. This applies to both route and departure time switching, since both are binary indicator variables (taking values zero or one), albeit with different systematic utilities and random utilities. To model the two decisions jointly, an auxiliary decision node is introduced to represent departure time switching, followed by five route switching decision nodes (j = 2,…6), and the utilities are specified to reflect this modification. The interdependence between-route and departure time switching decisions are accounted for in both the systematic and random utilities as follows. The random utilities of the two switching dimensions are assumed to be correlated. The systematic interdependence is captured through common variables (such as schedule delay, being stuck in traffic etc.) that influence the utility of both decisions.

7.2.2 Dynamic Kernel Logit (DKL) Formulation

In view of the detailed presentation of the DKL formulation in Chapter 4, Section 4.2, this section only presents an outline of the DKL formulation to model joint route and departure time switching decisions. According to the behavioral framework, a user will switch (routes/departure times) if the corresponding latent utility crosses a threshold. Following standard Random Utility Maximization (RUM) convention, the latent utility of switching is treated as a random variable whose expected value varies systematically as a function of user characteristics, experiences, information attributes and traffic conditions. As is typical with switching models, the corresponding switching thresholds are taken as zero, with no loss of generality. Following the presentation in Section 4.2, it is assumed that the error structure for the random component of the switching utility (both route and departure time) consists of two error terms. The first, is multivariate normally distributed with general covariance across decision instances. The second error term is independently and identically distributed according to the logistic distribution. Furthermore, the logistic error terms are assumed to be independent of the normal error terms. Note that the variance-covariance structure of the normal errors can capture correlations between route and departure time switching. Under these assumptions, conditional on the normal errors, the difference between the switching utility and the threshold is logistically distributed resulting in a closed dynamic kernel logit form for the conditional likelihood. The utility specification and log-likelihood derivation exactly parallel the DKL model proposed in Chapter 6. Consequently, the log-likelihood for a sample of I independent observations can be expressed as:

$$LL = \Sigma_i \log P_i$$

$$= \Sigma_i \log \left[\int_{\boldsymbol{\varepsilon}} \left(\Pi_{t=1}^{T} \Pi_{j=1}^{J} \{1 / [1 + \exp(\mu(1-2\delta^r_{ijt})V^r_{ijt})]\}\right) f(\boldsymbol{\varepsilon})d\boldsymbol{\varepsilon}\right] \qquad (7.1)$$

Unlike the formulation presented in Chapter 5, the systematic utility vector V^r_{ijt} (conditioned on the normal errors) is partitionable into two sub-vectors. The first, corresponds to the systematic utility

specification for the departure time switching decision conditioned on the normal error terms. The second sub-vector corresponds to the conditional utility specification for pre-trip and four en-route switching decisions. In contrast, the route switching model in Chapter 5 was comprised only of the second sub-vector.

7.2.3 Estimation Procedure

The maximum likelihood estimation procedure outlined in Chapter 4 is used to calibrate this model. The greater computational efficiency in this formulation relative to the MNP is due to the tractability of the embedded logit function. This formulation, at the same time, can preserve the flexible error structure of the MNP model through a suitable specification of the multivariate normal errors. The next section discusses issues relating to the specification of heterogeneity, state dependence, habit persistence, and variance-covariance structure.

7.3 SPECIFICATION ISSUES

7.3.1 Heterogeneity

Heterogeneity refers to taste variations in choice behavior across decision-makers. Two types of heterogeneity may be distinguished (Bhat, 1998). The first, referred to as preference heterogeneity, arises due to intrinsic differences across individuals in their propensities to choose various alternatives. The second source of heterogeneity is referred as response heterogeneity. This pertains to differences across decision-makers in their sensitivity to attributes of alternatives (for example the value of trip time can vary across decision-makers) and the consequent differences in the probability of choosing various alternatives.

Heterogeneity occurs, or appears to occur, in observed travel behavior choices due to the following reasons. First, the selection or decision process often involves a search in a multi-attribute decision space, and decision-makers apply different weights in searching for the desired alternative. Secondly, all the variables affecting a decision-maker's choice are not observed by the analyst. Differences in such unobserved attributes may persist over time and may result in differences in choices even among users with the same set of observed attributes (Figure 7.1).

Therefore, it is necessary to model both observed and unobserved heterogeneity (also referred to as systematic and random heterogeneity). Though it is possible to model heterogeneity with cross-sectional and longitudinal data, the latter enable a greater inferential power for the associated models. This is because between-person variability, which is a source of heterogeneity, can be better accounted for by repeated measurements over the same observational units capturing between-person variability (which is the source of heterogeneity). Models ignoring heterogeneity effects when present in the data, are likely to result in inconsistent and inaccurate estimates (Chamberlain, 1980; Roy et al., 1996). It is also important to model heterogeneity in longitudinal models to avoid the possibility of its mis-specification, mis-interpretation, and confounding with other structural effects.

To illustrate this notion, consider the route switching decision on a hypothetical set of two routes over two time periods. Users may exhibit variations in some unobserved attribute, say attitude towards

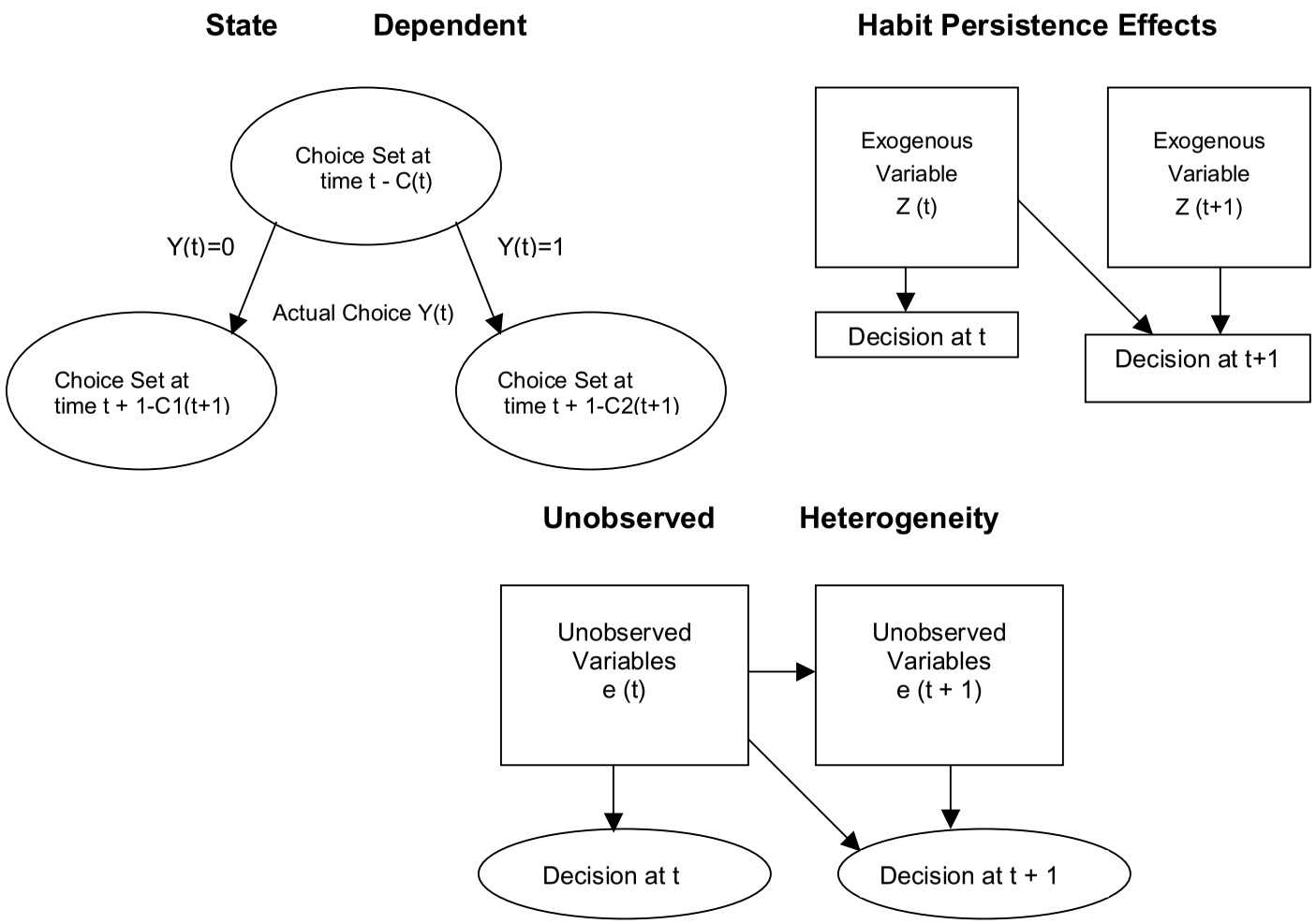

FIGURE 7.1
Schematic illustration of dynamic effects in commuter behavior.

risk. For simplicity, let the population consist of two segments in terms of unobserved attributes towards risk, namely, risk averse and risk seeking. Suppose that risk seeking decision-makers have a systematically higher propensity to switch routes than risk averse ones, and that this phenomenon is time-invariant (no loss of generality occurs in interchanging the user groups in this example). In such a case, it may be observed that users who switched routes in period one are more likely to do so in period two. Similarly, individuals who did not switch in period one are less likely to do so in period two. The decisions over the two time periods will appear to be positively correlated when the attitudes towards risk are not incorporated in the utility specification. Thus it is possible that time-invariant differences in individuals' unobserved attributes that may persist over time, can be easily mis-specified or confounded with actual structural time-varying effects in choice behavior.

Preference heterogeneity, which relates to the variation in the intrinsic choice propensities of alternatives across decisions-makers is modeled through the following specification of the alternative specific constant for switching:

$$\tilde{\beta}_p^{\,k} = \gamma_{p0} + \Sigma_i \gamma_{pi} Z_{pi}^{\,k} + \nu_p \qquad (7.2),$$

where $\tilde{\beta}_p^{\,k}$ *represents the alternative specific constant for switching for individual k*

γ_{p0} *is the* exp*ected value of this coefficient across individuals*

Z_{pl}^{k} *is the lth attribute influencing systematic preference heterogeneity*

γ_{pl} *is the coefficient corresponding to the attribute* Z_{pl}^{k}

ν_p *is the random component of unobserved preference heterogeneity with mean zero.*

Response heterogeneity, which reflects taste variation across users towards attributes of alternatives, is modeled through a specification of the following form for the coefficient of attribute X_r:

$$\tilde{\beta}_r^{\,k} = \delta_{r0} + \Sigma_l \delta_{rl} Z_{rl}^{\,k} + \nu_r \qquad (7.3).$$

where $\tilde{\beta}_r^{\,k}$ *represents the utility coefficient for individual k for the rth attribute* X_r

δ_{r0} *is the* exp*ected value of the coefficient across individuals*

Z_{rl}^{k} *is the lth attribute influencing systematic response heterogeneity*

δ_{rl} *is the coefficient corresponding to attribute* Z_{rl}^{k}

ν_r *is the random component of unobserved response heterogeneity with mean zero.*

The overall utility U_{ijt}, of an individual i, at decision node j, at time t can be written to include these heterogeneity effects as follows:

$$U_{ijt} = \tilde{\beta}_p^{\,i} + \Sigma_l \, \tilde{\beta}_l^{\,i} X_{lijt} + \varepsilon_{ijt} \qquad (7.4).$$

The presence of unobserved heterogeneity can be captured through an appropriate specification of serial-correlation over time and random error terms in the preference and response heterogeneity specifications in equations 7.2 and 7.3. Later in Section 7.3.4, a more general variance covariance structure is presented which accounts for various sources of unobserved heterogeneity.

7.3.2 Structural State Dependence

A more fundamental structural relationship between choices over time may also result in dynamic trends similar to the ones associated with unobserved heterogeneity (Figure 7.1). This type of structural relationship between discrete outcomes in different periods is termed as state dependence (Heckman, 1980; Heckman, 1981a). State dependence refers to temporal effects that arise when the consequence of a previous decision state substantially or causally alters the decision-maker's preferences, choice set structure or choice propensities relevant to future decisions. Possible reasons for such state-dependence include retention of choices over time due to inertia, satisfaction with choice, search costs, etc. State dependence has been shown to arise in a variety of empirical contexts, and has important implications for policy analysis and decision-making (Heckman, 1981). The following discussion illustrates how structural state dependence may occur in commuter behavior dynamics.

Users' past choices of route and departure time may influence their future choice and information sets. For example, the departure time choice and current path determines the next decision-location (cross-over link to other facilities), availability of alternatives (due to possible incidents or lane closures), and the attributes of alternatives (time-dependent trip times, congestion on alternative paths, etc.). It is also possible that arrival-time constraints may induce state dependence. For instance, the route chosen at an en-route decision location may be based on considerations of desired arrival time, elapsed trip time on current path, and expected (reported) trip times on available paths, all of which depend on the trip-maker's past choices in a causal manner. State-dependence effects may also occur due to the effect of past decisions altering the preference structure or choice propensities for various alternatives. For instance, a user's perception of attributes of alternatives (based on trip time reported by ATIS), may be influenced by his/her past experience with ATIS, which is in turn causally dependent on his/her past choices.

These examples demonstrate that structural relationship between discrete choices over time may be induced by several factors. Some of these may be observable to the analyst and/or the decision-maker (signals encountered on various paths given previously chosen path or facility constraints) and can be adequately accounted for by the systematic specification of the utility. Other relevant time-varying factors may be known to the decision-maker but may remain unknown to the analyst (e.g., perceptions of experiences). A third category of factors inducing causal time-dependent relationships between choices can be unobservable or unknown to both the analyst and the decision-maker (future traffic evolution and

network states). Note that, unlike heterogeneity, state-dependence effects can not be captured from cross-sectional data or models of marginal choice. Identification restrictions apply for the number of state-dependence effects that may be estimated with longitudinal data. It can be shown that for binary choice situations (J=2), with three or more time periods ($T \geq 3$), at least first-order state-dependence effects can be captured. For multinomial choice situation ($J \geq 3$), with ($T \geq 4$), at least first-order state-dependence effects can be obtained (see Table 4.1 in Chapter 4). With more than four panel periods, richer state-dependence specifications are possible.

The consequence of both state-dependence and persistent unobserved heterogeneity is to induce a correlation in observed choices over time. It is essential to distinguish between these two phenomena in trip-maker behavior due the following behavioral, econometric, and application considerations. The two specifications, though resulting in similar outcomes, can lead to substantially different behavioral interpretations. The presence of unobserved heterogeneity implies that individuals in the choice set vary significantly in their prior propensity to select various alternatives, and these variations are likely to persist over time. On the other hand, according to the state-dependence explanation, the very act of choosing a particular alternative (in a previous time period) causally influences the propensity of selecting various alternatives at a future time.

From an econometric perspective, mis-specification of one of these effects in terms can lead to serious estimation errors, through inconsistent parameter estimates and erroneous inferences. Distinction between the two formulations is also critical from an application perspective, as mis-specification could lead to inaccurate forecasts and gross errors in the assessment of policy impacts. Consider for instance the example of route choice with two available highways. Assume that the path choices of trip-makers are positively correlated over time. If highway one (H1) is over-utilized and the second highway (H2) is under-utilized, then from a traffic-management perspective it is desirable to induce shifting from highway one to highway two. If the observed correlation in route choices over time is due to state-dependence, then the provision of ATIS trip time information on highways one and two can lead to the desired route shifting behavior. In contrast, if the observed correlations are a consequence of persistence of some unobserved attribute say attitudes towards safety or signals, the provision of ATIS information would have little impact on route choice behavior. This example illustrates that it is necessary to distinguish between the two specifications to correctly assess the impact of alternative policy measures.

In the route and departure time switching (binary) contexts considered here, unobserved heterogeneity and structural state dependence may be distinguished by a specification of the following form.

$$U_{it} = V_{it} + \sum_{k=1}^{\infty} \gamma_k \, d_{i,t-k} + \varepsilon_{it}, \qquad (7.5),$$

where,

$d_{it} = 1$, iff $U_{it} \geq 0$,

$E[\varepsilon_{it}] = 0$, $E[\varepsilon_{it}^2] = \sigma_t^2$, $E[\varepsilon_{it}\varepsilon_{it'}] = \sigma_{tt'}$, $\rho_{t-t'} = \sigma_{tt'}/(\sigma_t\sigma_{t'})$, $t' \neq t$

In equation 7.5, the subscript i refers to an individual, and t to the choice context or time, and d_{it} is a binary indicator variable denoting switching behavior of interest (=1 if user i switched at time and 0 otherwise, and the node subscript j is suppressed for ease of exposition.

The coefficients γ_k in equation 7.5 need to be estimated on the joint choices of each decision-maker in order to avoid selectivity biases (Heckman, 1981). If $\gamma_k \neq 0$ for some k, and $\rho_{t-t'} = 0$ for all $t' \neq t$, then the observed dynamics is consistent with state dependence rather than unobserved heterogeneity. In case, $\gamma_k = 0$ for all k, and $\rho_{t-t'} \neq 0$ for some pair (t,t') such that $t' \neq t$, then the apparent time dependence in choices may be attributed to unobserved heterogeneity. A third possibility is that $\gamma_k \neq 0$ and $\rho_{t-t'} \neq 0$, indicating that both effects are significant. On the other hand, if $\gamma_k = 0$ for all k, and $\rho_{t-t'} = 0$ for all $t' \neq t$, then the data is consistent with the absence of either effect in choice behavior.

7.3.3 Habit Persistence

Another dynamic influence of interest is the delayed/lagged impact of exogenous factors on current choice decisions. Such an influence of past habits on future behavior has been observed in many empirical instances (Maddala, 1987) and has been referred to as habit persistence in the econometric literature (Heckman, 1981a). The presence of habit persistence can be tested with a specification of the following form (Heckman, 1982):

$$U_{ijt} = \beta X_{ijt} + G(l)U_{ijt} + \varepsilon_{ijt} \qquad (7.6),$$

where the generalized lag operator of order (l) is such that

$G(l)U_{ijt} = U_{ijt-l}$, and $d_{ijt} = 1$, if $U_{ijt} \geq 0$, and 0 otherwise.

Assuming that the variables X_{ijt} are not linear combinations of each other (over time), the absence of habit persistence effects can be rejected if the generalized lag operator G(l) is significantly different from 0 for some lag period (l). Note that it is possible to estimate habit-persistence effects consistently by modeling the marginal choice decision d_{ijt} (for particular j and t) even if the error terms ε_{ijt} are correlated over time (Heckman, 1982). This becomes evident by rearranging terms in equation (7.7) as follows:

$$U_{ijt} = (1- G(l))^{-1}\beta X_{ijt} + (1- G(l))^{-1}\varepsilon_{ijt} \qquad (7.7).$$

Equation (7.7) indicates that to identify habit persistence effects it is necessary to have lagged exogenous variables because the error terms ε_{ijt} are not observed. In contrast, state-dependence models can be estimated even in the absence of exogenous variables. While it is possible to model habit persistence effects consistently by marginal choice models, estimating state-dependence with such models can lead to selectivity bias.

Ignoring habit persistence effects, when present, may result in the misinterpretation of observed behavior as state-dependence, leading to forecasting and inferential errors. Ignoring the influence of X^{t-1} on U^t would lead to it's being aggregated in the error term at time t (if $cov(X^{t-1},X^t) \neq 0$), producing a spurious correlation between X^t and ε^t and inefficient coefficient estimates. It is also possible that the

correlation due to the stochastic process generating the explanatory variable X^t, may be manifested as serial correlation among the unobservables, if habit persistence effects are not considered.

7.3.4 General Variance-Covariance Structure

This section presents the error structure for the joint route and departure time switching model. In this problem context, each individual i, repeatedly makes switching decisions at six separate instances on a given day (j=1 corresponds to departure time, 2 refers to pre-trip route switching, and 3-6 refer to en-route switching) per day over 11 days (t=1,… 11). Accordingly the following error-structure is specified to account for three different sources of unobserved heterogeneity:

$$\varepsilon_{ijt} = \varepsilon_i + \varepsilon_{it} + \varepsilon_{ij} + \nu_{ijt} \qquad (7.8),$$

for i = 1,….. N, j = 1, … J, t = 1,… ,T.

The first error component, ε_I [~N(0,σ_1)], is an individual specific error term which represents variability in switching propensity across decision-makers in the sample, and is identical across repeated choices of a given decision-maker. The second component, ε_{it}, is intended to capture the unobserved variability in a trip-makers' choices from one day to the next. This error term could account for possible dependence of switching decisions on departure time choice, traffic conditions on a given day, and unobserved learning effects, that could vary from day-to-day for a given individual, but remains the same across all decisions made by a trip-maker on the same day. The error components ε_{it} are assumed to be first-order auto-correlated with variance σ_2 and a correlation coefficient of ρ_1. The third error component, ε_{ij}, is intended represent the variability across different decision dimensions (departure time, pre-trip and en-route choices). This error term remains unchanged for all decisions at a given node over time. To enable a general covariance pattern between error terms ε_{ij}, within day the vector of errors - [ε^r_{i1}, ε^r_{i2}, ε^r_{i3}, ε^r_{i4}, ε^r_{i5}, ε^r_{i6}] is assumed to be distributed multivariate normally $(0,\Sigma)$ where,

$$\Sigma = \begin{pmatrix} \sigma_3^2 & \rho_1\sigma_3\sigma_4 & \rho_2\sigma_3\sigma_5 & . & . & \rho_2\sigma_3\sigma_5 \\ & \sigma_4^2 & \rho_3\sigma_4\sigma_5 & \rho_3\sigma_4\sigma_5 & . & \rho_3\sigma_4\sigma_5 \\ & & \sigma_5^2 & \rho_4\sigma_5^2 & . & \rho_4\sigma_5^2 \\ & & & . & & . \\ & Sym & & & . & \rho_4\sigma_5^2 \\ & & & & & \sigma_5^2 \end{pmatrix}.$$

The variance of these error components represent the unobserved heterogeneity associated with a given decision-maker, across days, and at different decision locations respectively, while the covariances reflect the correlation between the switching decisions over time. These three components are assumed to be mutually independent. It is also assumed that the error components are independent

across individuals. For normalization purposes, μ (the logit scale parameter) is set to one. The resulting variance and covariance terms are computed and displayed in Tables 7.5 and 7.6. The within-day and day-to-day variance-covariance parameters are graphically illustrated in Figure 7.2. The parameters s1-s4 represent within-day variances, where as the parameters s8-s11 signify day-to-day correlations across different choice dimensions. Note that the day-to-day covariances are lag-dependent.

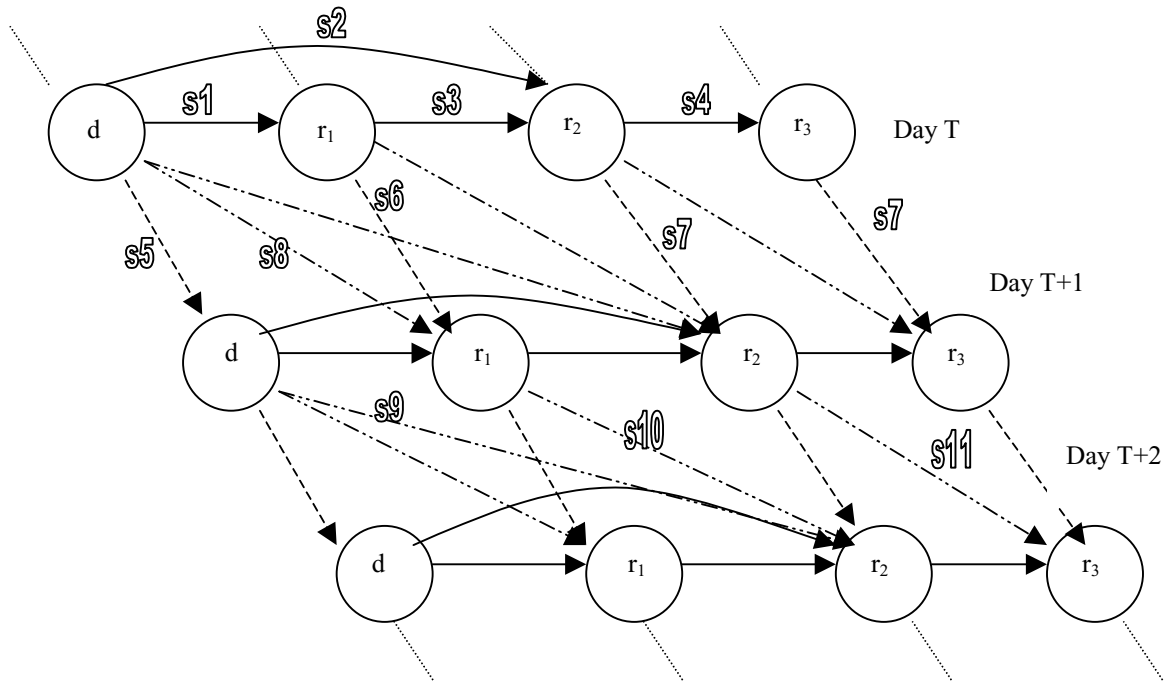

FIGURE 7.2

Schematic representation of first-order variance and covariances in joint route and departure time switching.

Notes: d – departure time witching node, r_1 – pre-trip route switching, r_2 – en-route switching (location 1), r_3 – en-route switching (location 2), s – variance covariance terms defined in Table 7.6-7.7

Three major advantages are derived from this variance components scheme. First, it allows for a general yet parsimonious, representation of the stochastic process generating the unobservables. To preserve generality in this specification, it is essential to allow for possible negative correlation between error components ε_{ij} across decision nodes, and ε_{ij} over days. Second, this error-components scheme is computationally more efficient than the assumption of a general MVN structure for ε_{ijt}. The efficiency gains are due to the reduction in the dimensionality of Monte-Carlo integration from JT in the general case to J+T +1 in the error-components scheme (55 to 17 here). A third but related advantage of this components

scheme is its robustness relative to the general covariance pattern of ε_{ijt} The estimation procedure involves the Cholesky decomposition of the variance covariance matrix. With a given correlation structure over time, the Cholesky decomposability of a given covariance matrix tends to decrease with increasing size especially with small variance parameters and relatively large negative correlation parameters. In contrast to a general matrix of size (55 x 55), the maximum size of the matrix to be Cholesky decomposed is reduced in this analysis to (11 x 11).

7.4 MODELING RESULTS

This section presents the calibration results for the joint model of route and departure time switching behavior. The results (in terms of log-likelihood at convergence) from alternative specifications are displayed in Table 7.1. Chi-squared tests indicate that the route and departure switching decisions are neither independent of each other, nor independent over time (based on a comparison between models 1 and 2). Both observed and unobserved heterogeneity effects are present in route and departure time switching behavior (evident from a comparison between models three and two, and models five and four respectively). State dependence effects in commuter behavior dynamics are also significant. Thus the most general specification that accounts for covariances, observed and unobserved heterogeneity, and state dependence is preferred to alternative specifications. In view of the large number of parameters (93) associated with the generic model, the presentation of model results is divided into the following sub-sections.

7.4.1 Route Switching Behavior

This section discusses factors influencing route switching behavior. Generic effects and observed heterogeneity are considered here, whereas, unobserved heterogeneity in both route and departure time switching are addressed in a subsequent section. The following discussion pertains to the calibration results for the route switching specification (Table 7.2). The model is interpreted based on the magnitude, signs, and significance of the calibrated coefficients, as with any typical discrete choice model.

7.4.1.1 Influence of ATIS Information on Route Switching Behavior.

Nature of Information

A greater route switching propensity is noted when prescriptive information is provided to users than when descriptive information is provided. In the absence of information on alternative routes in the prescriptive information case, it is conceivable that users may select paths using processes that may lead to trial and error path choice behavior, resulting in greater switching activity.

Information Type

Among the various information type levels described in the experimental design, prevailing information is chosen as the baseline level. Compared to the baseline, providing predicted information resulted in greater route switching activity among young males (< 40) and older females (40 years and older). A greater switching propensity is observed when the ATIS supplies differential (partial) information on the network conditions. In this case, no differences were observed between prevailing and predicted differential information strategies. However, there appears to be differences in route switching behaviors

under differential information depending on the age of the decision-maker. For instance, younger trip-makers are much more likely (1.6 times) to switch than older trip-makers. Thus, user responses to varying information strategies appears to vary across different socio-demographic segments of trip-makers. These differences across various user groups are critical in accurately evaluating the impact of information.

When the ATIS provides completely random information, all segments of commuters were less likely to switch. It is possible that users discount random information provided by the system, and only tend to rely on experience in selecting their path. Thus, they may retain the path selected based on their personal experience in the absence of reliable information to support route switching. As compared to other segments, young males are found to be more sensitive to random information. Young males also exhibit an increased route switching tendency, when the ATIS supplies perturbed information, possibly due to a higher sensitivity to trip-time information.

Feedback Effects

Providing feedback on the best path results in considerably increased switching. This may be expected since the provision of feedback on the best path allows a user to compare his/her choice with the optimal choices, and is therefore likely to encourage the selection of more efficient paths. Providing feedback on the recommended path results in a moderate increase in route switching when compared to the information strategy where feedback is provided only on the chosen path.

TABLE 7.1

COMPARISON OF ALTERNATIVE ROUTE AND DEPARTURE TIME SWITCHING MODEL SPECIFICATIONS

Model Description	LL	Df	$\chi 2$ critical	Comparison		
				$\chi 2$ actual	Model	Remarks
1. No heterogeneity, independent route and departure time switching decisions	-3869.15	36	-	-	-	-
2. Variance Covariance Structure + No heterogeneity	-3857.33	46	18.301	23.64	1	Reject Model 1
3. Covariance Structure + Observed heterogeneity	-3745.68	78	46.19	223.3	2	Reject Model 2
4. State dependence + covariance structure + observed heterogeneity	-3733.08	83	11.07	25.2	3	Reject Model 3
5. State dependence + covariance structure + observed heterogeneity + unobserved heterogeneity	-3723.47	93	18.301	19.22	4	Reject Model 4

TABLE 7.2

OBSERVED HETEROGENEITY AND OTHER EFFECTS IN ROUTE SWITCHING

Route Switching Variables	Coeff	t-stat
Constant	-0.001	-6.87
Socio-demographics		
young male	-0.68	-4.39
old female	-0.39	-3.44
Experience		
Early schedule delay on previous day	-0.01	-2.91
Late schedule delay (old males on pre-trip switches)	0.07	2.54
Late schedule delay (young respondent, en-route switches)	-0.04	-3.69
Late schedule delay (old male, en-route switches)	0.01	1.52
Cumulative proportion of switches to earlier departure times (female)	0.64	3.33
Cumulative proportion of switches to later departure times (female)	-0.29	-1.82
ATIS Information Attributes		
Overestimation error = max(0, rept. trip time - experienced trip time)	0.07	3.01
Underestimation error = max(0, experienced trip time - rept. trip time)	0.02	1.81
Reported early schedule delay on current path pre-trip	0.03	4.02
Reported early schedule delay on current path en-route	-0.02	-3.39
Reported late schedule delay on current path pre-trip (young male)	0.16	2.19
Reported late schedule delay on current path pre-trip (old male or young fem	-0.04	-4.21
Level of Service Measures on Network		
Relative triptime saving enroute (old)	1.99	5.82
Relative triptime saving enroute (young)	4.28	6.99
Expected congestion on next two segments of current path	0.69	7.94
Expected congestion on next two segments on least trip-time path	-0.34	-4.47
Expected congestion on next two segments on least trip-time path (young m	0.55	2.51
Inertial Factors		
Inertia (enroute, female) inertia= 1, if current path = best path, 0 otherwise	-2.69	-23.66
Inertia (enroute, male)	-2.36	-18.20
Inertia (pre-trip, young)	-1.84	-8.70
Inertia (pre-trip,old)	-2.38	-14.58
Additional switching cost (distance to switch from current path to best path)	-0.82	-6.27
ATIS Information Strategy		
Prescriptive information	0.24	3.09
Predicted information	0.22	2.17
Predicted information (young females and older males)	-0.19	-1.90
Random information (young male)	-2.19	-2.83
Random information (old)	-0.32	-1.86
Differential (both predicted and prevailing, young)	0.53	3.54
Differential (both predicted and prevailing, old)	0.29	2.53
Perturbed information (young male)	1.07	2.31
Feedback on recommended path	0.10	1.31
Feedback on best path	0.34	4.47
Facility Bias		
Highway 1 (old female)	0.84	4.48
Highway 2 (old female)	0.26	2.81

Generic Information Effects

Increased route switching activity is observed when ATIS supplies inaccurate information to users. This increase is noted when the reported information either overestimates or underestimates experienced trip times. Expectations regarding arrival time (by following the current path) also influence the switching decision. Trip-makers are unlikely to switch from their current path en-route when faced with possible early arrival, but are more likely to do so, pre-trip. Young males are more sensitive to potential late arrivals and switch more frequently (pre-trip), in such cases. Older males and younger females on the other hand, exhibit risk-averse behavior, as they switch routes less frequently even when faced with potential late arrivals, possibly suggesting that they are averse to selecting unfamiliar routes.

7.4.1.2 System Performance Measures. The decision to switch appears to be the outcome of a trade-off between the costs and benefits of switching. While increased trip time savings on the best path (relative to the current path) induces greater switching activity, increased cost (measured by the distance to switch) reduces the tendency to switch. Furthermore, the effect of system performance measures on switching behavior varies depending on the socio-demographic characteristics of the trip-maker. For instance, younger respondents are nearly twice as sensitive to trip-time savings as older respondents. Switching behavior also appears to be motivated by a desire to avoid congestion (downstream on the current path). However, as the congestion on the best path increases, the switching rate decreases, reflecting reduced rerouting opportunities in the network. These results confirm earlier findings on the influence of anticipated congestion reported in Chapter 5, Section 5.4. Young males, unlike other users, switch routes more frequently with increased congestion on the best path, perhaps, in an attempt to find a better path.

Users are less likely to switch from the current path when it coincides with the recommended path (explicitly prescribed, or implicitly – the path with the least reported trip time). This increased behavioral inertia is observed in all user segments. This inertial effect is much stronger in older respondents and females, for pre-trip and en-route switching respectively. These segments of trip-makers appear to exhibit risk-averse switching behavior.

7.4.1.3 Experience Effects. Early schedule delay on the previous day results in reduced route switching across all user segments. Older males, however, switch more often following late schedule delay, at both pre-trip and en-route switching opportunities. In contrast, younger respondents switch less frequently (en-route) following late arrivals on the previous day. A plausible explanation for this result could be that older males respond to late schedule delays by switching routes, whereas, younger respondents may change departure times instead. This conjecture is verified later by modeling the effect of schedule delay on departure time switching for younger males (see Section 7.4.2). The cumulative proportion of switches to later and earlier departure times significantly influences switching behavior, though only for females. Females are more likely to switch routes with increasing frequency of switches to earlier departure times, presumably following late arrivals. They also exhibit reduced switching propensity with increased proportion of switches to later departure times (possibly due to unacceptably many early arrivals).

7.4.1.4 Implications. These findings on commuters' route switching behavior have several important implications. First, the attributes of ATIS information including the nature of information provided to users, type of information (includes considerations of timeliness, extent of network coverage, and accuracy), and feedback provided on actual choices made by trip-makers strongly influence users' response. The significance of information quality on choice behavior provides empirical evidence for the presence of judgment processes in user behavior. Perceptions and expectations also play a significant role in how information is used in route selection decisions. For instance, potential early and late schedule delays that would be experienced by following the current path affects route switching behavior, though the nature of influence varies across different user segments.

The results also suggest that ATIS information can play a dual role on inertial tendencies in trip-maker behavior. On the one hand, information can assist users in overcoming behavioral inertia and induce the selection of more efficient choices (than the current path). For instance information, can lead to increased route switching, by making users aware of potential trip time savings and lower congestion on alternative routes. In other cases it is possible that information may enhance the behavioral inertia of trip-makers. For example, reduced route switching is noted when ATIS provides trip-makers with highly imperfect information (random). Increased inertial tendencies are also observed when ATIS information indicates that the current path also happens to be the best path for a given decision-maker. In view of these opposing effects of information on inertia, the actual impact of providing information on network performance would depend on which of these tendencies is dominant among users. This finding also raises questions about the nature and stability of network states resulting from trip-makers' choices in the presence of information, especially under information strategies with varying information quality and credibility. The results presented here also underscore the fact that the time-dependent network conditions encountered by users strongly influence their behavior. Therefore, it is essential to model user response and the associated decision processes, together with network performance measures, in order to assess the nature and extent of ATIS benefits.

Considerable heterogeneity is observed in user response to ATIS on the basis of age and gender differences. In general, younger respondents are more strongly influenced by information than other segments. Young males, in particular, exhibit a greater switching propensity when the ATIS supplies predicted, differential or perturbed information. Younger males are also more sensitive to performance measures than other trip-makers. For example, they are observed to switch more frequently to avoid congestion and achieve trip time saving. In contrast, older respondents and females, exhibit risk-averse route switching behavior. These differences in trip-maker behavior are of practical interest in the design and evaluation of alternative demand management strategies.

Experience acquired on previous commutes significantly affects the route switching behavior of users. The effect of experience, however, varies across different user groups. The significance of past experiences indicates the presence of learning and adjustment processes in trip-maker behavior in the presence of information. The correlation among the error terms, both within-day and day-to-day, also

confirm the presence of unobserved dynamic effects in user behavior. These findings also highlight the need for further investigations into dynamic aspects in user behavior.

7.4.2 Departure Time Switching Behavior

This sub-section focuses on generic effects and observed heterogeneity in departure time switching behavior. The alternative specific constant for departure time switching is negative and significant (Table 7.3), indicating some resistance on the part of trip-makers to switch departure times (with other factors at their baseline levels).

TABLE 7.3

OBSERVED HETEROGENEITY AND OTHER EFFECTS IN DEPARTURE TIME SWITCHING

Departure Time Switching Variables	Coeff	t-stat
Constant	-0.85	-10.38
ATIS Information Strategy		
Prescriptive information (young male)	1.02	4.03
Prescriptive information (young female)	-0.63	-4.58
Prescriptive information (old)	0.32	4.61
Random information (young male)	0.51	7.44
Random information (old female)	0.66	5.13
Differential information (prevailing)	0.63	8.03
Differential information (predicted, young)	0.49	6.84
Differential information (predicted, old male)	-2.18	-6.28
Feedback on best path (young male)	-0.72	-6.10
Feedback on best path (old male)	-0.39	-6.90
Experience		
Early schedule delay on previous day	0.04	7.26
Late schedule delay (young male)	0.07	4.17
Late schedule delay (old)	0.04	7.14
Stuck in traffic on previous day	0.16	4.54
Trip time variability with dep. time change (young male)	-0.35	-8.28
Cumulative proportion of switches to earlier departure time following early arrival on previous day (young male, young female, old male)	1.18	4.30
Cumulative proportion of switches to earlier departure time following late arrival on previous day (young)	4.30	4.00
Cumulative proportion of switches to earlier departure time following late arrival on previous day (old)	2.59	8.20
Cumulative proportion of switches to later departure time following early arrival on previous day (young male, young female, old male)	1.83	4.11
Cumulative proportion of switches to later departure time following early arrival on previous day (old female)	0.99	4.06
Cumulative proportion of switches to later departure time following late arrival on previous day (young male, young female, old male)	1.31	5.01
Cumulative proportion of switches to later departure time following late arrival on previous day (old female)	2.04	7.37
Other		
Highway 1 chosen on previous day (late arrival on previous day)	-2.33	-4.73
Highway 1 chosen on previous day (late arrival on previous day, young fema	1.61	5.59
Initialization effects (=1, if day >3, 0 otherwise)	-0.96	-5.39

Following a schedule delay (early or late arrival) on the previous day, users are more likely to switch departure times. Younger males are particularly more sensitive to late schedule delay than older respondents, whereas, lateness appears to have no effect on the departure time switching behavior of young females. However, dampened switching behavior is noted in younger males, when they encounter increased travel time variability on the network. In response to recent adverse experience (stuck in traffic on the previous day), a greater departure time switching propensity is observed among all users. In addition to the effect of schedule delay on the previous day, trip-makers' past switching history also significantly influences departure time switching behavior. Each user's past switching history is represented by the cumulative proportion of departure time switches to the earlier and later sides on preceding days. A greater proportion of switches to earlier departure times occur presumably in response to unacceptably many late arrivals, while a greater proportion of switches to later departure times may be prompted by frequent early arrivals. The greatest effect is observed among users who experience lateness frequently (greater proportion of switches to earlier departure times and lateness on the previous day). These users exhibit a marked increase in propensity to switch departure times.

Following consistent earliness (greater proportion of switches to later departure times and lateness on the previous day) too, users are more likely to switch departure times.

The magnitude of response to earliness is much smaller than the response to consistent lateness, confirming the asymmetric response to early and late schedule delays found in Section 5.4, and noted in previous studies (Chang and Mahmassani, 1988; Mahmassani, 1990).

There is also considerable heterogeneity in user responses to consistent earliness or lateness. Following consistent lateness, younger respondents are more likely to switch than older respondents (the corresponding coefficients are 4.30 and 2.59 respectively). In response to consistent earliness, all users are more likely to switch. Older females are also more likely to switch, but are nearly half as sensitive as the remaining user groups (younger males and females, and older males). However, older females with a greater cumulative proportion of departure time switches to later departure times on preceding days, are more likely to switch than other user groups, following lateness on the previous day.

The nature, type, and feedback supplied by ATIS also strongly influence observed departure time switching behavior. When the ATIS supplies partial (incomplete) or inaccurate information, a greater departure time switching tendency is noted. Users tend to switch departure times more often under random, differential and prescriptive information strategies. This increased switching activity is consistent with a trial and error adjustment behavior when information is either unavailable on some routes or is unreliable. An exception to this general trend is seen among older males. These users are less likely to switch when differential information is provided using a prediction mechanism. It is also observed that males are less likely to switch departure times when feedback is provided for the actual best path for the chosen departure time. This suggests that providing trip-makers with opportunity to compare the quality of their choices with optimal choices, possibly increases the credibility of the information system and reduces switching tendency among users.

7.4.3 Unobserved Heterogeneity

Random taste variation effects are tested only for a few key generic factors as shown in Table 7.4, in the interest of model parsimony. The results indicate considerable unobserved variability in the intrinsic route switching propensity across trip-makers. This is evident from the standard deviation (0.35) estimated for the route switching constant. Users' also exhibit significant unobserved variations in sensitivity towards relative trip time savings (standard deviation of 0.07), early schedule delay (0.04), congestion on best path (0.02), and potential early schedule delay (0.02). Interestingly, little unobserved variability was noted for the coefficients of late schedule delay, congestion on current path, and potential late arrivals on current path across respondents. Arrival-time constraints in the simulated commute might be partially responsible for this lack of unobserved variability in response to these attributes.

Unobserved response heterogeneity is also observed in departure time switching, particularly in the sensitivity of users to travel time variability on the network. However, unobserved variation in user response to being stuck in traffic on the previous day is not significant. It is possible that user's responses to negative experiences might be captured adequately by the generic and observed heterogeneity specification of the utilities, whereas, considerable unobserved heterogeneity exists in other factors including trip time variability, and early schedule delay. In summary, these results indicate the presence of both observed and unobserved heterogeneity in trip-maker behavior under real-time information.

TABLE 7.4

UNOBSERVED HETEROGENEITY IN ROUTE AND DEPARTURE TIME SWITCHING

Standard deviation for Random Coefficients	Coefficient	t-stat
Route Switching		
Constant	0.3499	8.11
Early schedule delay	0.0428	7.81
Late schedule delay	0.0032	1.31
Congestion on current path	0.0012	1.07
Congestion on best path	0.0208	5.67
Relative trip time savings on the best path	0.0739	5.68
Potential early arrival on current path	0.0229	6.18
Potential late arrival on current path	0.0038	1.21
Departure time Switching		
Stuck in traffic on previous day	0.00004	1.14
Trip time variability / unit change in dep. time	0.00309	5.68

7.4.4 State Dependence

State dependence effects in route and departure time switching are displayed in Table 7.5. Users past departure time switching decisions positively influence current switching decisions, though the extent of influence diminishes with increasing time lag. Only the departure time switches on the past two days

significantly affect the current day's departure time switching decision. State dependence effects are also seen in route switching behavior, though the duration of influence of past choices is smaller in this case

Pre-trip route switches on the previous day exert a strong effect (coefficient of 0.82) on current day's pre-trip route switching decision. In contrast, the effect of previous en-route switching decision on current en-route switching decision is much smaller (coefficient of 0.1). The positive coefficient in both cases may be attributed to the tendency of a user to consistently select more efficient routes. Fewer successive route improvement opportunities encountered en-route, may explain the smaller magnitude associated with en-route state-dependence. These results indicate the presence of state-dependence in route and departure time switching under information.

TABLE 7.5

STATE DEPENDENCE EFFECTS IN JOINT ROUTE AND DEPARTURE TIME SWITCHING MODEL

State Dependence	Coeff	t-stat
Departure time switch indicator - d1, on previous day (on day t-1 w.r.t t-2)	0.65	4.55
Departure time switch indicator - d2, on 2nd last day (on day t-2 w.r.t t-3)	0.23	2.30
Departure time switch indicator - d3, on 3nd last day (on day t-3 w.r.t t-3)	0.10	3.65
Route switch indicator - r1, for pretrip switching	0.82	1.49
Previous route switch indicator - r2, for en-route switching	0.10	0.60

Note: r1, r2 are defined for decision nodes 2 and 3 onwards, respectively
d1, d2, d3 are defined for days 3, 4, and 5 onwards, respectively

7.4.5 Variance-Covariance Structure

The error-components structure proposed in Section 7.3.4 introduces general correlations across the decision dimensions of interest (departure time switching, pre-trip route switching, en-route switching). This specification assumes that the stochastic process generating the unobservables is stationary. The resulting variance covariance structure is displayed in Figure 7.2. This variance covariance structure is parsimonious in terms of the number of parameters. With only 10 parameters, this specification represents 77 distinct elements of the variance-covariance matrix. This specification captures serial correlation due to repeated measurements performed on the same observational unit. The proposed structure also enables capturing temporal correlations between unobservables, both within a given day and from one day to the next. Another notable feature of this specification is that it permits correlations between choices made on different days to vary depending on the time lag between the choices. Note also that this specification relaxes restrictions in previous work by (Liu and Mahmassani, 1998) that the across day correlation at different decision locations is zero.

In view of the large number of distinct variance-covariance terms (77) in the specification, the following discussion limits its attention to the component parameters (Tables 7.6 and 7.7). The estimated variance-covariance parameters are displayed in Table 7.8. The individual-specific error component (ε_i) that represents unobserved variability across respondents has the largest variance ($\sigma_1^2 = 0.49$). This component also contributes to the correlation across repeated decisions made by a given user. The error

term (ε_{it}) denotes the component common to all decisions on a given day. The corresponding variance (σ_2^2) is estimated to be 0.16, which represents variability of decisions of a given user from day-to-day. The auto-correlation coefficient is –0.0001 indicating a mildly negative correlation of the day-specific error term from one day to the next.

TABLE 7.6

WITHIN-DAY COVARIANCE STRUCTURE FOR JOINT ROUTE AND DEPARTURE TIME SWITCHING MODEL

Within-day Variances	
Departure Time Switching $E[d_t^2]$	$\sigma_1^2 + \sigma_2^2 + \sigma_3^2$
Pre-trip Route Switching $E[r_{1t}^2]$	$\sigma_1^2 + \sigma_2^2 + \sigma_4^2$
En-route Switching $E[r_{2t}^2]$	$\sigma_1^2 + \sigma_2^2 + \sigma_5^2$
Within-Day Covariances	
Dep. Time and Pre-trip Route Switching $E[d_t,r_{1t}] = s_1$	$\sigma_1^2 + \sigma_2^2 + \rho_2\sigma_3\sigma_4$
Dep. Time and En-route Switching $E[d_t,r_{2t}] = s_2$	$\sigma_1^2 + \sigma_2^2 + \rho_3\sigma_3\sigma_5$
Pre-trip and En-route Switching $E[r_{1t},r_{2t}] = s_3$	$\sigma_1^2 + \sigma_2^2 + \rho_4\sigma_4\sigma_5$
En-route Switching at different locations $E[r_{2t},r_{3t}] = s_4$	[illegible]

The results also signify the presence of unobserved variability across decision dimensions (Table 7.8). For example, the standard deviation associated with departure time switching errors (ε_{ij}, j=1) is about 0.0005. A higher unobserved variability (standard deviation of 0.42) is associated with pre-trip route switching, and a standard deviation of 0.02 is estimated for en-route switching decisions. The greater unobserved variation in pre-trip route switching may be attributed to the differences in definition of pre-trip and en-route switching. The mild yet significant correlation between route and departure switching dimensions (reflected through correlation coefficients ρ_1, ρ_2, ρ_3) highlight the interdependence between the choice dimensions, particularly at the unobserved level. These findings confirm the need to model the

two decision dimensions jointly. Route switching decisions at different locations on a given day are also correlated. Pre-trip route switches are positively correlated with en-route switches, whereas, en-route switches at different decision locations are negatively correlated.

Because of the components of variance structure used in the specification, this negative correlation implies that the covariance between pre-trip and en-route switching utilities on a given day is larger than the covariance between en-route switching utilities on a given day. This is consistent with the higher variability associated with pre-trip switches, noted earlier. To summarize, the switching behavior in the presence of information reveals the presence of considerable unobserved variability. The error terms appear to be correlated within-day, day-to-day, and across decision dimensions.

TABLE 7.7

LAG-DEPENDENT DAY-TO-DAY COVARIANCE STRUCTURE FOR JOINT ROUTE AND DEPARTURE TIME SWITCHING MODEL

Day-to-day Covariances (Same Choice location)	
Departure Time Switching t, t' $E[d_t, d_{t'}] = s_5$, if $\|t-t'\| = 1$	$\sigma_1^2 + \sigma_3^2 + \rho_1^{t-t'}\sigma_2^2$
Pre-trip Route Switching t, t', $E[r_{1t}, r_{1t'}] = s_6$, if $\|t-t'\| = 1$	$\sigma_1^2 + \sigma_4^2 + \rho_1^{t-t'}\sigma_2^2$
En-route Switching t, t', $E[r_{2t}, r_{2t'}] = s_7$, if $\|t-t'\| = 1$	$\sigma_1^2 + \sigma_5^2 + \rho_1^{t-t'}\sigma_2^2$
Day-to-day Covariances (Different Choice locations)	
Dep. Time and Pre-trip Route Switching $E[d_t, r_{1t'}] = s_8$, if $\|t-t'\| = 1$	$\sigma_1^2 + \rho_2\sigma_3\sigma_4 + \rho_1^{t-t'}\sigma_2^2$
Dep. Time and En-route Switching $E[d_t, r_{2t'}] = s_9$, if $\|t-t'\| = 1$	$\sigma_1^2 + \rho_3\sigma_3\sigma_5 + \rho_1^{t-t'}\sigma_2^2$
Pre-trip and En-route Switching $E[r_{1t}, r_{2t'}] = s_{10}$, if $\|t-t'\| = 1$	$\sigma_1^2 + \rho_4\sigma_4\sigma_5 + \rho_1^{t-t'}\sigma_2^2$
En-route Switching at different locations $E[r_{2t}, r_{3t'}] = s_{11}$, if $\|t-t'\| = 1$	$\sigma_1^2 + \rho_5\sigma_5^2 + \rho_1^{t-t'}\sigma_2^2$

TABLE 7.8

COVARIANCE STRUCTURE PARAMETERS IN JOINT ROUTE AND DEPARTURE TIME SWITCHING MODEL

Variance Covariance Parameters	Coefficient	t-stat
σ_1 (standard deviation across individuals)	0.7083	6.33
σ_2 (standard deviation across days for individuals)	0.4006	7.08
ρ_1 (correlation across choices over different days)	-0.0001	-4.31
σ_3 (standard deviation across departure time choices)	0.0005	9.81
σ_4 (standard deviation across pre-trip route switching decisions)	0.4189	6.78
σ_5 (standard deviation across en-route switching decisions)	0.0168	5.65
ρ_2 (correlation between dep. time switching and pre-trip route switching decisions)	0.0496	7.51
ρ_3 (correlation between dep. time switching and en-route switching decisions)	0.0981	5.84
ρ_4 (correlation between pre-trip and en-route switching decisions)	0.0265	7.10
ρ_5 (correlation between en-route switching decisions across different en-route decision nodes)	-0.0456	-8.71

7.4.6 Habit Persistence

Using the specification outlined earlier, habit persistence effects in switching are investigated. Habit persistence effects are observed in both route and departure time switching behavior. The lagged exogenous effects in route switching indicate persistence in the influence of previous days early and late schedule delays. The cumulative proportion of departure time switches to earlier and later departure times in the past are also significant determinants of current route switching. Users also appear to respond differently to varying feedback supplied by ATIS. For instance, increased route switching is observed, when users are supplied with feedback on the recommended or best paths on the preceding two days, and a modest decline is found when this information is supplied three days prior to the current choice. These results hint at the existence of learning and adjustment processes in route choice behavior in response to information and feedback supplied by ATIS.

Evidence of habit persistence is also observed in the context of departure time switching. The lagged variables of interest include the effect of cumulative proportion of departure time switches on both sides in the past, and trip time variability. In addition to these, it appears that persistent effects are also associated with ATIS information type. Following the provision of inaccurate or partial information (random / differential prevailing) on the previous day, an increase in departure time switching rate was noted previously. However, when this information is provided for the past three days, a decrease in departure time switching propensity is observed, suggesting that users moderate their reaction (at least in terms of departure time switching) to inaccurate information over time.

7.5 SUMMARY

This chapter investigates various structural effects in commuter behavior dynamics in the presence of real-time information. The analysis of route and departure time switching indicates the presence of heterogeneity, habit persistence, and state dependence in user behavior. The errors arising from the non-inclusion and mis-specification of these effects are likely to have serious consequences from econometric, behavioral and application perspectives. Besides, the incorporation of these structural effects results in a considerably improved model fit with observed data. In contrast to the models in Chapter 5, where route and departure time switching decisions were modeled separately using data from the first set of experiments, this analysis models the two decisions jointly, using data from the second set of interactive experiments,

The empirical results presented here confirm earlier findings (in Chapter 5 using a different data set) regarding the influence of level-of-service (LOS) measures on alternative facilities and users past experience on switching behavior. It is also found that the nature, timeliness, and extent of ATIS (represented by the information strategy variables), as also its information quality are strong determinants of route and departure time switching behavior. Incidentally, these factors were also strong determinants of compliance behavior examined in Chapter 6.

The differences across users are noted in preferences towards switching and sensitivity to various attributes of the alternatives including time-dependent network performance measures and

information quality. The empirical results also substantiate the presence of considerable unobserved heterogeneity in user behavior from day-to-day, across decision nodes, and in different choice dimensions. In addition to these heterogeneity effects, state-dependence effects also play a significant role in influencing switching decisions. It is observed that users past switching decisions influence current switching decisions. However, the time frame of influence varies considerably between departure time and route switching decisions. In the case of departure time switching the switching decisions on the past three days significantly affect current switching decision. The nature of influence of past route switching is of a shorter duration, with only the switching decision on the past day significantly influencing current day's choices, especially pre-trip route switching decisions. Past en-route switches on the same day have a relatively small effect on current en-route switching decisions. The data also suggests the presence of lagged effects in both route and departure time switching behaviors.

The previous chapters investigated the major factors influencing commuter's choice behavior over time in the presence of information by examining the dimensions of route switching, departure time switching, and compliance. These analyses indicate that compliance and switching are important dimensions of behavioral response to information. A variety of other processes and mechanisms may be used by trip-makers in selecting routes and departure times. The following chapters explore and examine the cognitive processes and mechanisms underlying the observed choice dynamics. The next chapter specifically examines salient cognitive processes underlying these dynamic behavioral mechanisms, namely, learning, judgment, perception, and updating.

CHAPTER 8: DYNAMIC COGNITIVE AND DECISION PROCESSES IN COMMUTER BEHAVIOR UNDER INFORMATION

8.1 INTRODUCTION

In the previous chapters a framework is presented for modeling structural effects in commuter behavior under information (namely, route and departure time switching and compliance). In contrast to the last three chapters, where the focus was on modeling observed commuter behavior, the present chapter focuses on the latent cognitive and decision processes underlying this observed behavior.

Commuter behavior (route and departure time choices) in the presence of real-time information can be characterized as a real-time dynamic process in the sense of Edwards (1962) and Brehmer (1992). This characterization implies that a commuter responds adaptively in a dynamic environment, and the environment in turn changes due to the real-time decisions of all decision-makers, thus, producing a complex adaptive system. Studies in psychology reveal that such dynamic adaptive decision processes are often accompanied by a set of complex cognitive processes (Helson, 1964; Payne, 1967; Slovic et al., 1977). These cognitive processes accompanying behavior include the following stages: 1) collecting information about the environment, 2) identifying stimuli and establishing a stimulus-response linkage 3) identifying desirable and undesirable responses to stimuli based on the consequence of one's actions, and, 4) adaptive response processes and behaviors to changes in the environment (Einhorn and Hogarth, 1981; Klein et al., 1993).

In the information gathering and interpretation phase, evidence of learning processes in commuter behavior dynamics are examined and the role of perception and attitudes investigated. The linkage between stimulus and response is likely to be established by a comparison of the ATIS information with personal experience. Therefore, judgment models of ATIS information are critical for gauging user-responses to environmental stimuli in the transportation system and users' perception and learning about the environment (Einhorn and Hogarth, 1981; Mahmassani and Chen, 1991). Judgment models are presented here that relate perceived information quality (of ATIS) with experienced trip characteristics.

Based on information about the environment and ATIS information, trip-makers are likely to adapt and respond to changing traffic conditions (Payne et al., 1988; Howell and Cooke, 1989; Edland and Svenson, 1993). Two possible modes of adaptive response are considered here. The first is the updating process, which refers to the refinement/modification that a trip-maker makes to the underlying mechanism(s) and processes associating response to stimuli. This refinement is likely based on a cognitive combination of current and past experiences with ATIS information (Figure 8.1). The updating process influences several key entities affecting the choice processes,
including perceived quality of information, nature of expectations regarding existing and future traffic conditions, etc. Thus updating may be based on additional/external information about the ATIS, disconfirmation with personal experiences over time, information regarding within-day and day-to-day

changes in traffic patterns (both scheduled - e.g., football games or unscheduled - e.g., incident-related capacity reduction).

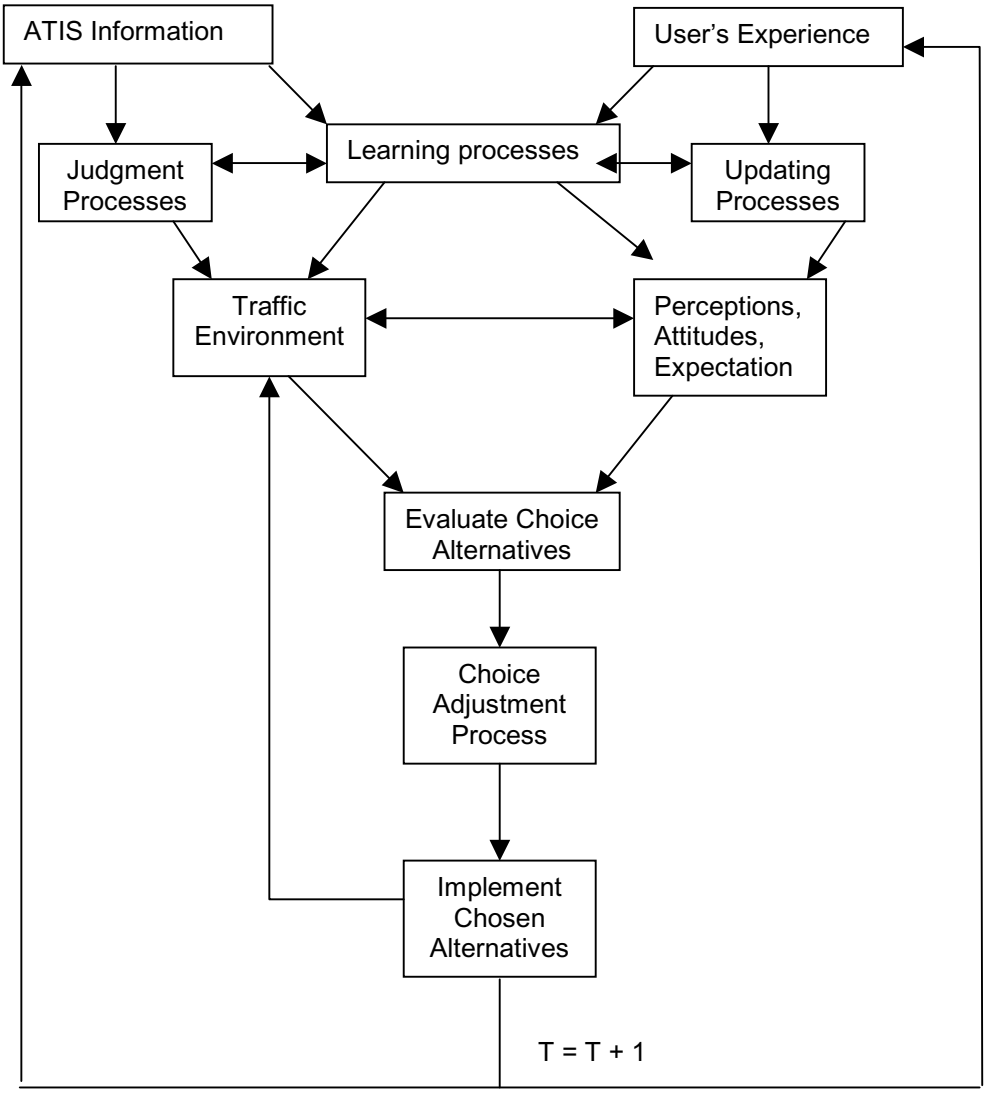

FIGURE 8.1

Overview of cognitive and decision processes in user behavior dynamics under real-time information.

The second manifestation of adaptive response is through the actual adjustment of trip-choices over time. The actual adjustment may occur as a response to dissatisfaction with current choice outcomes, or awareness of alternative opportunities that may be more desirable, or more efficient. This form of adaptive response is particularly critical for travel demand management, and the design of operational and strategic planning policies. This adjustment process implicitly introduces the notion of

satisfaction with the current choice. Accordingly, a trip-maker evaluates the suitability of the current/default choice for the next travel occasion. If found satisfactory, the current choice is retained. If on the other hand, the current choice is unsatisfactory in meeting desired user objectives (such as arrival at work on time), the user then adjusts his/her choices (departure time and route for instance). This review of current choice may be prompted by additional information, change in objectives/needs, knowledge of changes in environment, etc. Though updating and adjustment processes are inter-related, the distinction between the two can be best understood in terms of a cause and effect relationship. The former refers to modifications that a user makes over time to the factors and processes influencing the choice decisions, and hence precedes the actual adjustment in choices. The latter refers to the consequent changes in the choice decisions themselves. In the context of adjustment, models of route and departure time adjustment are presented in this chapter next.

The reminder of this chapter is organized as follows. The next section outlines the nature and characteristics of learning processes operating in commuter behavior, and presents related empirical evidence. In the third section, the role of users' perceptions and attitudes in dynamic behavior under ATIS are examined. Section 8.4 presents an overview of updating processes illustrated in the context of day-to-day updating of expected arrival time by trip-makers. Finally, the findings are summarized and future research directions proposed.

8.2 LEARNING PROCESSES IN COMMUTER BEHAVIOR

First, recent research on learning processes in traveler behavior is reviewed. Few efforts have focused on representing and modeling learning processes, particularly in trip-maker behavior. Among the few works in this area, a majority implicitly assume that learning occurs, perhaps basing their assumption on studies reported empirically in psychology and other decision fields (see for example, Bush and Mosteller, 1970; Howell and Cook, 1989; Payne et al., 1988). It has been assumed that learning primarily affects travel time predictions of users. Furthermore, it is also assumed that the learning process is largely influenced by factors including the discrepancy between reported travel times and past experience, update frequency of information, and diminishing influence of past experience with the passage of time (Iida et al., 1992; Koutsopoulos and Xu, 1993; Zhao et al., 1996; Liu and Mahmassani, 1998). A majority of researchers impose convenient a-priori assumptions including ones that suggest that learning occurs in a form consistent with an auto-regressive (exponential smoothing form) model structure. Such assumptions have rarely been operationalized (exceptions include Vaughn et al., 1995; and Mahmassani and Chang, 1986), let alone tested empirically, often due to data collection difficulties (Horowitz, 1984; Ben-Akiva et al., 1985; Hazelton and Polak, 1997; Jha et al., 1998).

The assumptions and limitations of extant literature in this area illustrate the need to address the following fundamental research issues relating to learning processes in the presence of real-time information. Do trip-makers learn from and about the traffic environment and from what sources? It is also essential to understand what aspects of the environment and behavior do trip-makers learn about, in order to address how learning affects choice decisions. Identifying various types (for example, as

characterized in cognitive psychology literature) of learning processes influencing user behavior. This will enable the design and development of effective information strategies (ATIS products and services). Insights into the nature of the learning process can assist data collection and experimental design efforts to further investigate learning processes in user behavior. The outcome of learning and the influence of learning processes on user choice dynamics are also relevant to travel demand management. Learning may promote users' awareness and propensity to choose more efficient alternatives, aid in achieving desired travel patterns, and lead to an improved awareness and knowledge of traffic patterns in the system. An outcome of the learning process, that is of interest, is users' assessment of the quality of ATIS information, particularly its accuracy and reliability. Modeling users' assessment of information quality has important implications for understanding how users' combine information with experience to adjust travel patterns.

Each of these issues is examined, by reviewing empirical evidence from experiments described previously and related research efforts. However, since these experiments were primarily designed to investigate choice behavior and not the cognitive processes underlying the choices, the reported evidence is, indirect and only provides preliminary insights into cognitive processes. However, direct measurements of cognitive processes could suffer from reporting and affirmation biases. An advantage of using the simulator-based data in this study is that the data are not contaminated by reporting biases as the choice behavior is observed and not merely reported. Nevertheless, it is essential to confirm these with independent evidence from other real-world data sources.

There is considerable evidence in the empirical travel behavior literature that is consistent with the notion that trip-makers learn about the traffic environment (both within-day and day-to-day). Examples of learning behavior include the effect of ATIS information and the effect of users' past traffic experience on trip-maker behavior. For example, it has been repeatedly observed that trip-makers tend to avoid departure times/routes that result in schedule delay or congestion induced delays (Cosslet, 1977; Small, 1982; Hendrickson and Plank, 1984). These findings clearly indicate that users do indeed learn about the traffic environment, from various sources including personal experience. Recent literature also suggests that trip-makers also learn about traffic through ATIS devices (Chang et al., 1988; Bonsall and Parry, 1991; Vaughn et al., 1995). In addition, trip-makers could also learn about the environment through direct observation of traffic, road and weather conditions, past traffic experience, experiences of other system users, and ATIS information (pre-trip, and en-route). In the absence of information regarding these other sources of learning, attention is restricted here to the role of information and users' personal experiences in learning processes.

It may be argued that the observed influence of ATIS on user behavior is not necessarily indicative of learning, but could be based instead on forming expectations regarding traffic conditions under the assumption that information is perfect. In other words, it may be possible that users do not necessarily learn about traffic conditions but merely follow the information reported by the ATIS. Contrary to this notion, it has been empirically observed that users adjust their behavior in response to the quality

of information (often judged in relation to their experience). This evidence supports the hypothesis that users learn about ATIS and the traffic environment in an iterative fashion through a mutual confirmation/disconfirmation process. Furthermore, it would be almost impossible to account for the considerable variability observed in commuters' route and departure time choices if commuters do not learn about their traffic environment over time (Hatcher and Mahmassani, 1992).

It is conceivable that some trip contexts are more conducive for the occurrence of learning processes than others. Since learning can be viewed as a mutual disconfirmation process between information and experience, it may be expected that users learn from trips repeated over a significant period of time. The presence of arrival time constraints, repetitive nature, and the fixed O-D character of the home-to-work commuting trips facilitates learning in the commuting trip. In contrast, the non-commuting trip is less suited because it is irregular and non-repetitive in nature, particularly, given the variable nature of destinations and departure times associated with such trips. Learning may also be motivated by the presence of unacceptably severe time or cost penalties (e.g. event related parking/ rerouting). In the absence of such time or cost constraints, the occurrence of learning processes in choice behavior may be reduced. The absence of trip-alternatives in the choice set is also likely to inhibit or eliminate learning effects.

8.2.1 Types of Learning

Empirical psychology literature (Kahnemann, 1973; Slovic et al., 1977; Howell and Cooke, 1989; Kirasic, 1991) categorizes and characterizes various types of learning as: stimulus-response reflex, conditional stimulus-response reaction, instrumental learning (induced by a reward or incentive), extinction of negative response, trial and error learning, and discriminative learning (learning about desirable and undesirable responses based on consequence). The first three are simple evolutionary mechanisms suited for modeling learning in the presence of few stimuli in relatively static environments. However, as the traffic environment is dynamic and complex in terms of the number of stimuli encountered by trip-makers. Hence the first three types are not suitable in the environment being considered here. Among the remaining three, negative response extinction is subsumed under discriminative learning. Discriminative learning may be described as the positive reinforcement of desirable behaviors and the negative reinforcement of undesirable ones. In trial and error learning (as is evident from its name), a user learns through successive steps of trial and error about the nature of environment and consequences of his/her actions. In the absence of relevant external information, a user may obtain information about the environment, through a process that can be approximated by a trial and error process. Empirical evidence regarding these two types of learning in trip-maker choice behavior is presented next.

In the context of discriminative learning, the following related threads are examined. First, evidence of positive reinforcement behaviors is considered. The larger choice propensities associated with more desirable outcomes are consistent with positive discriminative learning. An example of such behavior is the greater propensity to retain the current path (noted in switching results presented in

Sections 5.4.2, and 7.4.1), if it also happens to be the best path (Table 8.1). Support for positive reinforcement learning is also observed in the increased compliance propensity with better information quality (based on results presented in Section 6.3). Trip-makers are more likely to comply with more accurate and reliable information (Table 8.2).

A second possible outcome of discriminative learning is the negative reinforcement of undesirable behaviors. There is considerable empirical evidence consistent with the avoidance of alternatives leading to undesirable trip outcomes. For instance, it was shown in Section 5.3.2 that commuters are likely to switch departure times to avoid early and late schedule delays (Table 8.3). Trip-makers are more likely to switch routes in response to experienced or anticipated congestion. This can be inferred from the positive coefficient of anticipated congestion in route switching models calibrated in Sections 5.4 and 7.4 (Table 8.4).

Another instance of negative reinforcement is observed in the path choice model developed using the data from the second set of experiments (where information strategies were varied as part of experimental design). Users exhibited a greater disutility for the trip-time on a particular highway facility relative to others. The disutility of trip-time on highway 1 (HWY 1) is about 100 times larger than that of other highways when highway 1 was particularly congested. There was also a negative bias against highway one (HWY 1) (corresponding ASC coefficient is negative) relative to the other highways (Table 8.5). Negative discrimination learning is also found in the disutility associated with partial/imperfect ATIS information, noted in Chapter Six.

A substantially lower compliance rate is noted under random information. Compliance is also reduced, but to a smaller extent, when the ATIS supplies perturbed and differential information (Table 8.6). The tendency of users to learn about positive and negative outcomes is common to both trial and error learning and discriminative learning. The difference between the two, however, stems from the relative weight placed on personal experience in the two processes. While personal experience plays a greater, perhaps even a predominant role in trial and error learning, discriminative learning is likely to be based on information and experience.

In order to identify empirical support for the presence of trial and error learning, attention is paid to those information strategies with partial or erroneous information (where information was supplied only on a subset of available routes). Under these information strategies, a user learns about the environment and the quality of ATIS information primarily through personal experience. The following aspects of trip-maker behavior, observed under differential and inaccurate information strategies, are consistent with the presence of trial and error learning. The choice process in experiment two reveals a significant over-reaction on the part of users without reliable information and is consistent with a trial and error learning process.

TABLE 8.1

POSITIVE DISCRIMINATION LEARNING – THE ROLE OF INERTIA IN SWITCHING AND COMPLIANCE DECISIONS

Choice Variable Modeled	Route Switching		Compliance	
Data Set	coefficient	t-stat	coefficient	t-stat
Expt 1 – Random treatment	-1.11	-4.7	2.25	9.46
Expt 1 – Sequential treatment	-1.21	-6.64	2.98	16.42
Expt 2 – Information Quality	-2.41	-32.15	2.27	28.61

Note: variable reported is inert, a binary indicator variable =1, if current path = best path. The coefficients are calibrated on separate models and are not of the same scale.

TABLE 8.2

ROLE OF ACCURACY AND RELIABILITY ON COMPLIANCE DECISIONS AS EVIDENCE OF POSITIVE DISCRIMINATION LEARNING

Variable	Coefficient	t-stats
Relative overestimation error (%)	-0.27	-3.56
Accuracy (% deviation from predicted)	-0.69	-4.37
Reliability (30%)	0.1	3.72

Note: The coefficients reported here are from the data from information strategies experiment.

TABLE 8.3

EVIDENCE OF NEGATIVE DISCRIMINATION LEARNING IN DEPARTURE-TIME SWITCHING DECISIONS – THE EFFECT OF EARLY AND LATE SCHEDULE DELAY AND EXPERIENCED CONGESTION

Data Set	Random		Sequential		Information Strategy	
	Treatment		Treatment		Experiment	
Variable Description	coefficient	t-stat	coefficient	t-stat	coefficient	t-stat
Early schedule delay	0.134	1.43	0.145	3.47	0.028	3.63
Late schedule delay	0.155	1.67	0.014	1.01	-0.003	-1.09
Stuck in traffic on the previous day	1.43	1.67	0.428	1.01	0.62	3.49

TABLE 8.4

EVIDENCE OF NEGATIVE DISCRIMINATION LEARNING IN ROUTE SWITCHING BEHAVIOR

Data Set	Random Treatment		Sequential Treatment		Information Strategy Experiment	
Variable Description	coefficient	t-stat	coefficient	t-stat	coefficient	t-stat
Anticipated congestion downstream	0.65	5.98	0.1	0.78	0.6	6.72
Experienced congestion upstream	-0.084	-0.27	-0.4	-1.38	0.34	1.97

TABLE 8.5

EVIDENCE OF NEGATIVE REINFORCEMENT LEARNING AGAINST SELECTING HIGHWAY 1 (FROM ESTIMATED PTH CHOICE MODEL)

Variable Definition	coefficient	t-stat
Highway 1 (Alternative Specific Const)	-0.72	-1.86
Trip Time on Highway 1	-0.034	-4.72
Trip Time on Highway 2	-0.000191	-0.72
Trip Time on Highway 3	-0.00076	-2.68

Note - The results here correspond to data from ATIS information strategy experiments. Similar results were also observed in network loading experiments but are not reported here.

TABLE 8.6

NEGATIVE REINFORCEMENT EFFECTS OBSERVED IN COMPLIANCE MODEL

Information Strategy	coefficient	t-stat
Random	-0.29	-1.70
Differential Prevailing	-0.27	-2.16
Differential Predicted	*-0.16*	*-1.21*
Predicted Perturbed	*-0.16*	*-1.06*

Italicized coefficients are insignificant at 15% level.

TABLE 8.7a

EVIDENCE OF TRIAL AND ERROR LEARNING—THE EFFECT OF ATIS INFORMATION TYPE ON ROUTE SWITCHING

User State on Previous Link	P(Switching)
Complete Information	0.44
Random	0.65
Differential	0.6
Prescriptive	0.58

TABLE 8.7b

EVIDENCE OF TRIAL AND ERROR LEARNING—THE EFFECT OF BEING STUCK IN TRAFFIC ON ROUTE SWITCHING

User State on Previous Link	P(Switching)	P(Not Switching)
Stuck	0.56	0.44
Not Stuck	0.31	0.69

A preliminary examination of aggregate switching proportions, based on data from experiment two, indicates that the switching reaction to unfavorable experiences (such as being stuck in traffic on the previous segment) is the strongest in the random case, followed by partial information, and is the least when full information is provided (Table 8.7a). Using the same data, it is found that the route switching propensity increases immediately following an episode of being stuck on the previous highway segment (than when he/she is not). This may also be indicative of trial and error behavior aimed at avoiding negative experiences (Table 8.7b).

Evidence of trial and error learning is also found in departure time adjustment. It is observed that about 87% of departure time adjustments are in five minute increments from the previously chosen departure time. Nearly 70% of the adjustments chosen, fall within five minutes from the current departure time. This suggests a trial and error approach to selecting departure times with the current departure time being retained, if acceptable. Otherwise a minor adjustment of less than five minutes is often made from the previous day's departure time, and the process is repeated from day-to-day.

In the absence of direct measurements of learning, the evidence cited above is mainly indirect in nature. But the disparate pieces of evidence collectively support the presence of both discriminative and trial and error learning processes in user behavior dynamics and warrant a more thorough investigation of the learning processes.

8.2.2 Characteristics of Learning Processes

Several interesting features and characteristics of learning have been recognized and explored in other empirical learning contexts (Einhorn and Hogarth; 1981; Klein et al., 1993). These pertain to the role

of memory, attention, motivation, and readiness. The possible influence of these factors on trip-maker behavior dynamics are examined next.

8.2.2.1 Role of Memory. Evidence suggests that user behavior is influenced not by an objective memory of events, but by a subjective memory (Chang and Mahmassani, 1988; Mahmassani and Liu, 1997). In other words, users' memories of past events are asymmetric, with events with bad consequences for users being selectively retained for a longer duration. Examples of these have been reported by Chang and Mahmassani (1988) and Mahmassani and Liu (1996). In addition, the recency and frequency of events experienced also strongly influence learning. More recent events are weighted heavily in the choice process than events that occurred in the distant past. The effect of recent adverse experience and poor information quality on route switching, obtained by including additional explanatory variables in the model presented in Section 7.2, is reported in Table 8.8. This may be explained by the tendency of individuals to forget usual (regular) events, particularly those that occurred in the distant past.

TABLE 8.8

EVIDENCE OF HIGHER PREFERENTIAL WEIGHTS OF RECENT EVENTS ON ROUTE SWITCHING BEHAVIOR

Variable	Coefficient	t-stat
Stuck on previous link (binary)	0.53	2.87
Stuck on 2nd last link (binary)	*0.19*	*1.24*
Stuck on 3rd last link (binary)	-0.42	-2.19
Underestimation error on previous link (binary)	*0.016*	*0.97*
Underestimation error on 2nd last link (binary)	*-0.001*	*-0.13*
Underestimation error on 3rd last link (binary)	*-0.006*	*-0.54*
Overestimation error on previous link (binary)	0.126	3.43
Overestimation error on 2nd last link (binary)	-0.039	-1.55
Overestimation error on 3rd last link (binary)	-0.042	-1.52

Italicized coefficients are insignificant at 15% level.

Analogously, frequent events are weighted more heavily in the choice process than less frequent events (Table 8.9). For instance, it is observed, in data from experiment two, that trip-makers adjust their departure-time, route choices, and compliance decisions, based on the cumulative proportion of departure time switches on the early and late sides. This variable instruments the cumulative number of unacceptably late/early delays, and represents a Polya stochastic process.

8.2.2.2 Role of Attentional and Motivational Factors. Attentional and motivational factors assume significance in the light of numerous stimuli and informational cues encountered by users in the complex traffic environment. Given the cognitive processing limitations of trip-makers while driving, attentional and motivational factors enable the user to learn selectively from the diverse informational elements in the environment. They also assist a user in organizing and prioritizing these selected elements to functionally support decision-making. Conventional cognitive learning literature suggests that attentional and

motivational factors play an important role in learning, particularly in complex decision-making environments (Kahnemann, 1973; Beach and Lipshitz, 1993;Cohen,1993).

In this regard, two relevant questions arise. First, do users selectively pay attention only to a subset of stimuli? Second, are differential priorities accorded to different information elements in the choice processes? These questions are of critical importance for the design of ATIS services and for prediction of user behavior. This part of the analysis investigates whether users pay differential attention to the following information elements/cues provided by the ATIS: trip-time, congestion, feedback, and schedule delay (experienced, anticipated). To analyze whether users' accord different priorities to various information elements, the magnitude of corresponding coefficients in the utility of compliance are compared. The compliance model (calibrated in Section 6.3) reveals that trip-time and visual congestion information have the highest utility coefficients (Table 8.10). However, the magnitudes of coefficients are not necessarily a conclusive means of establishing different priorities across information elements, since the associated attributes are not commeasurable to the same scale).

TABLE 8.9

EVIDENCE OF HIGHER PREFERENTIAL WEIGHTS OF FREQUENT EVENTS IN ROUTE SWITCHING BEHAVIOR

Variable	Coefficient	t-stat
Route Switching Model		
Proportion of switches to later departure times	-0.22	-1.71
Proportion of switches to earlier departure times	0.27	1.83
Departure Time Switching Model		
Proportion of switches to later departure times	2.23	3.65
Proportion of switches to earlier departure times	1.50	3.52
Compliance Model		
Proportion of switches to later departure times	-0.27	-1.78
Proportion of switches to earlier departure times	*-0.18*	*-1.37*

TABLE 8.10

ROLE OF ATTENTIONAL FACTORS IN ROUTE SWITCHING—DIFFERENTIAL WEIGHTING OF ALTERNATIVE INFORMATION ELEMENTS PROVIDED BY ATIS

Variable	Coefficient	t-stat
Trip time saving (difference in trip time between best and current paths)	1.94	7.57
Congestion downstream	0.69	7.94
Feedback on recommended path	0.18	2.11
Feedback on best path	0.39	4.73
Potential early schedule delay on current path	-0.086	-1.65
Potential late schedule delay on current path	-0.0184	-3.19

Note: The specification for early and late schedule delays are for en-route decisions

To account for this difficulty, the corresponding aggregate elasticities are computed to determine the relative effect of different information elements on the utility of compliance. The aggregate elasticity is obtained by computing the change in the utility corresponding in a change in the value of informational element from its mean/median value. Therefore the ratio of ΔU_k / U is computed, where ΔU_k the change in the utility of compliance corresponding to a 10% change in the kth explanatory variable. The utility (U) of compliance is obtained by setting all explanatory variables at their median (mean) value for discrete (continuous) variables. The normalized relative weights - (ΔU_k / U), of informational elements are found to be in the following descending order: visual congestion, trip-time, feedback and schedule delay (Table 8.11). This ordering of informational elements is consistent with increasing cognitive burden, in terms of amount of information, ease of access, and computation involved, in processing these information elements. The relative weights of information elements may be attributed to differential sensitivity/attitudes of users' towards the informational elements. These findings illustrate the significance of attentional factors in trip-maker behavior, especially under real-time information.

Motivational influence, as represented by a disruption of the current state, is a significant influence on users switching and compliance behavior. The duration in the current state has a significant effect on the utility of switching and a positive effect on compliance decisions. For instance, following a disruption in the current state in the route switching, the likelihood of continuing in the immediately preceding state is diminished (Table 8.12). A greater duration in the state of compliance is likely to increase the propensity to comply. This variable is reset to zero following a state change, thus representing a renewal process.

8.2.2.3 Heterogeneity in Learning. As with the choice process, it is also reasonable to expect variation in the learning process across individuals. Possible sources of variation include differences in socio-demographic characteristics, attitudes towards risk, familiarity and awareness of the network, experienced traffic conditions (depending on past choices), and the availability of opportunities for learning.

Differences may also be expected in the time taken to perceive, process, and react to information among the various user segments. For instance, older respondents may be slower in acquiring and processing information (Evans et al., 1984; Kirasic, 1991; Lipman, 1991). As a consequence it is possible that they rely more on experience than information. While several sources of heterogeneity may be modeled, attention is limited here to the following two types of heterogeneity.

First, the differences in perception/response times in en-route choices are examined, with particular attention to the effect of age and gender differences on the response time (Table 8.13). Response times of users in the second experiment are regressed with relevant explanatory variables that reflect socio-demographic characteristics. The linear regression model in Table 8.13 indicates significant age and gender differences in response times. It is observed that younger females are the quickest to respond, while older males are the slowest. Younger males and older females have nearly equal response times. The results also indicate that the variability unexplained by these socio-demographic characteristics and other experimental factors is quite substantial. In fact, this model only accounts for nearly six percent of the observed variability in response times, further suggesting the presence of unaccounted heterogeneity effects.

Next, differences in observed route switching behavior in experiment two (among various user groups), are revisited to explore possible differences in learning underlying the choices. Younger respondents, notably young males, are more sensitive to information on trip-time saving than other segments (Table 8.14). The observed differences may be attributed to differences in elasticity or variations in the perception of traffic conditions. Younger respondents are also more sensitive to the type of ATIS information than older respondents, particularly to random and perturbed information. Older respondents tend to weight past experience more than younger respondents, as reflected in the larger coefficients of schedule delay and inertial variables.

Empirical evidence presented in this section indicates that learning occurs in trip-maker decision processes based on ATIS information and experience. However, the evidence presented here is indirect and alternative explanations may be advanced to account for the observed findings. Therefore, more systematic investigations into learning processes are essential for unraveling the relationship between learning and choice processes in user behavior.

TABLE 8.11

ROLE OF ATTENTIONAL FACTORS IN ROUTE SWITCHING—NORMALIZED RELATIVE WEIGHTS OF ALTERNATIVE INFORMATION ELEMENTS

	Descriptive Prevailing Current path is distinct from Best Path			Descriptive Prevailing Current path = best path		
Information Element	No feedback	Recommended	Best path	No feedback	Recommended	Best path
Congestion on current path	0.2	0.25	0.35	0.08	0.09	0.09
Relative Trip Time Savings	0.18	0.23	0.32	0.07	0.08	0.08
Potential Late Schedule Delay	-0.09	-0.11	-0.11	-0.04	-0.04	-0.04
Congestion on best path	-0.08	-0.1	-0.1	-0.04	-0.04	-0.04
Early Schedule Delay (previous day)	-0.07	-0.09	-0.12	-0.03	-0.03	-0.03
Late Schedule Delay (previous day)	0.04	0.05	0.07	0.02	0.02	0.02
Information Underestimation Error	0.04	0.05	0.07	0.02	0.02	0.02
Information Overestimation Error	0.02	0.03	0.04	0.01	0.01	0.01
Recommended Underestimation	0	-0.13	0	0	-0.05	0
Recommended Overestimation	0	0.01	0	0	0	0
Discrepancy from Best Feedback Path	0	0	-0.05	0	0	-0.01

TABLE 8.12

EVIDENCE OF MOTIVATIONAL ASPECTS IN CHOICE BEHAVIOR UNDER INFORMATION—THE INFLUENCE OF STATE DEPENDENCE

Data Set	Route Switching		Dep. time Switching		Compliance	
	coefficient	t-stat	coefficient	t-stat	coefficient	t-stat
Expt 1 - Random treatment						
Duration in state 0 (not switch or not comply)	-0.18	-3.14	*0.00*	*0.00*	-0.09	-0.91
Duration in state 1(switch or comply)	-0.14	-0.82	*-0.08*	*-0.96*	0.11	2.15
Expt 1 - Sequential treatment						
Duration in state 0 (not switch or not comply)	-0.07	-2.65	-0.31	-2.76	-0.09	-1.85
Duration in state 1(switch or comply)	-0.07	-0.56	0.22	1.59	0.08	2.60
Expt 2- Information Quality						
Duration in state 0 (not switch or not comply)	-0.10	-8.31	-0.30	-7.08	-0.22	-19.44
Duration in state 1(switch or comply)	-0.13	-3.18	-0.02	-0.26	0.30	20.36

TABLE 8.13

LINEAR REGRESSION MODEL OF RESPONSE TIMES FOR ROUTE CHOICE DECISIONS—INFLUENCE OF EXPERIENCE, HETEROGENEITY AND INFORMATION STRATEGY

Variable	Coefficient	Std.Error	t-stat
Intercept	1.766	0.071	24.74
Socio-Demographics			
OM	0.005	0.038	0.13
OF	0.073	0.034	2.14
YM	0.122	0.047	2.57
Information Strategy			
Prescriptive	0.040	0.029	1.35
Predicted	-0.033	0.030	-1.12
Differential (predicted)	0.035	0.046	0.76
Perturbed (predicted)	0.010	0.053	0.19
Random	0.165	0.051	3.20
Feedback (reco path)	0.087	0.035	2.48
Feedback (best path)	0.063	0.033	1.93
Experience			
Early sched. delay	-0.005	0.002	-3.36
Late schedule delay	0.003	0.002	1.78
Proportion of later dep. time switches	0.005	0.059	0.08
Proportion of earlier dep. time switches	0.181	0.052	3.48
Triptime	-0.003	0.002	-1.80
Time Effects			
Day	-0.016	0.004	-3.67

Summary Statistics	
Sample Size	1364
R^2	0.06
df model	17
df error	1346
p value for the H0: $\beta = 0$ for all variables	0.0001

TABLE 8.14

SYSTEMATIC HETEROGENEITY EFFECTS IN USERS ROUTE SWITCHING PROPENSITY (BASED ON MODELS CALIBRATED IN CHAPTER 7)

	Young male		Young female		Old male		Old female	
Variable	coefficient	t-stat	coefficient	t-stat	coefficient	t-stat	coefficient	t-stat
predicted perturbed information	0.71	1.59	0	-	0	-	0	-
random information type	-2.54	-3.29	0	-	-0.39	-2.22	-0.39	-2.22
Potential late schedule delay reported by ATIS								
pre-trip	0.12	1.73	0	-	0	-	0	-
en-route	0	-	-0.03	-3.58	-0.03	-3.58	0	-
Trip time saving	4.32	7.24	4.32	7.24	1.94	5.8	1.94	5.8
Information - Inertia Interaction								
= 1 if (cp = bp), 0 otherwise								
pre-trip	-1.83	-8.95	-1.83	-8.95	-2.35	-14.83	-2.35	-14.83
en-route	-2.32	-18.65	-2.72	-24.21	-2.32	-18.65	-2.72	-24.21
Experienced schedule delay								
late on previous day (for pre-trip switching)	0	-	0	-	0.06	3.02	0	-
late on previous day (en-route switching)	0	-	0	-	0.02	2.22	0	-
Proportion of switches to later departure times	0	-	-0.34	-2.12	0	-	-0.34	-2.12
Proportion of switches to earlier departure times	0	-	0.62	3.38	0	-	0.62	3.38
Facility bias								
Highway 1	0	-	0	-	0	-	0.69	3.81
Highway 2	0	-	0	-	0	-	0.18	1.77

Note '-' indicates that the variable was not significant at 20% level

8.3 ROLE OF PERCEPTION AND ATTITUDES

Besides the effect of response heterogeneity, differences in learning processes could also be caused by differences in perceptions regarding information and experience. Perceptions may vary across different users to reflect differences in: the propensity to switch, differences in attitudes/sensitivity to various explanatory variables, risk attitudes, tolerance levels for information errors and credibility, and attitudes towards information and past experience. Presenting evidence of perceptional variations in relation to trip- time, Zhao et al. (1996) report that users incorporate a margin of safety around reported trip-times. Further, they remark that the inclusion of a perception band significantly improved the explanatory power of the route choice model.

Based on related empirical work, it is postulated that perceptual and attitudinal differences influence the outcome of the choice process of users' in two stages. First, the reported ATIS information is converted to perceived information by allowing a suitable margin for error to account for information inaccuracy and uncertainty associated with traffic variations. In the second stage, users' combine the attitudes and perceived information with past experience to determine the behavioral outcome of interest. Thus, perceptual and attitudinal effects may be viewed as a cognitive filter for combining information and experience. They may be reflected in the choice processes directly through a modification of system performance variables such as reported trip-time and congestion. Perception and attitudinal factors may be manifested in the choice process, through differences in attitudes towards alternative facilities, the role of experience in trip-making decisions, and other subjective factors such as comfort, familiarity, safety, convenience, aesthetics, etc. Therefore, perceptual influences on choice may be reflected in a deviation of perceived attributes such as trip-time from the corresponding reported or measured attribute. The following four aspects regarding perception differences are considered next. First, a perception model of trip-time is proposed and calibrated based on route switching data. Next, the possible inter-relationship between response and preference heterogeneity and perception differences is examined by analyzing systematic patterns of response in various user segments to changes in independent variables across various user segments. The effect of attitudinal variables on route and departure-time switching intentions are analyzed by a confirmatory factor analysis on stated attitudes. Finally, the influence of stated attitudes is modeled by studying the effect of attitudinal factor scores on observed switching behavior.

8.3.1 Trip-Time Perception Model

It is assumed that a users' perception of trip-time (TT^p) is based on the trip-time reported by the ATIS. The following model of perception assumes that perceived trip-time is obtained from the reported trip-times (TT^r) by adding a margin of safety (Δ) as follows:

$$TT^p = TT^r + \Delta \qquad (8.1)$$

Further, if this margin of safety is applied as a relative fraction of the reported trip-time, the following perception model arises:

$$TT^p = TT^r + \Delta^r TT^r \qquad (8.2),$$

where, Δ^r represents the margin of safety as a fraction of reported trip-time.

The relative margin of safety may vary across respondents based on their socio-demographic and experience attributes. One possible functional form for the relative margin of safety is given as follows:

$\Delta^r = \Delta_0 \exp(\gamma Z) + \varepsilon^r$ (8.3).

where, Δ_0 represents the baseline level of relative margin of safety,

γ denotes a vector of coefficients affecting perception

Z represents the vector of attributes influencing perception

ε^r represents the error term (unobservable to the analyst) influencing the perception process.

This specification can also capture unobserved variability in how trip-makers perceive trip-time. Note that Δ^r could be positive or negative. The functional form above (8.3) is more general than the corresponding linear form. While a linear-in-parameters (LIP) specification generally ensures robustness against specification errors (Horowitz, 1981), such a functional form is not identifiable. This is because it is impossible to separate out Δ_0 and γ into distinct parameters in the following LIP specification,

$U = \beta X + \beta^r (1 + \Delta_0 \gamma Z) TT^r + \varepsilon$ (8.4).

In contrast to (8.4), the specification in (8.3), the utility can be expressed as follows:

$U = \beta X + \beta^r TT^r + \beta^r \Delta_0 \exp(\gamma Z) TT^r + \varepsilon$ (8.5).

In this specification β^r, Δ_0, and γ are uniquely identifiable up to a scale factor. The perception model in equation (8.5) calibrated using route switching data, from experiment two, is displayed in Table 8.15. The results indicate that the inclusion of trip- time perception significantly improves the model fit ($\chi^2 = 100 > \chi^2_{critical} = 3.84$). The coefficient Δ_0 is about 12 % suggesting that trip-makers adjust the reported time upward by about 12% on an average (*ceteris paribus*). A lower margin of safety is applied by older females, whereas, the perception adjustment is higher in case of males, both young and old. This upward adjustment may be intended to accommodate uncertainty about information quality and traffic conditions. The model results clearly indicate a significant indicate the significance of the perception process in route switching behavior. The model specification and functional form of the perception model, though, may be refined further with richer data on perception processes.

This simple model of perception can be generalized as follows. The perception updating process can be modeled by the inclusion of time-dependent explanatory variables Z^t in equation (8.5). The perception model can represent various stochastic process by adding suitable random error terms in equations (8.8) and (8.9). Other possible extensions include, representation of heterogeneity in perception, inclusion of day-to-day adjustments in perception in addition to the within-day perceptional changes suggested in (8.8), segmentation of perception model based on users' familiarity with the network, and information use characteristics.

TABLE 8.15

PERCEPTION MODEL OF TRIP TIME (DATA FROM EXPERIMENT 2)

Variable	coefficient	t-stat
Relative Margin on trip time on current path Δ_0	0.125	4.74
Young male ($\gamma 1$)	0.005	5.12
Old male ($\gamma 2$)	0.0031	8.06
Old female ($\gamma 3$)	-0.0012	-9.79

Summary Statistics

Log-likelihood of model without perception effects	-3094
Log-likelihood of model with perception effects	-3042
χ^2 value for H0: perception effects = 0	104
Critical value $\chi^2(4)$	9.49

Perception model: TT(perceived) = TT(reported)*[1+Δ_0*exp(γZ)]

8.3.2 Attitudinal Confirmatory Factor Analysis Model

Attitudinal data on the importance of trip-time savings, schedule delay, etc., on commuters' route and departure time choice were elicited using a questionnaire. The responses, from experiment two that are displayed in Table 6.3, are measured on a five-point Likert scale, and analyzed by the confirmatory factor analysis model described below.

Let X represent the vector of responses to the set of attitudinal questions.

The CFA model may be simply stated as:

$$X = \Lambda F + E \qquad (8.6),$$

where,

F represents the set of factors influencing the responses, Λ - the factor loadings (vector of coefficients mapping the factors to the responses), and, E denotes the error terms/uniqueness factors for each response.

It is assumed that,

Variance(F) = Σ_F,

$E \sim MVN(0, \Sigma_E)$,

where, the diagonal elements of Σ_F are set to 1. Further, it is also assumed that the correlations of the uniqueness terms (ε) are zero. Under these assumptions, the sample covariance can be expressed as:

$$\Sigma_X = \Lambda \Sigma_F \Lambda' + \Sigma_E \qquad (8.7).$$

This model is calibrated using a maximum likelihood technique that estimates parameters ($\Lambda, \Sigma_F, \Sigma_E$) which maximizes the likelihood of observing the given sample variance covariance matrix Σ_X.

The results of the CFA model factor loadings (Λ) are presented in Table 8.16. The parameter estimates generally follow expectations with regard to the magnitude and signs of factor loading coefficients. Importance ratings of trip-time saving of less than five minutes, for both route and departure-time decisions load positively on the trip-time factor. Users who value trip-time savings of less than five minutes very highly are likely to place a greater weight on the trip-time factor in the switching decision. The importance rating of five to 15 minutes savings for route and departure switching correlates moderately positively with the trip-time factor. In contrast, the importance of more than 15 minutes trip-time savings on route switching decisions loads negatively on the trip-time factor but positively on the schedule delay factor. This suggests that respondents are probably more likely to switch routes when faced with trip-time savings of more than 15 minutes, more due to schedule delay considerations, than with the objective of saving trip-time.

The congestion factor loads positively with attitudinal responses to the effect of congestion and incidents on original route on departure time switching. The schedule delay factor is found to strongly influence attitudinal responses to questions on the importance of lateness on original route, trip-time savings of 15 minutes or more, and effect of arrival time constraints on route switching decisions. Attitudinal responses to the importance of 15 more minutes or more of trip-time savings and lateness avoidance considerations on departure time switching also loaded positively on this factor. Attitudinal responses to questions on the preference for route guidance and parking information loaded significantly on the familiarity factor.

The results further indicate a strong positive correlation among three of the four underlying factors as shown in Table 8.17. The trip-time factor has an estimated correlation of nearly 0.56 with the congestion factor, and a still greater correlation (0.75) with the schedule delay factor. Congestion and schedule delay factors were also positively correlated (0.63). All the estimated correlations were significant at the usual five percent level.

The model statistics for the confirmatory factor analysis are displayed in Table 8.18. The model statistics indicate a model with the goodness of fit measure of 0.71. The goodness of fit index adjusted for degrees of freedom is 0.63. The critical sample size required is 49 compared to the actual sample size of 116. The model is satisfactory as the χ^2 test for goodness of fit rejects the null model in favor of the given model (at the p value of 0.0001).

TABLE 8.16

FACTOR LOADINGS FROM CONFIRMATORY FACTOR ANALYSIS (CFA) ON ATTITUDINAL QUESTIONS ABOUT SWITCHING

Factor Loadings on Questions	Coefficient	t-stat
Trip time Factor (Factor 1)		
Trip time saving (< 5 min) on route switching	0.43	4.64
Trip time saving (5-15 min) on route switching	0.18	1.3
Trip time saving (15-30 min) on route switching	-0.68	-2.8
Trip time saving > 30 min on route switching	-0.74	-3.41
Trip time saving (< 5 min) on departure time switching	0.61	6.9
Trip time saving (5-15 min) on departure time switching	0.94	12.48
Trip time saving (>15 min) on departure time switching	*0.19*	*1.36*
Congestion Factor (Factor 2)		
Trip time saving > 30 min on route switching	0.12	1.38
Congestion on original route	0.72	8.02
Incidents on original route	0.82	9.3
Congestion avoidance on departure time switching	0.61	4.78
Schedule delay factor (Factor 3)		
Trip time saving (5-15 min) on route switching	0.65	5.18
Trip time saving (15-30 min) on route switching	1.38	6.66
Trip time saving > 30 min on route switching	1.17	6.16
Arrival time constraints on route switching	0.3	3.25
Late arrival by original route	0.56	6.44
Trip time saving (>15 min) on departure time switching	0.67	5.12
Avoid congestion on departure time switching	*0.11*	*0.99*
Avoid lateness on departure time switching	0.45	5.01
Familiarity and other (Factor 4)		
Route guidance information desired	0.45	2.43
Parking information desired	0.29	1.95
Familiarity with alternate route on route switching	*0.12*	*0.3*
Avoid earliness on departure time switching	-0.3	-2.52
No additional information desired	-0.15	-1.07

TABLE 8.17

CORRELATION MATRIX Σ_F FOR THE CONFIRMATORY ANALYSIS FACTORS (F1-F4)

$$\Sigma_F = \begin{pmatrix} 1.0 & 0.56_{(6.69)} & 0.75_{(8.70)} & 0 \\ & 1.0 & 0.63_{(8.22)} & 0 \\ & Sym. & 1.0 & 0 \\ & & & 1.0 \end{pmatrix}$$

Note: The subscripted numbers represent the t-statistics of the correlations between factors. The factors correspond to attitudes towards trip-time, congestion, schedule delay, and familiarity respectively.

TABLE 8.18

SUMMARY STATISTICS FROM THE CONFIRMATORY FACTOR ANALYSIS MODEL

Fit Criterion		**4.0295**
Goodness of Fit Index (GFI)		**0.7131**
GFI Adjusted for Degress of Freedom (AGFI)		**0.6211**
Root Mean Square Residual 9RMR)		**0.1328**
Parsimonious GFI (Mulaik, 1989)		**0.5968**
Chi-square=467.4178	**df = 159**	**Prob>chi**2=0.0001**
Null Model Chi-square:	**df = 190**	**1131.9421**
RMSEA Estimate	**0.1293**	**0%C.I. [0.1158, 0.1430]**
Bentler's Comparative Fit Index		**0.6726**
Normal Theory Reweighted LS Chi-square		**466.6149**
Akaike's Information Criterion		**149.4178**
Bozdogan's (1987) CAIC		**-448.7679**
Schwarz's Bayesian Criterion		**-289.7679**
McDonald's (1989) Centrality		**0.2677**
Bentler & Bonnett's (1989) Non-normed Index		**0.6987**
Bentler & Bonett's (1980) NFI		**0.5871**
James, Mulaik, & Brett (1982) Parsimonious NFI		**0.4913**
Z-Test of Wilson & Hilferty (1931)		**11.6070**
Bollen (1986) Normed Index Rho1		**0.5066**
Bollen (1988) Non-normed Index Delta2		**0.6830**
Hoelter's (1983) Critical N		**49**

8.3.3 Influence of Attitudinal Variables on Choice Behavior

Based on the confirmatory factor structure proposed in the previous sub-section, factor score regression coefficients are computed using the SAS CALIS procedure (SAS Institute, 1990). These coefficients indicate the relative contribution of responses to attitudinal questions on each factor as displayed in Table 8.19. These regression coefficients are used to compute factor scores for each observation in the sample. The factor scores are then included as explanatory variables in the utility specification of route switching model and their influence on choice decisions are reported in Table 8.20. Thus attitudinal responses are combined with revealed user attributes in modeling observed choice behavior.

TABLE 8.19

FACTOR SCORE REGRESSION COEFFICIENTS FROM CFA MODEL ON ATTITUDINAL QUESTIONS

Attitudinal Questions	Trip time Factor	Schedule Delay	Congestion Factor	Other
Preference for incident information	-	-	-	0.000
Preference for route guidance	-	-	-	0.322
Preference for parking information	-	-	-	0.176
No additional information	-	-	-	-0.415
Trip time saving (< 5 min) on route switching	0.043	0.006	0.020	-
Trip time saving (5-15 min) on route switching	0.109	0.015	0.079	-
Trip time saving (15-30 min) on route switching	-0.060	0.011	0.575	-
Trip time saving > 30 min on route switching	-0.050	0.070	0.041	-
Congestion on original route	0.016	0.268	0.008	-
Incidents on original route	0.027	0.456	0.014	-
Arrival time constraints on route switching	0.013	0.002	0.011	-
Familiarity with alternate route on route switching	-	-	-	0.060
Late arrival by original route	0.031	0.005	0.027	-
Avoid earliness on route switching	-	-	-	-
Trip time saving (< 5 min) - departure time switching	0.078	0.010	0.037	-
Trip time saving (5-15 min) - departure time switching	0.728	0.097	0.343	-
Trip time saving (>15 min) - departure time switching	0.108	0.015	0.078	-
Congestion avoidance on departure time switching	0.021	0.208	0.014	-
Avoid lateness on departure time switching	0.021	0.003	0.019	-
Avoid earliness on departure time switching	-	-	-	-0.088

TABLE 8.20

EFFECT OF ATTITUDINAL VARIABLES ON ROUTE SWITCHING DECISIONS (EXPERIMENT 2)

Factor Score Variables	Coeff	t-stat
trip time factor score*relative triptime savings	*0.096*	*0.396*
congestion factor score* congestion on current path	0.205	4.674
congestion factor score *cong on best path	-0.093	-2.453
congestion factor score* stuck on prev. link	0.276	4.073
schedule delay factor score*late schedule delay on previous day	*-0.004*	*-0.963*
schedule delay factor score*early schedule delay on previous day	*-0.004*	*-0.798*
schedule delay factor score*reported early schedule delay today	*0.003*	*1.340*
schedule delay factor score*reported late schedule delay today	*-0.020*	*-0.920*
attitudes towards familiarity and other	*0.026*	*0.206*
LL1 (without factor scores)	-2743	
LL2 (model with factor score)	-2716	

Note:

χ^2(9) - critical value for rejection of model without factor scores	16.92
χ^2(actual) = -2*(LL1 - LL2)	56

The inclusion of attitudinal factor scores improves the route switching model fit considerably (as is evident from a likelihood ratio test). The explanatory variable interacting the user's attitude towards congestion (congestion factor score) with expected congestion on current path (displayed visually by means of color code) is significantly positive. This indicates that users' who perceive congestion avoidance as an important factor influencing route switching, are indeed observed to switch routes more often when faced with increasing congestion on downstream segments. However, with increasing (expected) congestion on the best path reported by ATIS, a lower switching propensity is observed, reflecting reduced re-routing opportunities in the network. Respondents who are averse to congestion are also observed to switch more often in response to past congestion episodes, especially in response to being stuck in traffic on the immediately preceding segment. However attitudinal responses on the schedule delay factor do not significantly influence the route switching decision.

The results in this section highlight strong perceptional and attitudinal effects in trip-maker decision processes. The next section explicitly examines how trip-makers perceive and judge information quality based on their experience.

8.4 JUDGMENT MODELS

Decision-makers are likely to continually assess and evaluate ATIS information and personal experiences in relation to each other and adjust their expectations and choices accordingly. This section examines how trip-makers judge the quality of ATIS information. Specifically, the effect of personal experience, trip characteristics, and other user characteristics on the judgment process are explored. The next section analyzes how decision-makers' update their expectations of trip attributes on the basis of past experience and information. In Chapters

Four and Five, it was observed that information quality, particularly, its accuracy, reliability, and errors adversely affect compliance propensity and result in increased switching from the current path. The previous analysis provides no information on whether users explicitly perceive variation in information quality or merely adjust their behavior in response to traffic variations. In contrast to these models, the question of whether users' perceive differences in information quality is explicitly dealt with in this section.

To measure and model judgment of ATIS information quality, each user was asked to rate the information quality on a scale of 1-10, after each information strategy was administered in experiment two. Each information strategy, it may be recalled, consists of a combination of information quality factors, and was applied for four days in succession. The experienced conditions are recorded and aggregated for each strategy to explicitly account for their influence on the users' judgment processes. The reported rating of information quality is analyzed by a time-series cross sectional regression procedure (SAS Institute, 1993). The results are displayed in Table 8.21. Users' judgments of information quality are strongly influenced by the nature of ATIS information. While random information is judged to be the most inaccurate (most -ve coefficient), predicted/prevailing information are perceived to be the most accurate information type, with partial information being rated in the middle of the range.

Furthermore, the data also suggest that the ratings of information quality are also affected by users traffic experiences, notably adverse ones. The empirical data also indicates considerable variability in information quality ratings across observational units, suggesting heterogeneity in the judgment process. These findings, based on the reported quality of ATIS information, are generally consistent with the results reported in Chapter Six. Users' judgment of information quality strongly influences observed choice decisions. Further, the quality of information is judged in relation to experience and is affected by users' choice behavior. Therefore, the judgment process is endogenous to the choice process.

Judgment models are important for assessing the efficacy and usage rate of ATIS products and services. ATIS information could have little impact on behavior if users' judge it to be of a poor quality and consequently ignore it. When the information is judged to be satisfactory, a significant number of users may comply or switch on the basis of this information. The resulting distribution of traffic on the network may not be consistent with the information (e.g., reported trip-time). Thus, it is desirable for ATIS to supply information that is consistent with user behavior after taking into account users reaction to information.

Insight into users' judgment of ATIS information is also critical from a traffic management perspective, particularly, for developing information strategies that avoid information-induced concentration and over-reaction problems. Judgment models can guide the development of design guidelines for ATIS, particularly, as related to update frequency, and temporal and spatial resolution of information. Judgment models are also important from the standpoint of modeling the decision to acquire information, and for reliable travel demand forecasting in the presence of ATIS. It is, however, necessary to recognize and account for possible endogeneity between judgment and choice processes.

TABLE 8.21

LINEAR REGRESSIONS MODEL OF USERS JUDGMENT RATINGS OF ATIS INFORMATION QUALITY

Variable Description	Parameter Estimate	t-stat	p-value
Intercept	8.11	34.42	0.0001
ATIS Information Strategy			
Predicted information	0.60	3.44	0.0007
Random information	-0.98	-3.05	0.0025
Experience Effects			
Cumulative proportion of switches to earlier departure times	-1.08	-3.31	0.0010
Late schedule delay on previous trip	-0.04	-1.94	0.0527
Average congestion anticipated on current p	-0.89	-2.53	0.0118
Socio-demographics			
Young male	0.00	0.01	0.9892
Old male	0.39	1.59	0.1117
Old female	0.51	2.25	0.0253

Summary Statistics	
R^2	0.1642
Adjusted R^2	0.1455
SS Model (df = 8)	167.4
SS Errors (df = 357)	852.2
F Statistic	8.77
Prob > F	0.0001

8.5 UPDATING PROCESS

Two related outcomes occur as a consequence of the learning and judgment processes in trip-maker behavior. The first, referred as updating process, can be defined as the refinement and revision of expectations and perceptions in response to new information, knowledge, or experience acquired in the system over time. This process generally remains latent (unobservable to the modeler). In contrast, the second, namely, adjustment process, may be observed and modeled with panel data, when measured with appropriate network performance measures and information attributes. In this section, empirical support for the updating process is analyzed, whereas a detailed investigation of the choice adjustment process is presented in the next chapter. Trip-makers can revise both their perceptions and expectations of trip characteristics to reflect and incorporate new information, recent experiences, changed objective(s), and increased awareness of system evolution (Tong et al., 1987; Mahmassani, 1996).

The perception adjustment process has generally been represented by an exponential smoothing process, where the updated variable (say trip-time) is a weighted linear combination of past perceptions and experience (Vaughn et al., 1995; Liu et al., 1998). This process may be expressed as follows:

$$X^p(t) = \alpha X^p(t-1) + (1-\alpha) X^{actual}(t-1), \; 0 \le \alpha \le 1 \qquad (8.8)$$

where, $X^p(t)$ represents the users' perception of an attribute X experienced at time t, and X^{actual} is an objective / reported measure of the corresponding attribute experienced by the user. The perception updating mechanism is then specified completely by the following three components. The parameter α represents the persistent influence of past perceptions. The initial perception model $X^p(0)$ represents the perception at the beginning of the duration of interest. The final component is the reported/objective values of the attributes of interest, namely, $X^{actual}(t)$ for all time periods of interest. The perception updating model is calibrated as follows. Note that the indices t here, denote the decision instances on a given day.

The initial trip-time perception model (on a given day) assumes that a user perceives the trip-time on a path (pre-trip) by combining the free-flow trip-time with a component reflecting time-dependent congestion prevailing at his/her chosen departure time. This simple model of initial perception of trip-time on path k for an individual i departing at time t can be given as:

$$X^p_{ik}(0) = TT^f_k + \beta Z_{ikt} + \varepsilon_{ik} \qquad (8.9),$$

where,

TT^f_k represents the free flow trip-time on path k, and,

Z_{ikt} indicates the congestion prevailing downstream on path k at time t (presumably known to the user through ATIS information), and

ε_{ik} represents the residual in the initial perception model.

Since the perception process is essentially latent, the coefficients in (8.9) are calibrated by means of the following procedure. It is assumed that the residuals of the initial perception model are independent of other explanatory variables in the model. For arbitrarily chosen starting parameter values of α and β, the initial perceived trip-times and within day trip-times are computed from equations (8.9) and (8.8) respectively. These variables are then included as the explanatory variables affecting the utility of corresponding path k in the path choice / (route switching) model. In addition to perceived trip-times, expected congestion on alternative paths, and path specific constants complete the systematic utility specification.

The model parameters α and β are calibrated using MLE techniques. This model invokes the standard Gauss-Markov assumption of independence between perception attributes (Z_{ikt}) and error terms of the utility, thus circumventing endogeneity issues. Separate perception coefficients are calibrated for the data sets corresponding to the sequential and random treatments, described previously in Section 3.5.

The results indicate that the parameter α, which represents the memory and retention effects of past perception, is considerably stronger for the sequential treatment than the random treatment. In the sequential treatment, trip-makers appear to weigh current information by about twice as much as their past perceptions (α= 0.35). In contrast, the influence of past perception is considerably diminished (to

about α= 0.12) in the random treatment. Thus, when traffic conditions fluctuate drastically from day-to-day, current reported information is given a considerably greater weight (about eight times as much as past perception).

It must be noted, however, that in this experiment, ATIS supplied generally accurate prevailing information. Under inaccurate information, different perception updating weights may be observed when both the information quality and network conditions vary considerably. The results also indicate that the coefficient of the congestion is positive for both the random and systematic treatments. In fact, the congestion weight on initial perception is greater in the random treatment than the systematic treatment (or vice versa), further indicating a greater emphasis on current information in drastically varying traffic environments. These findings confirm previous results in Chapter Five regarding the effect of network congestion levels on user behavior under random and sequential treatments, but also suggest that users may factor in prevailing congestion in how they perceive trip-time information.

The following subsection models anticipated arrival time variations from day-to-day (based on data from experiment two presented in Section 3.6) to analyze how trip-makers update their expectations of trip performance based on information and past experiences. After each day's commute, users' are provided with feedback on the previous day's trip attributes (trip-time, arrival time, and schedule delay on the chosen path). They are requested to select a departure time for the next day. For the chosen departure time, the users' are also requested to supply the anticipated arrival time for the next day's commute. This anticipated arrival time might be viewed as a measure of expected trip-time (since the departure time is known) with some margin of safety to accommodate information errors. This anticipated arrival time is modeled using a continuous linear model by virtue of its continuous nature. Furthermore, as it is observed across several decision-makers (different cross-sectional units) over several days, it is modeled as a time-series cross-sectional model. The following linear-in-parameter (LIP) specification is adopted.

$Y_{it} = \beta X_{it} + \varepsilon_{it}$,

$\varepsilon_{it} = \alpha_i + \beta_t + \nu_{it}$,

$\alpha_i \sim$ i.i.d Normal$(0,\sigma_i^2)$,

$\beta_t \sim$ i.i.d Normal$(0,\sigma_t^2)$,

$\nu_{it} = \rho\, \varepsilon_{i\,t-1} + \delta_{it}$,

$\delta_{it} \sim$ i.i.d Normal$(0,\sigma^2)$,

where, Y_{it} represents the anticipated trip-time for user i on day t = $AAT_{it} - DT_{it}$,

AAT_{it} represents the anticipated arrival time for user i on day t;

DT_{it} denotes the departure time for user i on day t.

These error components account for heteroscedasticity through the component (α_i), and contemporaneous correlations through the error term β_t. The error terms (ε_{it}) are also assumed to be first order auto-regressive. This repeated-measurement model of the continuous dependent variable

(expected arrival-time – departure-time) is calibrated using the time series cross-sectional procedure TSCS (SAS Institute, 1990).

The modeling results (Table 8.22) indicate that the influence of lagged trip-time experiences on trip-time expectations in the network decreases as the lag duration increases. In fact, only the trip-times experienced on the preceding three days are significant determinants of anticipated trip-time for the next day. The coefficients reveal that the current day's trip-time (0.53) is weighted about eight times as much as the trip-time on the previous day (0.07). The influence on the third last day's experience is still smaller with a coefficient of (0.04), which is about 13 times smaller than the current day's effect.

Another factor that influences the expectations of trip-time on the following day is the delay (on the late side) experienced on the current day. Following early schedule delay on the current day, users' expectation of trip-time for the next day tends to increase. Following a late arrival episode on the current day, users tend to revise their trip-time estimate downward for the next day. A plausible explanation for these somewhat counter-intuitive results is that users in response to lateness switch to earlier departure times expecting lower congestion, and hence lower trip-times, thereby decreasing their trip-time estimates. In response to earliness, users may switch to later departure-times and tend to increase their trip-time expectations. These conjectures were generally borne out in further testing with one notable exception. It was observed that for one segment of users', expectations of trip-time (and hence arrival-time) decreased following lateness on the previous day and a switch to a later departure-time. Users' with greater proportion of cumulative switches to later departure-times who experience early schedule delay tend to considerably decrease their expectations of trip-time for the next day. In a similar vein, users' with a greater cumulative proportion of switches to the early side who experienced late schedule delays also decrease the expectations for trip-time on the following day.

Expectations of trip-time vary significantly with the average commute time in the real-world. Users' who experience greater commute time in the real-world tend to have reduced expectations of trip-time on the following day, than users' with shorter commutes.

Finally information supplied by ATIS also significantly influences anticipated trip- time. With increasing information quality and credibility, users' tend to reduce their expected trip-times. For example, when the ATIS supplies predicted information or feedback on the recommended and best path, it is observed that users tend to reduce the trip-time estimates by about 1.4 to 1.5 minutes. This corroborates findings reported by Zhao et al. (1996) using a survey-based approach that the perception band of trip-time reduces with increasing accuracy of information.

The parameters of the variance-covariance structure above indicate the presence of considerable between-person variability. The corresponding variance component contributes nearly 35% of the total error variance. The contemporaneous correlation in the sample was very small (with less than two percent of the total variance). The first-order auto-correlation was also significant with a coefficient of 0.2059.

TABLE 8.22

CALIBRATION RESULTS OF UPDATING MODEL OF ANTICIPATED ARRIVAL TIME

Variable Description	Coefficient	t-stat	p-value
Intercept	12.1887	13.5290	0.0001
Past Experience			
Trip time previous day	0.5357	18.7890	0.0001
Trip time (second last day)	0.0719	4.8170	0.0001
Trip time (three days prior to current day)	0.0408	3.1020	0.0020
Early schedule delay (previous day)	0.2849	10.5790	0.0001
Late schedule delay (previous day)	-0.4348	-11.9900	0.0001
Early schedule delay * # switches to later dep. times	-0.0712	-4.9690	0.0001
Late schedule delay * # switches to earlier dep. times	-0.0093	-0.4630	0.6433
Choice Adjustments			
Switch dep.time to early (current day)	2.3736	5.4500	0.0001
Switch dep.time late (current day)	-1.5333	-3.5780	0.0004
ATIS information			
Prescriptive Information	-0.5858	-1.6180	0.1060
Differential predicted	-0.6778	-1.1950	0.2324
Recommended Path feedback	-1.4990	-3.4660	0.0005
Best Path feedback	-1.4181	-3.5210	0.0004
Other			
Average commute time (in real-world)	-0.0344	-3.4180	0.0007
Summary Statistics			
R^2	0.3339		
Adjusted R^2	0.3262		

Empirical evidence presented and reviewed in this section indicates that users' tend to update both their perceptions and expectations based on ATIS information and experience. While these results substantiate the presence of these processes, they also highlight the need to investigate the mechanisms and factors influencing this process in-depth. Another important line of inquiry concerns the nature of linkages between the updating process, with learning, judgment, perception processes (described previously), and adjustment process discussed in the next chapter.

8.6 SUMMARY

The cognitive and decision processes underlying dynamics in observed choices are investigated in this chapter. These processes are classified into four broad categories: learning, perceptions and attitudes, judgment, and updating processes.

The learning process refers to the phase wherein a user collects and interprets data and information about the environment (both traffic and ATIS). Learning may be viewed as a mutual disconfirmation process between information and experience over time. The empirical data are consistent

with the presence of discriminative and trial-and-error learning. Additional evidence presented suggests that the learning process is influenced by the role of memory, attentional and motivational factors.

Perceptional and attitudinal influences relate to cognitive differences in the manner in which different trip-makers perceive and view the traffic environment based on ATIS information and personal experience. These influences reflect the inherent preferences and attitudes of different users towards the stimuli they encounter. The perceptional and attitudinal phase enables users to encode and internally represent the stimuli based on their intrinsic propensities and to determine a response accordingly. A simple empirical model proposed to accommodate perception effects on trip-time provides interesting insights. The results suggest that users' perceive trip-time to be on an average about 12% higher than the reported trip-time. This margin of safety may be intended to hedge against uncertainties in both traffic conditions and information supply. The results also suggest heterogeneity in perceptions across different socio-demographic segments of users'. Attitudinal effects are modeled through confirmatory factor analysis of users' responses to attitudinal questions. Users' attitudes, as instrumented by factor scores on congestion, strongly influenced their switching behavior.

Another important cognitive process, namely judgment, is also empirically analyzed. This process is exemplified by the continual assessment and evaluation of ATIS information and personal experience with respect to each other. Information quality, information strategies, and past experiences are significant determinants of how users judge ATIS information.

Users may be expected to update their perceptions and expectations over time in response to new information, knowledge, or experience in the system. This refinement and revision process is modeled using data from experiment two, described in Section 3.6. The following results from updating models are noteworthy. First, the perception updating process varies considerably with day-to-day variation in network loads. When the day-to-day evolution is systematic, past perceptions are weighted considerably in the updating process; nearly half the weight of current ATIS information. However, when the network loads fluctuate dramatically from day-to-day, the weight of past perceptions on the updating process drops drastically, and is about one-eighth of that placed on current information. Second, users update expectations of arrival time for the following day's commute based on a finite memory of past trip-time and schedule delay experiences.

The empirical evidence presented in this chapter indicates the operation of learning, perception and attitudinal influences, judgment, and updating processes in commuter behavior under real-time information. Some confounding between learning and observed choice behavior is likely, as the experiments were not designed to investigate cognitive processes. Therefore, more systematic investigations focusing on cognitive and decision processes are needed to disentangle the interactions between the cognitive and choice processes of interest. While this chapter examines cognitive processes underlying user choice behavior, the next chapter addresses how users' adjust their choice behavior over time in response to information and experience.

CHAPTER 9: ADJUSTMENT PROCESSES IN COMMUTER BEHAVIOR DYNAMICS

9.1 INTRODUCTION

Chapters Five and Seven characterize dynamics in trip-maker responses to information primarily through the dimensions of route and departure time switching. Route switching decisions are defined with reference to the current path of the trip-maker (defined in Section 5.2.6). Departure time switching decisions are defined relative to the current day's departure time. Dynamics in commuter behavior is also represented in Chapter 6 through models of users' compliance with information. The compliance decision is defined (in Section 6.1) in relation to the best path ('least reported trip time path'), or the prescribed path depending on whether ATIS supplies descriptive or prescriptive information. The models of compliance and switching proposed in previous chapters offer valuable insight into the role of experimental factors, trip-maker characteristics, time-dependent network conditions, and information attributes in commuter behavior dynamics. However, these models provide an incomplete description of the choice phenomena (route and departure time choice) in the sense that given the switching or compliance outcome, it is not possible to uniquely determine the route or departure time chosen. For instance, knowing that a trip-maker switched departure times provides no indication of the magnitude of the departure time adjustment. Similarly, the knowledge that a user switched routes is insufficient to determine which route was actually chosen, when three or more routes are available. However, from a demand modeling and forecasting standpoint, it is of interest to characterize and represent the time-dependent flow patterns on the network links, in turn determined by the departure time and route choices of all trip-makers. Thus, models of switching and compliance are inadequate for modeling and forecasting time-dependent demand for travel on alternative facilities. In view of the practical limitations of the switching and compliance models, this chapter specifically investigates and models adjustment processes in commuter behavior.

The adjustment processes refer to systematic changes in users route and departure time choice behavior (over time) in response to information and experience. Such adjustments may be manifested over the short, medium or long term. The notion of adjustment inherently implies the existence of a review process, where the current choices are evaluated for their suitability (periodically or aperiodically), and the choice for the next time-period is determined. In what follows, two principal decision dimensions are considered - route and departure time choice, along with the associated time-frames of decision adjustments - within-day and day-to-day. The departure time adjustment models proposed in this chapter, analyze the decision to switch departure times together with the magnitude of the departure time shift. The path choice adjustment process proposed here explicitly models the path actually chosen in terms of a user's propensity to switch routes.

Traditional travel choice modeling and commuter behavior analyses have generally modeled choice behavior under the RUM paradigm, using cross-sectional data. Under this framework, each decision-maker obtains information regarding all available alternatives on each day, evaluates the utility associated with each alternative, and selects the one that maximizes his/her utility. This behavioral

framework, while being elegant in terms of its micro-economic foundation, imposes the following unrealistic restrictions on the decision process. All decision-makers have access to perfect information about all alternatives and the environment, and that cognitive and search costs do not influence the choice process. Furthermore, all decision-makers are assumed to be adequately equipped (analytically) to undertake this utility maximization, and that the information acquisition is exogenous to the choice process (Tong et al., 1987; Garling, 1998). Due to cognitive limitations imposed by the real-time driving environment, it is more reasonable to assume that users acquire information only on a subset of alternatives. Processing limitations also suggest heuristic searches to guide the choice of an alternative from among this subset, rather than utility maximization over a dynamic multi-attribute decision space. A general satisficing paradigm for users' decisions over time (for simplicity a series of days is considered) is presented below, that is consistent with these assumptions. The user initially (on day one) selects an alternative from the choice-set (using heuristic search or other means). The current day's choices form the default choices for the next day. The default choice is then reviewed in terms of its suitability for the next day, based on additional information, updated perceptions, learning, and expectations following the most recent trip. If the default choice is suitable, no other alternatives are considered further. Otherwise, the nearest (in a sense to be made more precise later) alternatives are considered as potential choices, and information regarding these obtained. These alternatives are then evaluated for their suitability. If a suitable alternative is found, the search is terminated. Otherwise, the information acquisition and evaluation processes continue until a suitable choice is found. This decision cycle is repeated from day-to-day. In this framework, the dynamics of choice behavior are determined in two decision stages - the first is an evaluation or review of the default choice, and the second is an adjustment contingent on an unfavorable review of the default choice. This behavioral framework is essentially based on notions of satisficing behavior and limited heuristic search of alternatives. While this framework is not new (see Mahmassani 1996) it has only been implemented to a limited extent. One version of this satisficing framework has been operationalized by Mahmassani and Chang (1987) and Hu and Mahamassani (1997). These researchers postulate a set of indifference bands for route and departure time decisions centered around a user's current trip choices.

The route and departure time decisions are viewed as the decision to switch from the current choices. The indifference bands (thresholds) for switching are calibrated from the observed switching decisions. However, this implementation only provides a partial representation of the choice process, since the decision to switch routes does not completely determine the alternative chosen, but merely eliminates the current choice from the choice-set for the next decision period. This has remained largely unrecognized in the dynamic route choice literature, wherein, the majority of researchers have focused on modeling switching/diversion decisions.

In modeling the departure time choice process, Chang and Mahmassani (1988), have proposed the following departure time adjustment mechanism conditional on the decision to switch departure time.

$$DT^{t+1} = PAT - ETT^{t+1} \qquad (9.1).$$

$ATT^{t+1} = g(TT^{t}, Z, \theta) + \varepsilon$ (9.2).

In equations (9.1) and (9.2) the various entities are defined as follows for user i:

DT^t = departure time on day t,

PAT = preferred arrival time for user (assumed to be fixed over time),

ATT^t = anticipated trip time for commute on day t,

Z = vector of socio-demographic attributes affecting ATT,

θ = corresponding vector of parameters in equation (9.2).

The first equation implies that the departure time adjustment takes place in two stages. The user first estimates the trip time for the next day (ATT^{t+1}) based on current day's experienced trip time TT^t, and other situational and user attributes Z, and his/her sensitivity to these attributes θ. A random error term, ε, is included to reflect perception errors in the estimation of trip time. In the second stage, the user adjusts/resets his/her departure time to enable arrival at the preferred arrival time (PAT), given his/her prediction of trip time for the next day.

In the following sub-sections modeling frameworks are proposed to explicitly analyze route and departure time adjustment processes. The proposed frameworks are based on a satisficing behavioral notion and consist of the following essential features: It is assumed that the adjustment process is anchored on the current choice, and an inertial mechanism is associated with the default choice to reflect the costs involved in switching. The utilities of alternatives are defined in a manner that prioritizes satisfactory alternatives that are sufficiently 'close' (e.g., least cost in switching) to the current choice. A heuristic choice-set reduction scheme is proposed, by defining the alternatives through suitable nesting structures. This ensures that all alternatives are not evaluated simultaneously, and the heuristic search process evaluates alternatives in a selective manner. This implies that the decision-maker effectively only considers a subset of alternatives during the adjustment process. Econometric procedures such as maximum likelihood estimation or method of moments estimation procedures can be used to calibrate adjustment models under various heuristic rules. The calibration procedure assumes utility maximization over the alternatives considered at each stage. However, this does not necessarily imply that the user selects the alternative with the maximum global utility. Instead, he/she selects the first locally optimal alternative. Furthermore, the utilities are specified to include search costs and benefits, thus incorporating elements of satisficing behavior. Thus it is possible in the proposed framework to combine elements of both satisficing and local utility maximizing behavior.

The rest of this chapter is organized as follows. The next section presents the framework for modeling departure time adjustment behavior and discusses empirical results. Section 9.3 elaborates on path choice adjustment process, models, and calibration results, followed by a summary in Section 9.4.

9.2 FRAMEWORK FOR MODELING DEPARTURE TIME ADJUSTMENT PROCESS

The departure time choice on a given day is significant in determining the within-day distribution of traffic, congestion, and queuing patterns on the network. The adjustment of departure time from day-to-

day can govern the day-to-day dynamics in the network through shifts in demand from peak to off peak periods, and changes in temporal and spatial distribution of vehicles on the network. These two dimensions of network dynamics are important from the perspective of traffic operations and management. Thus analysis of departure time adjustment is of considerable significance in congestion modeling, design of alleviation measures, and network performance analysis. This section presents a framework for modeling departure time adjustment and discusses its implementation using empirical data.

9.2.1 Exploratory Analysis of Departure Time Adjustment Behavior

As a part of the exploratory analysis into departure time adjustment behavior, the frequency distribution of observed day-to-day departure time variations (aggregated across days and across respondents) is analyzed using data from the second experiment(Table 9.1). The frequency distribution reveals several interesting observations (see also Tables 9.2 and 9.3). A majority (64 %) of respondents do not adjust their departure time from the current choice, lending support to the hypothesis that the departure time choice behavior is anchored on the current choice. Second, about 87% of observed departure time adjustments are in multiples of five minutes from the current departure time. This suggests that users perceive departure time alternatives in discrete intervals of five minutes. In other words, there appears to be a coarseness or granularity in users' perceptions of departure time adjustment alternatives.

TABLE 9.1

FREQUENCY DISTRIBUTION OF MAGNITUDE OF DEPARTURE TIME ADJUSTMENTS

Adjustment Magnitude	Relative Frequency (%)
10+ (early)	2.33
6-10 (early)	4.09
1-5 (early)	13.08
No adjustment	64.03
1-5 (late)	10.11
6-10 (late)	3.61
10+ (late)	2.25

Finally, the distribution suggests that the proportion of respondents who adjust departure times progressively decreases with increasing adjustment intervals from the current departure time. The greatest proportion of respondents who switch, switch to the nearest interval (< 5 min), followed by (5-10 min), and so on. Note also that the adjustment process appears to be symmetrically distributed around the current choice, reflecting that the proportion of departure time switches to earlier and later departure times are nearly well-balanced. The direction of adjustment appears to be predominantly determined by the arrival outcome on the previous day. Following on time arrival or lateness, nearly 97% of respondents either retain their current departure time or switch to earlier departure times. Similarly, following earliness, about 91% either retain their current departure time or switch to later departure times.

The exploratory analysis provides two meaningful cues for developing departure time adjustment models. First, it appears reasonable to aggregate the adjustment

TABLE 9.2

ADJUSTMENTS IN DEPARTURE TIME RELATIVE TO PREVIOUS DAY'S SCHEDULE DELAY

Arrival outcome on previous day	Departure Adjustment on Current Day		
	Proportion switches to earlier departure time (%)	Proportion retaining departure time (%)	Proportion switches to later departure time (%)
Late	40	58	2
On time	22	75	3
Early	9	68	23

TABLE 9.3

TESTING FOR POSSIBLE DIFFERENCES IN DEPARTURE TIME ADJUSTMENT BETWEEN EARLY AND LATE SIDES

Model Description	df	LL	comparison of alternative specifications
1. Unsegmented ordered response probit (ORP)	14	-1179.9	Base Model
2a. Segmented early side ordered response probit	13	-742.67	Model 2 vs Model 1: χ^2 (act) = 24.48 χ^2 (12) = 21.03
2b. Segmented late side ordered response probit	13	-424.99	conclusions: model 2 is superior to 1
3. Unsegmented ordered response except for reco and best (early & late)	16	-1172.2	Model 3 vs Model 2: χ^2 (act) = 11.08 χ^2 (10) = 18.31 conclusions: model 3 is preferred to 2 due to parsiomony

choices into shifts of discrete five-minute intervals. Thus a zero minute shift (non-switching) is labeled as alternative 1, an adjustment of between one to five minutes is labeled as alternative 2, and so on. The symmetry of the adjustment behavior can reduce the choice set dimension by considering only the absolute value of adjustment. Second, the data appears to suggest a natural hierarchical scheme in the search process to determine the magnitude of adjustment. In other words, a user is more likely to consider alternative 1 first and alternative 5 last.

There are two main objectives in this analysis of the departure time adjustment process. The first objective is to compare alternative structural specifications for the adjustment process. In particular, the following three specifications are considered: unordered response, ordered response (ordinal), and ordered choice departure time adjustment models. In the unordered response mechanism, the alternatives are unordered and uncorrelated and can be represented as independent discrete alternatives as shown in Figure 9.1.

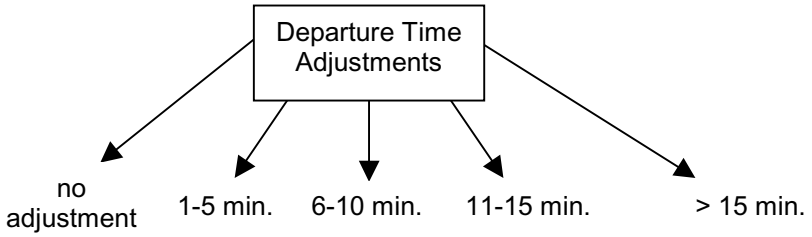

FIGURE 9.1
Unordered response departure time adjustment model.

In the ordered response case, the alternatives can be ordered in an increasing fashion. In this case, a pair of ordered thresholds is associated with each alternative (Figure 9.2). The user then chooses an alternative if his/her utility (associated with the choice context and not the alternatives) falls within the range of the corresponding thresholds. Furthermore, the thresholds are arranged such that the upper threshold of an alternative k, also happens to be the lower threshold for the next alternative (where k is not the first or the last alternative).

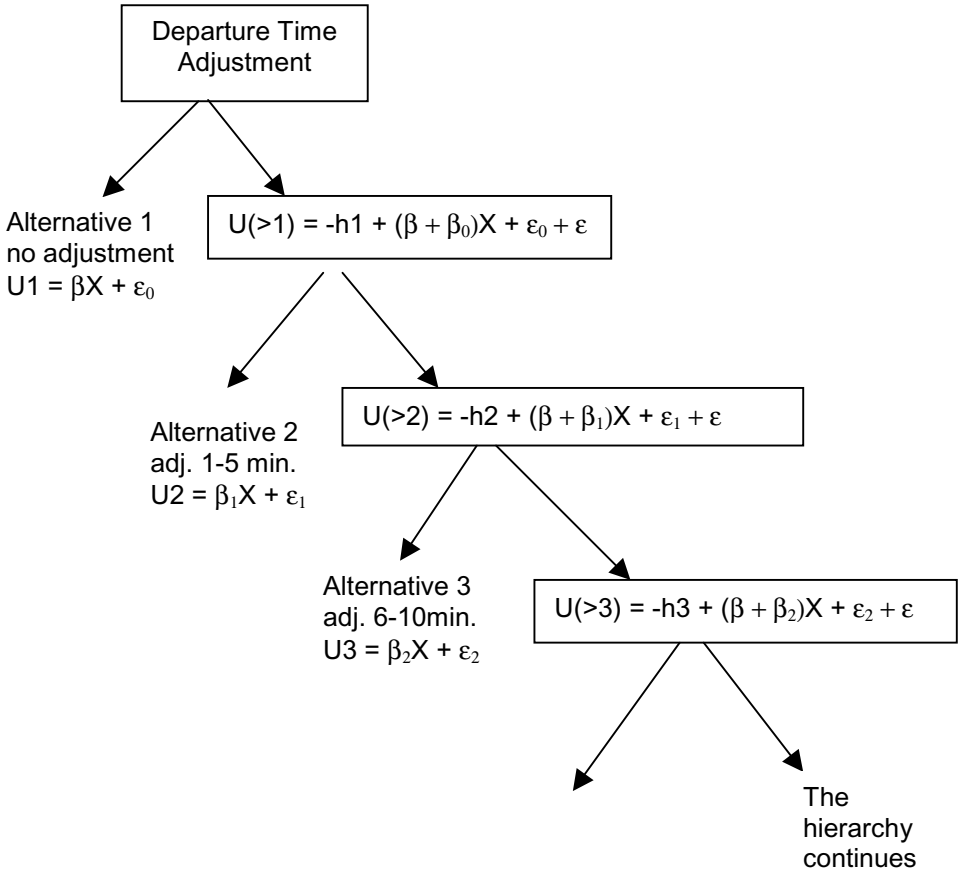

FIGURE 9.2

Ordinal response model of departure time adjustment.

The third specification, referred to as the sequential binary ordered search model, is an extension of the ordered response models (Figure 9.3). The difference between the two (second and third formulations) is that the latter specification relaxes the assumption of thresholds, while maintaining the ordering structure among the alternatives. The specifications of these alternative structures are presented in detail in the following sub-sections. The analysis of alternative

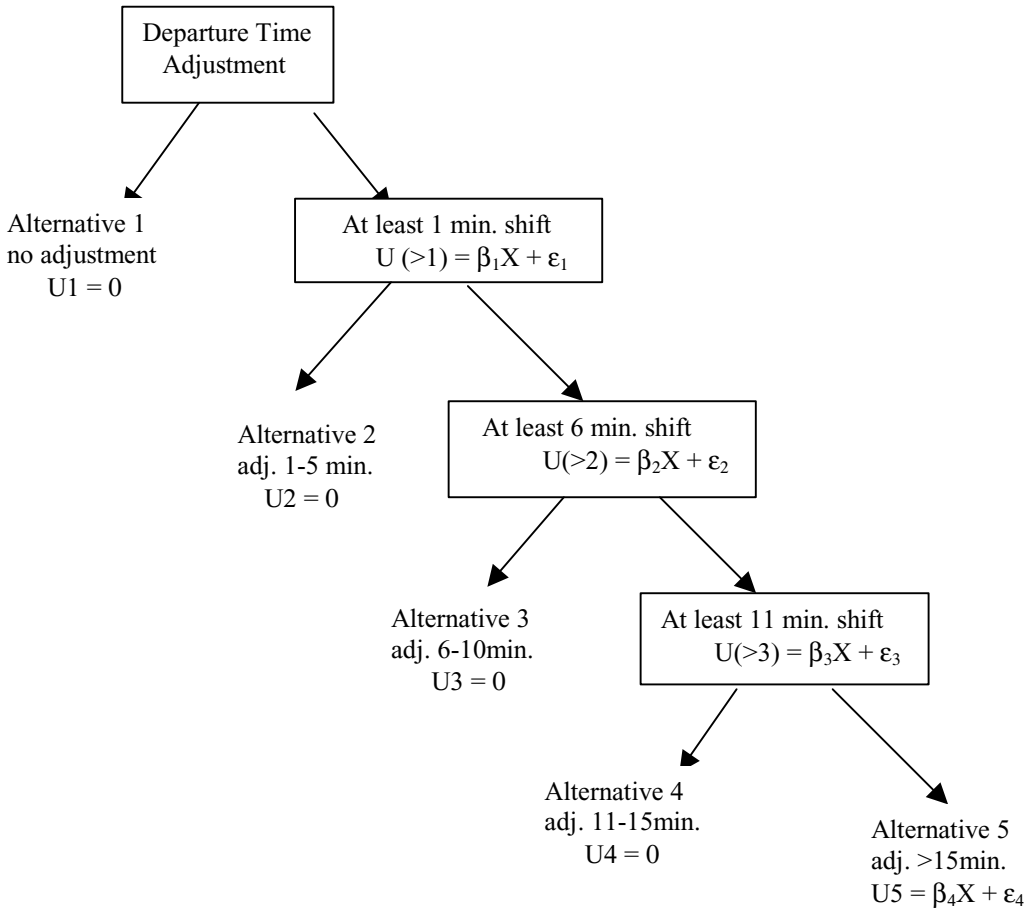

FIGURE 9.3
Sequential search adjustment model of departure times.

departure time structures can provide significant insights into the mechanisms underlying these processes.

The second objective of the adjustment analysis is to identify key factors influencing departure time adjustment decisions. In particular, the role of system performance measures and users' past experience in the network is of interest. Other factors of interest include the influence of ATIS and socio-demographic characteristics on adjustment behavior. This analysis could lead to the identification of distinctive behavioral patterns among various user segments that could then be exploited for demand management, or targeted ATIS information provision.

9.2.2 Departure Time Adjustment Modeling Framework

The magnitude of departure time adjustment (X_{it}) for a user i on day t is defined as the absolute deviation (in minutes) between the departure time on the previous day (day t-1) and current day's (t) departure time. This adjustment variable (X_{it}) is non-negative, continuous, and censored at zero. Further, the magnitude of adjustment is discretized into five minute intervals, as described previously, to obtain discrete alternatives (Y_{it} - departure time adjustment alternative chosen by individual i on day t). The correspondence between the chosen discrete alternative C_{it} and the continuous adjustments X_{it} can be expressed as follows:

$C_{it} = 1$ iff $X_{it} = 0$,

$C_{it} = 2$ iff $X_{it} \in [1,5]$,

$C_{it} = 3$ iff $X_{it} \in [6,10]$,

$C_{it} = 4$ iff $X_{it} \in [11,15]$,

$C_{it} = 5$ iff $X_{it} >= 15$ minutes (9.3).

9.2.2.1 Unordered Response Model. Let U_{ijt} represent the utility that an individual i associates with the discrete alternative j (J= 1,..5), on day t. Let C_{it} denote the alternative chosen by user i. Let Z_{it} and β represent the vector of attributes and the vector of parameters affecting the departure time adjustment decision. The utility U_{ijt} may be expressed as the sum of the following components, a systematic component V_{ijt}, and a random component ε_{ijt}.. In the unordered response case, it is assumed that there is no inherent structure or shared unobserved attributes among the alternatives. Furthermore, it is assumed that the correlations between repeated departure time adjustment decisions by a given individual are captured adequately by time-varying experience variables included in the systematic utility specification. Hence the error terms are independent across alternatives.

Under these assumptions, the probability that an individual i selects a sequence C of adjustment choice alternatives can be expressed as:

$Pr\{C_i\}= Pr\{C_{it}, t = 1,\ldots T\}$

$= \Pi_t Pr\{C_{it}\}$

$= \Pi_t Pr\{U_{Cit} \geq U_{ijt}, \forall j \neq C_{it} \text{ at time } t\}$ (9.4).

Assuming that individuals make adjustment decisions independently, the likelihood of observing the sequence of choices made by the respondents in the sample, referred to henceforth as sample likelihood, can be expressed by the following equation:

$L = \Pi_{t\ i} Pr\{C_i\}$ (9.5).

Under the assumption of identically and independently distributed multivariate normal error terms this likelihood corresponds to a simple multinomial probit model (IID) with five alternatives.

9.2.2.2 Ordinal Probit Model. The notation for this model is modified to distinguish it from the previous model. Let W_{it} represent the utility that an individual i associates with the choice context at time t. Let l_{ijt}, and h_{ijt} represent the thresholds that individual i associates with alternative j at time t. Let δ_{ijt} be a binary

indicator variable taking on a value of one if individual i chose alternative j at time t, and 0 otherwise. Without loss of generality, l_{i1t} is set to zero, and U_{i5t} is set to infinity for all users. The behavioral rule in the ordinal probit model requires that an individual i will choose an adjustment alternative j at time t iff his/her utility is in the range of the thresholds associated with that alternative (McKelvey and Zavoina, 1975).

Thus,

$C_{it} = j$ iff $l_{ijt} \leq W_{it} < h_{ijt}$ (9.6).

The ordinal response model further assumes that the thresholds are monotonically ordered across alternatives in an increasing fashion (the alternatives may be relabeled to achieve this increasing ordering). This can be expressed as:

$l_{ijt} < l_{ij't}$, and $h_{ijt} < h_{ij't}$ for all j' > (9.7).

It is assumed that the alternatives are contiguously arranged in an ascending order. This can be ensured by imposing the constraint that the upper threshold of a given alternative should also be the lower threshold of the next alternative (for all the alternatives except the last one). In other words,

$h_{ijt} = l_{i\,j+1t}$ (for $j \neq J$) (9.8).

Denoting ordering constraints (9.7) and (9.8) by the feasibility set S, and the vector of thresholds by L and H, the likelihood of a sequence of choices by an individual can be written as:

$\Pr\{C_i\} = \Pr\{C_{it}, t = 1,\ldots T\} = \Pi_j \Pi_t \Pr\{ (l_{ijt} \leq W_{it} < h_{ijt}) \cap (L, H \in S)\}^{\delta ijt}$ (9.9).

It is assumed that the repeated choice decisions made by an individual are independent of each other. Further, assuming that individuals make adjustment decisions independently (of each other), the likelihood of the sample can be expressed as follows:

$L = \Pi_i \Pr\{C_i\}$ (9.10).

The standard ordinal response probit model is obtained with the following assumptions: the utility specification is linear-in-parameters (LIP), the error terms for the thresholds are independently and identically normally distributed error terms for the thresholds, and the threshold set is constant across the population. This model is calibrated by a maximizing the likelihood in equation 9.10.

9.2.2.3 Sequential Ordered Search Model. The ordered structure among the alternatives is retained in this model, as with the previous one. However, this model is more general than the previous formulation, because of its less restrictive assumptions. It is assumed here that the decision-maker conducts a heuristic search among the alternatives in the following ordered fashion. The user first decides on whether or not to adjust departure time for the next day. If he/she decides not to switch, alternative One is chosen (user does not switch departure times); otherwise, the user rejects alternative One and searches for the next satisfactory alternative. A user who decides to change his/her departure time, next faces the decision of whether to adjust by at most five minutes or by more than five minutes. If he/she decides to switch by at most five minutes, alternative Two is chosen; otherwise, he faces the next binary decision (of switching by six-ten minutes or more than ten minutes) and so on. Thus, it is suggested that the adjustment is a heuristic, sequential search process. The search process, consisting of a series of ordered binary decisions, terminates when an adjustment alternative is chosen for the next day.

This choice scheme is represented by the nested structure shown in Figure 9.1, and can be translated into the following likelihood formulation. The choice of an alternative k implies that it is preferred to the previous k-1 alternatives. It is also preferred to larger adjustment magnitudes (alternatives k+1, k+2, etc.). The subscripts i and t denote the trip-maker, and the day under consideration respectively. The utility of non-adjustment (choice of adjusting by zero minutes) is set to be zero, and the relative utility of a switching (adjustment by at least one minute) is indicated by U_{i1t}. Similarly, the utility of alternative Two (adjustment by up to five minutes) is set at zero, and the utility of adjustment by at least six minutes is denoted by $U_{i2t.}$ Note that this utility scheme merely indicates that the difference in utility between switching by more than five minutes relative to an adjustment of one-five minutes is U_{i2t}. Analogously, the utilities U_{i3t}, and U_{i4t} are associated with adjustments of more than ten minutes (relative to a six-ten minute adjustment) and more than 15 minutes (relative to six-ten minute adjustment) respectively. Since U_{i3t},, U_{i4t},, and U_{i5t}, share the same nest (as shown in Figure 9.2), it can be expected that U_{i3t} is correlated (correlation coefficient - ρ_{1i}) with U_{i4t} and U_{i5t} due to shared unobservables. In a similar fashion since U_{i4t} and U_{i5t} are nested within U_{i3t}, and are correlated with each other with a correlation coefficient ρ_2.

Under this formulation the likelihood that an individual i will select an alternative k on day t can be written as:

$Pr(C_{it} = k)$

$= Pr\ \{(U_{ijt} \geq 0,\ \forall j < k) \cap (U_{ikt} \leq 0)\}$

$= Pr\ \{(V_{ijt} + \varepsilon_{ijt} \geq 0,\ \forall j < k) \cap (V_{ikt} + \varepsilon_{ikt} \leq 0)\}$ (9.11),

where,

V_{ijt} represents the systematic utility of alternative j (relative to a larger departure time adjustment) for individual i on day t, and, ε_{ijt} represents the corresponding random error.

Equation (9.11) assumes, with no loss of generality, that the systematic utility of the alternative represented by the left-hand side branch in Figure 9.1 is set at zero. This formulation explicitly accounts for the sequential nature of the search process among ordered alternatives. In addition, the ordering among the alternatives is also partially represented by the variance-covariance structure (Σ) of error terms.

This error structure reflects shared unobservable error terms among alternatives sharing a given nest.

$$\Sigma = \begin{pmatrix} 1 & 0 & 0 & 0 & 0 \\ & \sigma_1^2 & 0 & 0 & 0 \\ & & \sigma_2^2 & \rho_1\sigma_2\sigma_3 & \rho_1\sigma_2\sigma_4 \\ & Sym. & & \sigma_3^2 & \rho_2\sigma_3\sigma_4 \\ & & & & \sigma_4^2 \end{pmatrix}$$

The adjustment process in this model can be viewed as a heuristic greedy search by a decision-maker who accepts the first satisfactory outcome. Unlike in the unordered response model, where the

chosen alternative is optimal across alternatives (on each day) in terms of utility, the chosen alternative in this model is only a local optimum.

9.2.3 Departure Time Adjustment Modeling Results

The results from the three formulations are presented in Table 9.4. The likelihood ratio test for non-nested models (test proposed by Horowitz, 1981) is used to compare the three formulations. The results indicate that model 3 provides the best model fit to observed data among the three models. This suggests that the departure time adjustment is consistent with a sequential greedy heuristic search strategy. In view of these findings, only the substantive results from the best model, representing a sequential binary ordered search process for departure time adjustments, are presented hereafter (Table 9.5).

The sequential binary ordered choice model in Table 9.5, cannot be interpreted in the same manner as a multinomial logit model. For example, the nearly equal coefficients for the alternative specific constants for one-five minute, and six-ten minute, might tempt one to conclude that alternatives Two, Three, and Four are less preferred to alternative One, by nearly the same extent. However, the proposed ordering scheme implies the following hierarchical structure among the adjustment alternatives. Alternative One is preferred (*ceteris paribus*) to adjustment of more than one minute (corresponding to a utility difference of about 0.9). Similarly alternative Two (adjustment of one-five minutes) is preferred to an adjustment of more than six minutes by about the same amount, and so on.

TABLE 9.4

COMPARISON OF ALTERNATIVE DEPARTURE TIME ADJUSTMENT MODELS

Model Description	LL(final)	df
Multinomial Logit (generic variables)	-1197.5	14
Multinomial Logit (alternative specific variables)	-1153.8	54
Ordinal Probit (independent errors, generic variables)	-1187.7	14
Sequential Binary Choice Ordered Probit (generic variables)	-1185.47	17
Sequential Binary Choice Ordered Probit (independent errors, alternative specific variables)	-1147.79	54
Sequential Binary Choice Ordered Probit (correlated errors, alternative specific variables)	-1143.39	56

It is evident from the calibration results (Table 9.5) that the utilities are alternative specific and not generic. In other words, variables such as trip time, schedule delay have a different influence in the

choice between no adjustment and adjustment of one or more minutes, as compared to the choice between adjustment of 11-15 minutes and more than 16 minutes.

TABLE 9.5

SEQUENTIAL BINARY CHOICE ORDERED PROBIT MODEL FOR DEPARTURE TIME ADJUSTMENT

Variable Description	no adjustment		1-5 min. adj.		6-10 min. adj.		11-15 min. adj.	
	coefficient	t-stat	coefficient	t-stat	coefficient	t-stat	coefficient	t-stat
Alternative specific constant	0.71	11.25	0.92	11.86	0.32	4.92	-2.05	-9.65
Early schedule delay	-0.014	-9.73	-0.058	-5.64	0.015	3.36	0.004	2.28
Late schedule delay	-0.0476	-5.88	-0.066	-4.73	-0.046	-9.83	-0.071	-3.23
Cumulative proportion of switches to earlier departure times	-0.044	-2.2	0.046	3.18	0.136	14.82	0.89	-1.56
Cumulative proportion of switches to later departure times	-0.1044	-10.19	-0.029	-2.25	-0.256	-11.49	-2.01	-5.64
Triptime variability with dep.time change	-0.181	-6.28	0.16	4.53	-0.252	-6.21	3.08	1.65
Overestimation error	-0.027	-3.15	-0.132	-6.77	0.078	3.36	-0.93	-1.6
Underestimation error	0.006	4.696	0.09	15.74	0.096	10.55	-0.149	16.35
triptime on previous day	0.023	9.85	-0.0011	-4.99	0.036	11.54	0.287	13.65
prescriptive information	-0.155	-5.67	0.571	3.64	-0.368	-1.19	-1.473	-1.1
random information	-0.308	-2.56	0.115	1.92	-1.808	-1.51	-3.96	-1.9
differential information (prevailing)	-0.807	-2.79	0.46	1.85	-0.822	-3.37	-3.56	-2.87
differential information (predicted)	0.566	2.02	1.431	5.26	-0.54	-2.17	0.473	1.65
feedback on recommended path	0.24	4.57	-0.016	-1.32				
Correlations								
between alternatives 3-4, 3-5 = $\rho 1$	0.096	2.19						
between alternatives 4-5 = $\rho 2$	0.279	2.398						

Among the system performance measures in the network, both experienced trip time and its variability (with departure time changes) are determinants of departure time adjustment behavior. With increasing trip times, the adjustment of six-ten minutes is preferentially favored to adjustments by more than 11 minutes. However, with increasing trip time at either extreme end, a lower departure time shift is preferred. For instance, users tend to retain the current departure time rather than adjust departure time by at least one minute, when longer trip times are experienced on the previous day. Similarly adjustments of between 11-15 minutes is preferred to larger departure time adjustments. Trip-makers appear to accommodate increasing trip time variability faced in the system (measured as the ratio of difference in trip-times on the two preceding days to the magnitude of departure time shift corresponding to the two days) by choosing larger shifts at the lower end of the adjustment spectrum, and smaller adjustments at the higher end of the adjustment spectrum. For instance, users are more likely to hedge against variability in the system by shifting their departure times by at least one minute, In contrast, at the other end of the spectrum, trip-makers tend to prefer adjustments of 11-15 minutes to larger magnitudes of shifts.

ATIS information also significantly affects users' departure time adjustments. Users react to information quality variations in an expected manner. Following overestimated trip time information, users appear to prefer larger departure time adjustments, especially at the higher end, reflecting an increased expectation of trip time. For instance, it is observed that an adjustment of more than 16 minutes is

preferred to a shift of between 11-15 minutes. With increasing underestimation of actual trip times by ATIS, smaller departure time shifts are preferred. For example, the adjustment alternatives of one-five minutes and six-ten minutes are preferred to adjustments of more than six minutes, and more than 11 minutes respectively. An exception to this trend is noted at the higher end of the adjustment spectrum. With increasing underestimation errors, an adjustment of more than 16 minutes is preferred to an adjustment by between 11-15 minutes.

In addition to the quality of ATIS information, the geographical extent (coverage) of information also affects users' adjustment behavior. For instance, providing partial information (information not available on all routes on the network) significantly influences adjustment behavior. The nature of influence, however, varies depending on whether the ATIS supplies prevailing or predicted differential information. In response to prevailing partial information (information is not provided on one highway) a preference for larger departure adjustment intervals is observed, though not uniformly across all choice decisions. For instance, adjustment alternatives of one-five minutes and 16+ minutes are more likely to be chosen than alternatives of not switching and adjustments by 11-15 min., respectively. In response to predicted partial information, smaller departure time adjustment alternatives are preferred at the lower end of adjustment spectrum (alternatives One, Two, and Three). Trip-makers are more likely to retain their current departure time than to select other adjustment alternatives. Similarly shifts of between one and five minutes are preferred to larger adjustments. These observed differences in departure time adjustment between prevailing and predicted partial information strategies suggest that users are sensitive to forecasting errors associated with prevailing information. The effect of inaccurate information is considerably more pronounced when the ATIS supplies random information. In such cases, users tend to prefer greater departure time adjustments, especially at the upper end of the adjustment spectrum. It is seen that adjustments of more than ten minutes are preferred to adjustments of between six-ten minutes. Similarly, an adjustment of more than 16 min. is favored over a shift by 11-15 minutes.

Departure time adjustment decisions are also affected by the nature of ATIS information. When ATIS supplies prescriptive information, a moderate adjustment of one-five minutes, is preferred to the alternatives of not switching and adjustments by more than six minutes. The increased switching under prescriptive information, may be partly attributed to the lack of trip-time information on alternative routes. In this case, users may be more likely to hedge against uncertainty due to variation in traffic conditions by switching departure times. The model results suggest that the adjustment of departure times by commuters, is strongly influenced by the nature and type, and quality of ATIS information.

Users' departure time adjustments are also sensitive to past experiences in the system. Following a late arrival episode on the previous day, users tend to select larger shifts at all binary decisions, e.g., adjustments of at least one, six, and 11 minutes are preferred to no adjustment, one-five minutes, and six-ten minutes respectively. The adjustment response to early schedule delay, however, is more moderate, as reflected in the smaller magnitude of coefficients. Following early schedule delay, users' tend to prefer a moderate adjustment of between six-ten minutes compared to larger departure time

shifts; more than five minutes compared to a one-five minute shift, but no differences are observed in other sequential decisions. With increasing cumulative proportion of departure switches to earlier departure times on the preceding days, two distinct departure time adjustment patterns are observed. The larger adjustments are preferred at either end of the adjustment spectrum, whereas smaller shifts are preferred in between. For instance, a shift of at least one minute is preferred to retaining the current departure time, and an adjustment of more than 16 minutes is preferred to departure time shifts of between 11-15 minutes. However, shifts by one-five minutes are preferred to shifts of more than six minutes, and shifts of six-ten minutes are preferred to adjustments by more than 11 minutes. Users' with greater cumulative proportion of delayed departures (presumably following earliness), prefer larger shifts in departure time across the board. For example, an adjustment of 11-15 minutes is less preferred to shifts of more than 16 minutes.

9.3 FRAMEWORK FOR MODELING ROUTE CHOICE PROCESS

In this section it is proposed that the path choice in response to real-time information, is anchored to a set of default choices. Specifically, it is proposed that the observed path choice can be modeled by incorporating two principal mechanisms, namely compliance and inertia. Compliance refers to the tendency of a user to follow the best path suggested by the ATIS, where as, inertia refers to the propensity of a user to retain his default path (current path). This analysis is based on data from experiment One, discussed in Section 3.5.

The analysis presented in Chapters Four and Five suggest that compliance and inertia are significant determinants of path adjustment decisions in response to information and experience. However, treating the two as exogenous factors imposes the unlikely restriction that these effects are constant over time and across choice instances. In fact, previous studies (Bonsall and Parry, 1991; Mahmassani, 1996) demonstrate that compliance and switching (reflective of inertial effect) vary dynamically in response to experienced congestion, information supplied, and user characteristics. In contrast to the exogenous treatment, the analyses in Chapters Four and Five treat switching and compliance respectively as observed choices. However, compliance and switching may only be inferred consequences of observed route choice decisions. Modeling compliance and switching as actual choices made by trip-makers reduces the multinomial choice situation (with at least three alternatives) to respective binary decisions (namely, to switch from current path or not, and comply with information or not). This limitation becomes evident when reconstructing the chosen path from compliance and switching outcomes. While compliance implies that the best path was chosen, non-compliance merely indicates that the best path was not chosen. When only two paths are available, the selected path is trivially determined. However, when several paths are available, the chosen path cannot be determined on the basis of this information alone. Similarly, while non-switching completely defines the chosen path, switching merely eliminates one path from the choice set. Thus treating compliance and switching (inertia) as dependent variables results in an inefficient use of choice-related information and a loss of predictive power.

Conceivably, switching and compliance may be treated as joint choices made by the decision-maker. However, the two decisions are interrelated, which introduces partial endogeneity, thus further complicating modeling efforts. This endogeneity arises because compliance and non-switching are equivalent when the current path is identical to the best path. Similarly, when the current path is distinct from the best path, compliance is equivalent to switching. The converse, however, is not true. Even with joint models, compliance and inertia (reflected through switching) are only partial determinants of the observed route choice, though the loss of information is smaller here.

9.3.1 Exploratory Analysis

Exploratory analysis results are presented here as a prelude to the development of the framework to model route choice. Given the topology of the corridor network under consideration (See Figure 3.4), it is assumed that users perceive and identify a path in terms of its major highway facility. As mentioned in Chapter Three, Section 3.4, a path in this analysis consists of a single major facility (to the destination) along with its connecting link. Therefore the user effectively considers only three paths to the destination at each decision location.

First, aggregate path choice behavior is examined using data from experiment one. The current path (cp) followed by a user is defined in an obvious manner when examining en-route choices. For pre-trip choices, the current/default path on a given day is defined as the path chosen, pre-trip, on the previous day. The path corresponding to the least trip time reported by the ATIS is referred to as the best path (bp). In general, both the current path and best path can vary over time.

Route choice is examined when the current path coincides with the best path reported by ATIS (cp = bp). In this case, it was observed that 85%, 13%, and 2% respectively chose the current path, the faster of the two alternative paths, and the slower alternative path, respectively, under the random treatment (from day-to-day). The corresponding proportions were 57%, 33%, and 10% for the systematic treatment. When the two paths (current and best) are distinct, the proportion choosing the current path, best path and alternative path were 50%, 42%, and 8% respectively, in the random treatment, and 43%, 44%, and 13% in the sequential treatment. Chi-squared tests confirm that the differences in the two cases (cp=bp, cp≠bp) are indeed statistically significant. The test-statistics in random and sequential treatments are 110.70 and 33.69 respectively, compared to the critical value of 5.99 for two degrees of freedom. Thus, for both treatments, choice behavior varies depending on whether the current path happens to be the best path. Note that whether the current path coincides with the best path (cp=bp) is exogenous to a user's decision (at the next decision location), since the best path is determined collectively by the choices of all trip-makers on the network. Two other interesting observations are noteworthy. The choice of current and best paths together comprise about 60-90% of the observed route choices. The likelihood of choosing the current path and the best path are nearly equal when the two are distinct.

The propensity to choose the current path is due to an inertial effect. This inertial factor may reflect the lower cognitive costs of information search and processing, lower switching cost, habit persistence with satisfactory choices, and familiarity with alternatives. In spite of this inertial effect being

observed in a substantial body of route choice literature (Mahmassani, 1990; Mannering et al., 1994; Abdel-Aty et al., 1994; Polydoropolou, 1996; Zhao et al., 1996; Abdel-Aty et al., 1997), it has (with a few exceptions) hardly been explicitly captured. This oversight is attributable to the following experimental design and specification limitations. A majority of studies model the route diversion decision (from a given current path) instead of path choice. Consequently, the inertia effect is captured through an alternative-specific constant that is generally confounded with the baseline levels of other categorical variables in the models, thus losing behavioral robustness associated with a generic variable. Furthermore, many of the studies are cross-sectional in nature, with the result that the switching decision is observed only once for each observer. This precludes a generic specification of the propensity (over time) to retain the current path. A few researchers, however, have noted the presence of behavioral inertia as a counteracting force to switching (Polydoropolou, 1996). Mahmassani and Chang (1987) propose indifference band models of route switching that represent tradeoffs between habit persistence of users and the factors inducing switching.

One such factor that could induce switching is the information supplied by ATIS. By supplying information regarding more efficient opportunities, the ATIS can encourage the user to select the best path (reported) instead of continuing on his/her current path. The propensity to switch to the best path (as recommended by ATIS) is driven by a compliance mechanism. Compliance with ATIS information (for simplicity perfect information is assumed) may be motivated by awareness of opportunities, trip time savings, congestion avoidance, and schedule delay considerations.

The inertial effect increases the utility of the current path, whereas the compliance effect increases the utility of the best path. As a preliminary test for the presence of inertial and compliance effects in choice behavior, the following trinomial logit model is estimated. The route choice alternatives for each user correspond to the three paths available at each decision location, as described in Section 3.4. The utility of each alternative consists of a generic component (that includes trip time to the destination, and congestion on the segment downstream of the current link), and route-specific constants (for two of the three alternatives). In addition, binary indicator variables (inert, compl) are activated for the current and best path respectively. The estimation results reported in Table 9.6 suggest significant compliance and inertial effects in route choice.

The observed differences in Table 9.6, however, may have alternative explanations. One plausible explanation is that trip-makers are more likely to choose the best and second best paths on the basis of information. The observed propensity to choose the current path may be a consequence of the current path coincidentally being the best or the second best path. To test this conjecture, an indicator variable was added to the utility of the second best path. This factor was not significant under the random treatment, while under the systematic treatment this was significant, though only at the 10% level. However, this factor was smaller than the inertial factor by about five times (coefficients of 0.27 to 1.30). The model fit of this specification was inferior to the model incorporating compliance and inertia for both treatments (Table 9.6).

TABLE 9.6

CALIBRATION RESULTS FROM EXPLORATORY ROUTE CHOICE ANALYSIS

Variable	Random		Systematic	
Description	Coefficient	t-stat	Coefficient	t-stat
ASC (Highway 1)	0.17	1.09	-0.23	-1.80
ASC (Highway 2)	0.41	4.01	0.50	6.25
Triptime (reported)	-0.06	-3.08	-0.06	-3.31
Congestion (next segment)	-0.68	-6.12	-0.53	-7.14
Inert (=1, if route = cp, else 0)	1.29	14.48	0.96	11.42
Comply (=1, if route = bp, else 0)	0.81	7.50	1.43	20.44
No. of Observations	800		1469	
LL(0)	-878.89		-1613.9	
LL(final)	-550.53		-942.36	

Notes: The likelihoods in the random treatment for comply only, inert only, (fastest 2nd fastest path) specifications are -669.2, -576.02, -574.34 respectively.
The corresponding likelihoods in the sequential treatment are -1194.7, -1004.7, -985.39 respectively.

Thus, route choice appears to be influenced significantly by inertia and compliance. The next section proposes a modeling framework to incorporate these effects as mechanisms influencing route choice.

9.3.2 Modeling Compliance and Inertia as Behavioral Mechanisms

It is evident that compliance and inertia significantly influence choice, though not exogenously, as their effect varies with the choice context. However, treating them directly as choice outcomes is also undesirable. To resolve this dilemma, they are characterized as mechanisms influencing route choice. A mechanism, in this context, is defined as a set of principles or rules that operate, in isolation or in conjunction, in the decision process to determine the behavioral outcome of interest. The advantage of this notion is that it allows f compliance and inertia to be modeled as functions of other exogenous variables and choice context, without any loss of observed choice information. Although route choice behavior is likely to be influenced by other possible mechanisms, attention is restricted to these two in the rest of this chapter. These two mechanisms and their associated characteristics are described next.

Inertia is defined as the mechanism underlying a decision-maker's tendency to retain his/her current path. Compliance is the mechanism related to the tendency of a trip-maker to comply with the best path (as recommended by the ATIS). Both may act jointly in favor of a particular alternative in some cases (cp=bp), whereas in others cases they may favor distinct alternatives (cp≠bp). In general, the two mechanisms may operate simultaneously and the observed choice may be the result of a trade-off between the two. In addition, a given user may apply different mechanisms to determine path choice under different choice instances. The formulation, presented next, incorporates these mechanisms simultaneously in the path choice process.

Each user faces the decision of selecting a route from a set of alternatives (three in the experimental scenario) over repeated choice instances (both within-day and day-to-day). In each instance, it is assumed that the user selects the alternative with the highest utility (consistent with Random Utility Maximization framework). In addition to a path-specific utility, U_p, considered in previous specifications, the total utility of alternative p, $\tilde{U}_p$, also accounts for the utilities of U_a, and U_c, associated with inertial and compliance mechanisms (if route p is either the current or the best path). These mechanism-specific utilities are unobserved, and can vary across individuals and choice instances. Therefore, the mechanism-specific utilities are modeled as latent random variables whose means vary systematically with level-of-service measures, and trip-maker attributes. They may be expressed as:

$$U_a(i,t) = f(Z(i), X_a(i,t), \beta_a) + \varepsilon_a(i,t) \quad (9.12),$$

$$U_c(i,t) = f(Z(i), X_c(i,t), \beta_c) + \varepsilon_c(i,t) \quad (9.13),$$

where, i denotes the user, t denotes the choice instance, Z(i) denotes the trip-maker attributes, $X_a(i,t)$ and $X_c(i,t)$ represents the vector of attributes related to the inertia and compliance utilities, and $\varepsilon_a(i,t)$, $\varepsilon_c(i,t)$ refer to the corresponding error components; β_a and β_c represent the vectors of parameters associated with inertia and compliance.

The total utility for each of the path alternatives is constructed from the path-specific components and the mechanism-related utilities as described for the following two cases of interest. For simplicity, the arguments i and t are dropped and attention is focused on a single choice instance for a given individual. Following the preliminary analysis, the route choice decision is decomposed into the following two cases based on whether or not the current path is identical to the best path.

Case 1: The current path happens to be the best path recommended by the ATIS. In this situation, following the current path is consistent with both compliance and inertia. Hence the utility of the current path consists of U_a, and U_c, in addition to a path-specific component. An interaction component $U_{a,c}$, (given by $U_{a,c} = f(\beta_{a,c}, Z, X_{a,c}) + \varepsilon_{a,c}$,) is introduced to capture the interaction effect between compliance and inertia. The choice of the remaining alternatives involves non-compliance and non-inertia (switching). Hence the corresponding utilities consist only of path-specific components. Since unobservables may be shared across alternatives that involve non-inertia and non-compliance, it is assumed that the error components of these alternatives are correlated. This is modeled through a common error component (η) as shown in the nesting structure on the left half of Figure 9.4.

Case 2: The current path is distinct from the best path recommended by the ATIS. In this case, the inertial utility component is associated with the current path, and the compliance utility with the best path. The mechanism-related components do not contribute to the utility of other alternatives. The error term associated with the current path is correlated with other paths that involve non-compliance. Similarly, the best path is expected to be correlated with other paths sharing non-inertial error terms. The resultant nesting structure is displayed on the right half of Figure 9.4, and mathematically formulated next.

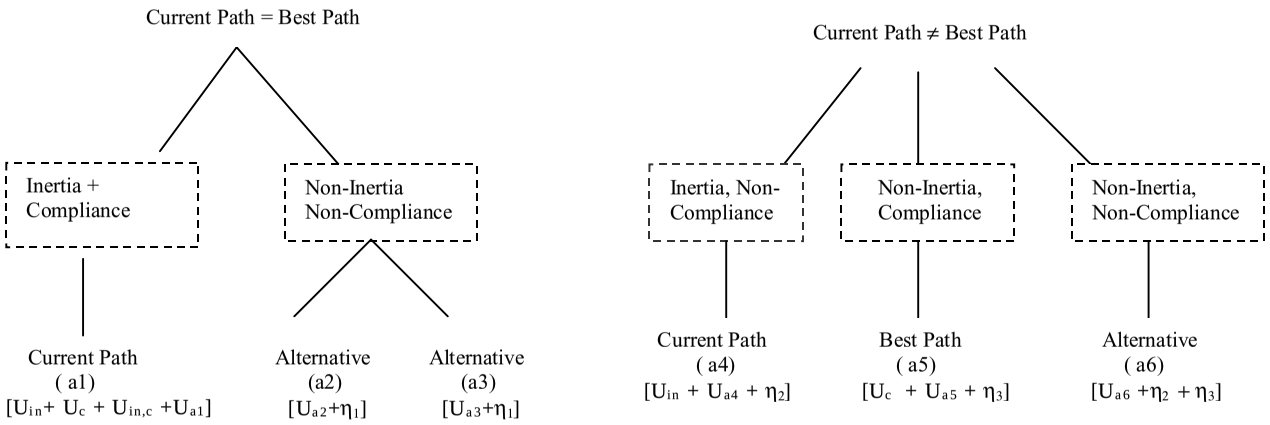

FIGURE 9.4
Route choice structure incorporating both inertia and compliance mechanisms

9.3.3 Model Formulation

The path choice utilities for the data (from experiment one discussed in Section 3.5) in the experimental scenario with three path alternatives are now presented. The utility construction scheme can be easily generalized to route choice with more than three alternatives. The following notation is introduced for the rest of the analysis.

Let p1, p2, p3 represent the current path and the remaining alternative paths, respectively, in case 1 (cp=bp). Let p4, p5, p6 represent the current path, best path and the remaining alternative in case 2 (cp≠bp). The mechanism utilities may be expressed as:

$U_a = V_a + \varepsilon_a$, $U_c = V_c + \varepsilon_c$, and $U_{a,c} = V_{a,c} + \varepsilon_{a,c}$ (9.14). Path-specifc utilities can be written as:

$U_k = V_k + \varepsilon_k$, (9.15),

where, k =1, … 6.

It is assumed that the error components above are independently normally distributed with mean zero. The nesting and decomposition of route choice into the two cases above introduces the following correlations between the utilities of the route choice alternatives. Alternatives p2 and p3 share error term η_1, while, η_2 represents the shared error term component between alternatives p4 and p6. The error term component common to alternatives p5 and p6 is denoted by η_3. Aggregating the utilities of the alternatives to form the total utility

$\tilde{U}_k = \hat{W}_k + \nu_k$, (9.16a),

where,

$\hat{W}_1 = V_1 + V_a + V_c + V_{a,c}$, (9.16b),

$\hat{W}_4 = V_4 + V_a$, (9.16c),

$\hat{W}_5 = V_5 + V_c$, (9.16d),

$\hat{W}_k = V_k$ otherwise (9.16e).

and the ν_k are obtained similarly by aggregating the error components.

It can be shown that the error term assumptions and the shared unobservables above across alternatives lead to a covariance structure of the following form (see figure 2):

$[\nu_1, \nu_2, \nu_3]' \sim \text{MVN}\ [0, \Sigma_1]$

$[\nu_4, \nu_5, \nu_6]' \sim \text{MVN}\ [0, \Sigma_2]$, where,

$$\Sigma_1 = \begin{pmatrix} \sigma_1^2 & 0 & 0 \\ 0 & \sigma_2^2 & \rho_1\sigma_2\sigma_3 \\ 0 & \rho_1\sigma_2\sigma_3 & \sigma_3^2 \end{pmatrix} \quad and \quad \Sigma_2 = \begin{pmatrix} \sigma_4^2 & 0 & \rho_2\sigma_4\sigma_5 \\ 0 & \sigma_5^2 & \rho_3\sigma_5\sigma_6 \\ \rho_2\sigma_4\sigma_5 & \rho_3\sigma_5\sigma_6 & \sigma_6^2 \end{pmatrix}$$

where σ_k, k = 1,…6, represents the standard deviation of error term associated with the paths p_k, and the ρ_m, m = 1,..3, captures the correlation between the alternatives between paths sharing unobserved errors as shown in Figure 9.4.

It can be seen that the error-components scheme shown in Figure 9.4, leads to this structure. Consider, for example, when cp = bp, the nesting structure implies that alternative pairs (p_1, p_2) and (p_1, p_3) do not share any unobservables. Hence their correlation is zero. In a similar vein, the utilities of alternatives p_4 and p_5 are independent when the current path is not the best path. When cp=bp, alternatives p_2 and p_3 share the same nest, whose correlation is denoted by ρ_1. Correlations ρ_2 and ρ_3 may also be described in a similar fashion.

In both cases, the resulting choice can be modeled as a trinomial probit with the utilities and covariance structures above. The probit structure is used to capture the correlation across alternatives. Due to identification considerations, the variances are assumed to be equal across alternatives for both Σ_1, and Σ_2. For purposes of scaling these variances are set to unity, i.e., σ_k = 1, k = 1,…6. The coefficients of the systematic components and the correlation parameters are then estimated for the experimental data and are presented in the next section.

9.3.4 Route Choice Adjustment Modeling Results

Alternative route choice adjustment models are calibrated using data from the first set of experiments. In the first model only the inertial mechanism is operative, while in the second, only the compliance mechanism is operative. The third model corresponds to simultaneous operation of both inertial and compliance mechanisms, and the final model corresponds to a scenario where neither mechanism is active. The log-likelihoods of these formulations are reported in Table 9.7. The model with both mechanisms is significantly better than the other models for both treatments. The model with inertial mechanism only outperforms the model with only the compliance mechanism. Either model is superior to the model including neither mechanism. The route choice model is calibrated based on the formulation above with both mechanisms (Table 9.8). Since the formulation with both mechanisms is superior in terms of model fit, the corresponding results are discussed next.

TABLE 9.7

COMPARISON OF ALTERNATIVE ROUTE ADJUSTMENT MODELS

Model	Random Treatment		Sequential Treatment	
Description	Log-likelihood	df	Log-likelihood	df
Neither Mechanism	-695.39	4	-1239.3	4
Inertia only	-503.22	13	-953.45	16
Compliance only	-562.04	15	-1110.2	18
Inertia and Compliance	-483.96	22	-883.07	23

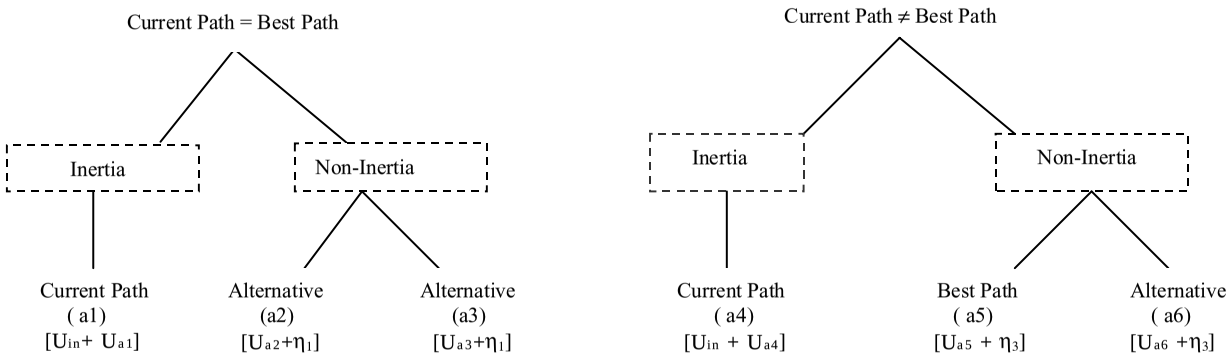

FIGURE 9.5
Route choice structure accounting for inertial effects only

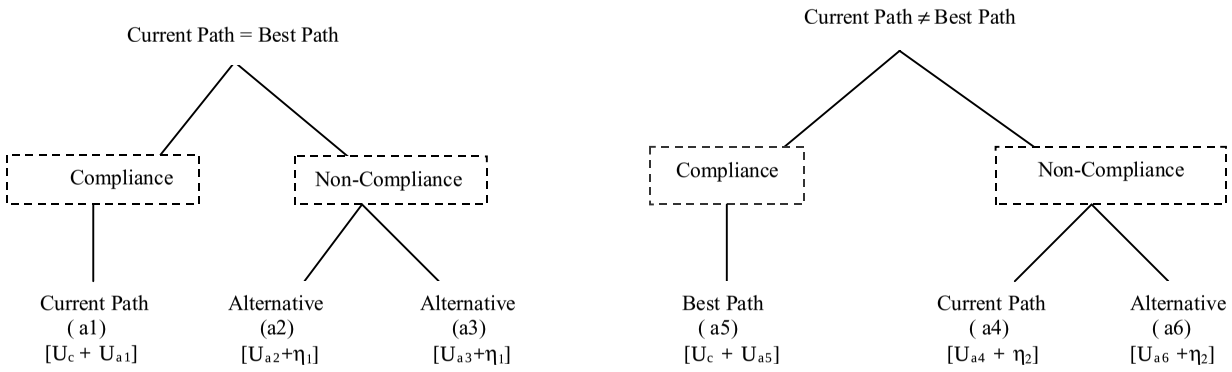

FIGURE 9.6
Route choice structure accounting for compliance effects only

TABLE 9.8

ROUTE CHOICE MODEL INCLUDING COMPLIANCE AND INERTIA MECHANISMS

Variable Definition	Random		Sequential	
	Coefficient	t-stat	Coefficient	t-stat
Inertia				
Constant	1.82	5.86	3.63	9.03
Network Loads and Conditions				
Level 2 (pre-trip)	-	-	-1.17	-2.33
Level 3 (pre-trip)	-0.65	-2.05	same	same
Level 2 and 3 (en-route)	-	-	-0.45	-2.53
Relative Trip Time Saving (%)	-	-	-2.35	-1.55
Information Quality				
Over estimation Error	-0.98	-2.52	-0.73	-2.94
Under estimation Error	-0.60	-1.63	-0.17	-2.24
Past Traffic Experience				
Early Schedule Delay (prev. day)	-	-	-0.04	-2.93
Cumulative proportion of switches to later departure times	0.77	2.30	-1.00	-2.36
Cumulative proportion of switches to earlier departure times	-	-	-0.99	-1.89
Compliance				
Constant	-0.46	-0.83	1.50	4.07
Network Loads				
Level 2 and 3 (en-route)	0.50	2.54	-	-
Costs and Benefits				
Relative Trip Time Saving (%)	3.65	2.00	1.83	1.48
Switching Cost (miles)	-1.86	-4.10	-1.72	-4.40
Information Quality				
Over estimation Error	-0.94	-2.53	-0.80	-3.16
Past Traffic Experience				
Late Schedule Delay (prev. day)	-	-	0.02	3.21
Cumulative proportion of switches to earlier departure times	-	-	1.01	2.56

TABLE 9.8

ROUTE CHOICE MODEL INCLUDING COMPLIANCE AND INERTIA MECHANISMS (CONT'D..)

Inertia-Compliance Interaction				
Constant	-1.26	-1.90	-2.11	-3.07
Information Quality				
Over estimation Error	1.09	1.34	1.22	2.34
Under estimation Error	1.68	2.12	-	-
Past Traffic Experience				
Cumulative proportion of switches to later departure times	-0.76	-1.33	1.65	1.47
Path Specific Utility				
Trip Time (min)	-0.23	-4.46	-0.05	-3.19
Anticipated Congestion	-0.70	-5.69	-0.61	-7.15
Highway 1 (ASC)	0.52	2.66	0.05	0.31
Highway 2 (ASC)	0.39	3.18	0.42	4.25
Correlations				
$\rho 1$	0.05	2.51	0.02	2.24
$\rho 2$	0.03	1.91	0.09	3.21
$\rho 3$	0.04	2.22	0.07	1.81
Log-Likelihood	-483.96		-883.07	
LL(0)	-841.54		-1613.9	
Number of Observations	766		1469	

Network Loads

The magnitude of network loads influences both the compliance and inertial mechanisms. However this influence varies considerably between the random and systematic evolution in the network. In the random treatment, there is very little effect of network loading on inertia with one significant exception. Following the highest loading level on the previous day (level C), a reduced inertial tendency is observed (i.e. increased switching occurs). In the systematic treatment, increased network loads on both current and previous day (levels B and C) result in decreased inertial effect, with the latter being considerably larger than the former. These findings are consistent with the results presented earlier in Chapter 5 where the effect of network loads on route switching indifference bands was investigated. Increased loading on the current day (levels B and C) results in increased compliance with information

under the random treatment. In contrast, network loads have no effect on compliance in the sequential treatment.

Experience

Users' past experience in traffic significantly influences both the compliance and inertial mechanisms. Specifically, the effect of early and late schedule delays, and the cumulative relative frequency of departure time switches to later and earlier departure times are examined. Experience variables were found to have a smaller impact when the day-to-day evolution is random. A similar finding was also noted in the perception model where current information is weighted more than past perception in the random treatment. Trip-makers with more frequent switches to later departure times (presumably in response to early arrivals) tend to retain their current paths. However when the current path coincides with the best path this effect is insignificant. The remaining variables did not significantly affect either mechanism in the random treatment.

When the day-to-day evolution of traffic is systematic, an increased compliance tendency is observed following lateness on the preceding day. However, increased route switching (decreased inertial effect) is noticeable in response to early arrivals at the work place. A greater number of switches to earlier departure times leads to increased switching and increased compliance. This behavioral response may be explained by the failure to meet aspirations regarding preferred arrival time (due to unacceptably many late arrivals). In contrast, with increased switches to earlier arrival times (too many early arrivals), trip-makers display a decrease in both inertial and compliance propensities. The difference in experience effects between random and systematic treatments indicate that when the traffic conditions fluctuate drastically from day-to-day, users are less likely to adjust their behavior on the basis of their experience. The results also indicate that under systematic evolution, where a user can learn about traffic evolution over time, the influence of ATIS is enhanced following unacceptably late arrivals (since compliance increases). This suggests that the presence of arrival time constraints and opportunity to learn about network conditions is likely to encourage users to seek more efficient alternatives.

System Performance Measures

The effect of trip time saving (on the best path relative to the current path) is investigated. While this factor exerts a significant and positive influence in the anticipated direction (positive) on the inertial mechanism in the systematic treatment, it is insignificant in the random treatment.. The positive coefficient of the inertial constant in both treatments indicates that a decreased switching propensity is observed with increasing switching cost. This highlights the fact that the outcome of route choice actually depends on the cost of implementing that choice (namely switching). Unlike the inertial mechanism, the role of trip time saving and switching cost on the compliance mechanism is stable across the two treatments. Increased trip time saving leads to increased compliance, whereas increased cost results in lower compliance. The effect of trip time saving and switching cost confirms similar findings in Chapter Six on compliance behavior.

Two other system performance measures, trip time and anticipated congestion downstream, are included in the path-specific utility of each alternative. Both are significant and negative as expected, for the random and sequential treatments. The relative magnitudes of the coefficients indicate that when the network conditions vary randomly, trip-makers are more sensitive to trip time than if they vary systematically.

Information Quality

To represent the effect of information quality, the following measures of information accuracy are incorporated in the utility specification. As it may be recalled, the underestimation error reflects discrepancy between the reported time and experience when the reported time is smaller. Overestimation error represents a discrepancy in the other direction. It is observed, for both treatments, that increased overestimation errors lead to decreased inertia and reduced compliance. In contrast, underestimation error merely reduces the tendency to continue on the current path. However, when the current path also happens to be the best path, the negative effect of the information errors on this choice is diminished for overestimation error in both cases and underestimation errors in the random treatment. These findings corroborate earlier findings on the effect of information quality on route switching behavior reported by Liu and Mahmassani (1998).

In light of the nature of the experiments, network structure used, and associated experimental conditions, the usual caution should be exercised in interpreting these results. Nevertheless, the proposed framework provides a flexible basis to incorporate mechanisms in modeling route choice behavior in the presence of ATIS. The insights into route choice adjustment process obtained here need to be externally validated with empirical data from actual commuting systems. While transferring these insights, there may be discrepancies in the magnitude of effects estimated from the set of experiments. For instance, it is possible that the inertial effect found here may underestimate the corresponding effect in real-world systems due to the nature of simulation experiments used for this study. Another limitation of this work is that the route choice model is proposed for the three-alternative case. However, this model may be generalized to larger path sets by extending the nesting structure to include additional alternatives. While the attention is restricted here to commuting trips (particularly home to work), it is possible that the inertial mechanism may play a smaller role for other trip types (non-commuting, recreational trips, or work to home trips). This work can be extended to model unobserved heterogeneity and structural effects in a manner similar to the one presented in Chapter Seven.

9.4 SUMMARY

It is proposed that heuristic strategies and behavioral mechanisms drive the adjustment processes in route and departure time choices over time. It is suggested that users tend to select a set of default choices (close to their current choices), review them for suitability from day-to-day, and if found unsuitable, search other alternatives till a satisfactory choice is obtained. An adjustment process of this type can lead to the selection of alternatives that are locally optimal, unlike the global optima (across alternatives for each time) sought in the case of utility maximization behavior. The proposed adjustment

processes explicitly account for the presence of search cost, cognitive processing cost, and physical cost of implementing various alternatives in choice adjustment behavior.

A comparison of alternative specifications for the departure time adjustment process indicates that a greedy-type heuristic search process has considerably higher explanatory power than the ordinal response and unordered response choice models. This finding suggests that a user may determine a suitable departure time adjustment through the following series of decisions. First, he/she decides whether or not to adjust departure time. Conditional on the decision to switch, the data suggests that other alternatives are evaluated sequentially (in five minute increments), e.g., if a shift of one-five minutes is found unsatisfactory a user is likely to consider an adjustment of six-ten minutes alternatively. The directionality of adjustment is governed largely by the schedule delay experienced on the preceding day, with users switching to earlier departure times following lateness, and vice versa. The significant determinants of the observed departure time adjustment behavior include: system performance measures, including trip-time and its variability; ATIS information, its quality, nature and type; and users' past experience in the system. The departure time alternatives in the proposed heuristic search process are found to share unobserved attributes in a nested and ordered fashion.

Route choice decisions observed in the presence of real-time information appear to be based on the underlying behavioral mechanisms of compliance and inertia. The influence of these mechanisms on route choice behavior is modeled by decomposing the path choice structure into two states based on the user's current choice and the information supplied by ATIS. These cognitively simple behavioral mechanisms relate directly to the propensity of choosing the current path or the best path. However, the model structure does not preclude the choice of other alternatives. This framework is implemented to model route choice data from interactive experiments using a multinomial probit model. The results demonstrate that these mechanisms considerably increase the explanatory power of the route choice model.

Inertial tendency is generally reduced with increasing congestion under both sequential and random day-to-day evolution, though this influence is considerably stronger in the sequential evolution. The propensity to retain the current path is also diminished by information quality errors. The experience of users (schedule delay and cumulative proportion of departure time switches) exerts a mixed influence on inertia. With an increase in either of the two variables, an increase in behavioral inertia is observed under the random treatment, whereas, a decrease is observed under the sequential treatment.

Increased compliance propensity is observed with increased trip time savings and lower switching costs. However, the compliance propensity reduces with inaccurate information (over-estimation errors). Past late arrivals (relative to preferred arrival time) seem to increase the likelihood of compliance in the sequential treatment.

The results also indicate that compliance, inertial, and path-specific components of the utility are influenced by network conditions both within-day and day-to-day. This is evident from the significance of network loads, and level-of-service measures such as trip time and anticipated congestion. It is

noteworthy that the influence of network loads, and user's past experience in traffic have varied impacts depending on whether network conditions change from day-to-day in a random or systematic manner. Random changes are reflective of incident-induced congestion in actual traffic networks.

This chapter focuses on heuristic behavioral rules and mechanisms in commuters' choice adjustment behavior in the presence of information. In addition to the mechanisms proposed here, it is possible that the observed adjustment behavior is also influenced by alternative behavioral rules. Identifying and operationalizing the mechanisms in these and other choice dimensions promises to be a challenging area for future research. Further investigation is also necessary to examine the trip-maker decision processes for other trip-types such as non-commuting, recreational, and return-home and personal business. Following a summary of the contributions from this research, the next chapter also recommends directions for future work.

CHAPTER 10: CONCLUSIONS

Technology today makes it feasible to supply drivers with real-time traffic information in their cars through a range of Advanced Traveler Information System (ATIS) devices. Such ATIS devices will likely enjoy widespread usage and popularity. Information supplied by ATIS can offer considerable and substantial benefits to trip-makers by offering them more desirable and efficient alternatives. ATIS information could potentially be used as a tool to achieve transportation system management objectives by redistributing the Origin-Destination (O-D) desires on the network, to effectively reduce externalities (congestion, accidents, pollution), and increase efficiency (trip-time savings, throughput etc.). However, the effectiveness of ATIS, or indeed for that matter any other system management measure based on real-time information on network conditions, will critically depend on users choices over time, and the resulting time-dependent interactions between network conditions, real-time information, and user behavior. Among the three components, user behavior is arguably the most critical since the network conditions are a collective consequence of the choices of all users on the network. Two principal time frames are of interest in user behavior analyses. Users' decisions on a given day determine time-dependent congestion patterns and associated system performance measures. Changes in routes and departure times from day-to-day result in changes in O-D flows on the network, which is also of interest for tactical and strategic planning purposes.

Despite its practical significance, considerable progress remains to be made in representing and quantifying user behavior, particularly with regard to its dynamic aspects, especially in the presence of real-time information. In addition to enabling the calibration of behaviorally richer and more accurate choice models, the analysis of dynamic aspects in user behavior also has important applications in dynamic traffic management, network state prediction, evaluation of demand management measures and traffic control strategies. This technical report attempts to augment the growing body of knowledge pertaining to user behavior under ATIS by specifically examining dynamic aspects in commuter behavior under real-time information. The interaction between time-dependent network conditions and various ATIS information strategies on users' choice behavior are observed and analyzed on the basis of a set of interactive simulator-based experiments. An array of models based on alternate behavioral paradigms are proposed and calibrated to analyze various choice dimensions in commuter behavior. The proposed models explicitly recognize temporal inter-relationship s between the users' choices at both the systematic and unobserved levels. The results provide insight into factors influencing user response in the presence of real-time information. Further, the study analyzes five cognitive processes underlying observed commuter choice dynamics, and proposes a set of constituent models.

The rest of this chapter presents an overview of the contributions from this work, outlines the empirical findings, highlights their significance, and identifies directions for future research.

10.1. CONTRIBUTIONS

The major contributions emerging from this work can be classified as methodological, behavioral, and substantive as described below.

10.1.1 Methodological Contributions

In this technical report, the Dynamic Kernel Logit (DKL) model is presented for analyzing commuter behavior dynamics. The DKL formulation proposed here extends recently developed mixed logit models in two important respects. First, the proposed formulation enables the analysis of general dynamic patterns in longitudinal discrete choice data, both ordered and unordered. Second, this formulation enables a computationally more efficient calibration of both cross-sectional and longitudinal discrete choice data with a large dimensionality of choice alternatives and/or time periods of interest.

Distributional analysis and numerical experiments demonstrate that the DKL formulation is a suitable methodological alternative to MNP for modeling longitudinal discrete choice data. Computational complexity analysis and numerical experiments establish that the DKL formulation is computationally superior to the corresponding MNP formulation (by more than an order of magnitude) with increasing number of alternatives or time periods or both. In fact, it is shown that the proposed formulation has a pseudo-polynomial complexity in contrast to the exponential complexity of the MNP frequency simulator.

The proposed formulation is sufficiently versatile to accommodate a wide range of discrete choice models. Specific instances of this generic formulation to model ordered and unordered response data are presented in Chapter Four. This generic formulation is flexible enough to represent decision making under alternative behavioral paradigms. The application of this formulation to calibrate indifference bands based on boundedly-rational behavioral rules is presented in Chapter Five. The compliance models, presented in Chapter Six, demonstrate its applicability under random utility maximization paradigm. Furthermore, the application of this framework to model longitudinal choices in multiple discrete choice decisions is illustrated through a joint model of dynamic route and departure time switching decisions in Chapter Seven. This feature is particularly advantageous in simultaneously modeling several inter-related choice dimensions influencing activity-travel behavior over time. Thus, the proposed framework offers considerable potential for obtaining richer insights into behavior and developing more accurate and robust models. This framework may also be applied in the following areas including traveler behavior, activity-travel analysis, consumer behavior, information acquisition and search etc.

Through empirical applications of this framework, this dissertation highlights the need to represent dynamic aspects operating in and influencing decision making in the presence of real-time information. The proposed framework enables the representation of general dynamic patterns in choice behavior including, state-dependence, heterogeneity, and habit persistence. The results presented earlier indicate that these effects are indeed significant, highlighting the potential limitations of cross-sectional models of user behavior under real-time information. Such models are likely to be plagued by serious mis-specification errors leading to inaccurate inferences and poor quality forecasts. A second advantage of this formulation is the ability to represent and statistically test alternative stochastic patterns that might

generate the unobservables in the observed data. Using this formulation, it is possible to model both stationary and non-stationary error generation processes, although, in the applications presented here, attention is restricted to first-order markovian state-dependence and auto-regressive error-structures.

10.1.2 Behavioral Contributions

The work presented in this technical report enhances the behavioral understanding and representation of commuter behavior under real-time information in the following respects. First, the modeling framework and proposed constituent models of behavior significantly relax many restrictive assumptions, associated with the elegant but often unrealistic micro-economic theory of choice (see Garling, 1998). Decision making models are calibrated based on alternative behavioral rules including boundedly rational behavior, heuristic sequential search strategies, and other mechanisms, that do not necessarily lead to the choice of the alternative with the maximum utility. Such behavioral rules can substantially explain inconsistent preferences observed in choice behavior in the real-world. Besides, these decision-making paradigms explicitly account for the cognitive burden and costs involved in real-time decision making contexts. In contrast to typical behavioral choice models, the decision dimensions of route and departure time switching are modeled explicitly as inter-dependent decisions, through both systematic variables and correlation between unobservables.

Second, the proposed models allow for the presence of systematic biases and unobservable influences in information representation and use in decision making. For instance, the calibrated models suggest a significant role of socio-demographic characteristics in users' perception and judgment of ATIS information, and a strong effect of experience on compliance decisions of users.

A third major behavioral assumption relaxed here relates to the implementation of choices (Garling, 1998). According to the micro-economic theory of choice, each user evaluates the utility of all the alternatives at each time selecting the one that provides him/her with the greatest utility. There is no cost associated with evaluating the alternatives or implementing the chosen alternative. In stark contrast, this work provides considerable evidence of automation in decision making, especially, over repeated choice instances. The substantial influence of switching cost and inertia on route choice behavior highlight the role of cognitive and physical costs of implementing the decisions and time constraints operating in the traffic environment. Empirical support is also observed for the presence of habit formations that are not generally accounted for in conventional behavioral models.

The models calibrated in this study provide a richer behavioral representation of commuter behavior processes under real-time information. Specifically, this research is distinct from most modeling efforts till date in the following respects. Pertinent factors influencing choice such as time-dependent network conditions, users' experiences in traffic, and users' perceptions and attitudes are observed at a greater temporal resolution and at a highly disaggregate level and their influence on behavior is explicitly captured. These factors are often neglected in behavioral studies due to data collection difficulties. The use of stated preference techniques in many studies to elicit such information often introduces reporting,

selectivity, and justification biases. In contrast, these variables are directly observed in a simulated setting, thereby minimizing these sources of data error.

The modeling approach also explicitly accounts for the presence of heterogeneity in the choice process. In contrast to standard behavioral models of route and departure time choices, the proposed models allow for variations in both intrinsic preference towards alternatives, as well as sensitivity to exogenous variables across respondents, even when faced with the same choice contexts. The proposed model represents heterogeneity in commuter behavior under ATIS at both systematic and unobserved levels.

A third distinguishing feature of this work relates to its treatment of temporal relationship between users' choices in the presence of real-time information. Most travel behavior models to date have either ignored temporal aspects or examined them to a limited extent due to data collection and methodological difficulties. This study analyzes the inter-relationship of users' choices over time by examining three relevant threads. First, the influence of time-dependent exogenous variables on the choice process is modeled through the specification of systematic utility. Second, structural effects such as state-dependence and habit persistence over time are explicitly investigated. Finally, the correlation over time, not accounted for by the systematic specification, is captured by the specification of a suitable variance-covariance structure for the error-terms.

Another significant behavioral contribution emerging from this work is the preliminary empirical insight into the decision and cognitive processes underlying the observed choices. Empirical evidence supports the presence and operation of the following processes in user behavior dynamics: learning, perception, judgment, and updating processes. The nature and extent of influence of these processes on commuter behavior are explored qualitatively and through analytical models. In particular, adjustment models for both route and departure time choices are proposed on the basis of heuristic behavioral mechanisms. The factors influencing the adjustment behavior are identified using empirically calibrated models. Adjustment models incorporating behavioral mechanisms are found to be statistically superior to specifications that do not account for them.

10.1.3 Substantive Contributions

This research investigates the following substantive issues that have not been systematically addressed in previous behavioral research efforts. User behavior in the presence of ATIS is examined under varying degrees of network congestion. The role of network conditions (the effect of magnitude of loads and its day-to-day evolution) in commuters' route and departure time switching decisions is investigated using boundedly-rational behavioral rules. The indifference bands for route and departure-time switching vary considerably with the congestion levels encountered in the network. The influence of information quality, system performance measures, and user experience on the network, are also explicitly modeled.

Besides network conditions, another important dimension of behavioral response to ATIS, namely compliance, is also examined. The compliance behavior of commuters under ATIS information strategies

of varying information quality and credibility is observed in simulator-based experiments by systematically varying the nature, type and feedback supplied by the ATIS to the users. A disaggregate discrete choice model is proposed to analyze users compliance behavior over time. In addition to exploring the effect of ATIS information strategies, the proposed specification also examines the influence of information quality, information-supply interaction, and the effect of past experiences on compliance response of users. Significant findings from this study, most of which derive from these substantive issues, are presented in the next section.

10.2 SIGNIFICANT FINDINGS

The major empirical findings from the research in this dissertation are presented in this section and their implications discussed in the next section. The Dynamic Kernel Logit (DKL) formulation is proposed as a suitable methodological alternative to the multinomial probit (MNP) framework for the longitudinal analysis of discrete choice data based on both theoretical and computational considerations. The results indicate that the DKL formulation is computationally less expensive than the MNP asymptotically with increasing number of alternatives, time periods or both. However, when the product of the number of alternatives and time periods is fewer than twenty five, it is empirically observed that little advantage is derived with the DKL framework relative to the MNP. In terms of computational accuracy, numerical experiments and convergence results indicate that the DKL estimates are comparable to the MNP parameter estimates. It is noteworthy that both DKL and MNP formulations necessitate the maximization of a generally non-concave multi-dimensional integral. Therefore, the likelihood functions in both frameworks may converge to local maxima and/or lead to identification problems.

Commuter behavior, especially users' compliance response, is strongly influenced by real-time information, as expected. Users' appear to be particularly sensitive to the quality of information provided by the ATIS. When the ATIS provides inaccurate or unreliable information, users' exhibit reduced compliance propensity. Users' also display a range of compliance behaviors in response to variation in ATIS information strategies. Each information strategy, tested empirically, consisted of a combination of the following factors: nature of information, type of information, and feedback levels. The strategies are designed to reflect varying levels of information availability, timeliness, scope, and format of information provision, that drivers may encounter with real-world ATIS. Among the different information strategies, users' appear to respond more favorably (in terms of compliance) to prescriptive information than descriptive information. Substantially reduced compliance rates are observed when ATIS supplies random (highly inaccurate and unreliable) information. The supply of incomplete or partial information by ATIS also results in a significant decrease in compliance propensities. The greater compliance observed with predicted information (relative to prevailing information) can be attributed to its greater accuracy and reliability. Providing feedback on trip performance results in favorable compliance behavior. A plausible reason for the increased compliance is that supplying feedback to users' provides them with an opportunity to review their trip performance relative to optimal choices.

Considerable variability is observed in commuters' route and departure time switching patterns in response to dynamic variations in network conditions, particularly loading patterns. These differences are observed with changes in magnitudes of network loads, as well as its day-to-day evolution. With increased network loads, users increase their route switching indifference bands and switch less frequently, reflecting expectations of increased trip time in the systematic treatment. In contrast, no effect of increased network loads is discernible when network loads fluctuate randomly from day-to-day. Users increase indifference bands for schedule delay on both the early and the late sides, when network loads increase in a systematic manner from day-to-day. However, in the random treatment, users are observed to switch departure times in a more risk-averse manner, switching more often following lateness, and less often following early arrivals. In the random case users appear to accommodate increased uncertainty by increasing their indifference bands for schedule delay compared to the sequential treatment. Moderately higher, but not significant, route switching is also observed in the random case relative to the systematic evolution.

Network performance measures on alternative facilities, and opportunities for switching strongly influence users' compliance and switching decisions under information. An increased route switching propensity is noted with increased potential trip-time savings on alternate routes. Both experienced congestion and anticipated congestion (as reported by ATIS) are significant determinants of compliance and route choice behavior. Thus time-dependent variations in network conditions caused by interactions between user behavior, ATIS, and supply conditions, significantly govern dynamics in observed choice behavior. The findings suggest that information supply strategies may be used to minimize if not eliminate, imbalances in capacity utilization across alternative facilities. Further, interactions between users past choices and supply conditions also significantly influence user behavior. This is evident from the increased inertial tendency found when the path the user is currently on, also happens to be the best path (as determined by prevailing supply conditions).

Users’ decisions of route and departure time choices are colored by past traffic experience. The influence of past traffic experiences is seen in route and departure time choices following unacceptable schedule delays, being stuck in traffic, or frequent early or late arrivals in the past. Users’ also appear to estimate the variability in traffic conditions on the basis of past experience. For instance, users’ reduce their schedule delay indifference bands (increase departure time switching rates) when faced with greater trip-time variability. Negative experience on the previous day also inhibits compliance, suggesting that the quality of information may also be assessed based on past experience.

Modeling results reveal the existence of various structural effects in commuter behavior dynamics. Considerable evidence of heterogeneity and its persistence over time are reported. Both systematic and unobservables sources of heterogeneity are found to significantly influence route and departure switching decisions. Heterogeneity is observed in the inherent propensity to switch, and in the sensitivity of users to attributes affecting choices, as well. State dependence effects are noted in users' route and departure time choice decisions. This implies that a user’s current choice can causally alter the

decision-maker's preferences, choice sets and/or information sets for future decisions. The current decisions are also affected by lagged effect of attributes experienced previously, as noted earlier. Thus the users response to information exhibits habit persistence, in addition to state dependence and heterogeneity.

The variability in user behavior over time, hint at the presence of complex cognitive and decision processes underlying observed choice dynamics. An examination of the choice behavior revealed considerable support for the presence of four component processes, namely, learning, perception, judgment, and updating processes. Specifically, two types of learning processes, namely, discrimination and trial-and-error learning, are observed in user responses in a dynamic traffic environment. The significant effect of recent and frequent events on user behavior, highlights the role of memory in learning processes. Learning processes are also affected by motivational and attentional factors. Users' perceptions and attitudes towards alternatives and their attributes play an important role in their choice behavior. These processes serve as a cognitive filter through which a user combines his/her experience, information, and attitudes to functionally support decision-making. The data suggests considerable variability across users in their attitudes towards schedule delay and congestion. Further, these attitudes are also reflected in their choice behavior. The model of the perception process presented here seems to indicate that users' adjust their trip time perception from the reported trip time to accommodate uncertainty regarding traffic conditions and information accuracy. The perceptions and expectations of traffic are updated over time in response to new information and experience, thus affecting user behavior dynamics. When the traffic conditions vary substantially from day-to-day (random treatment), the updating process places a greater weight on ATIS information than past experience perceptions. In contrast, when traffic evolution in the network is systematic, a considerably higher emphasis is placed on past perceptions. In addition, it is observed that users base their expectations of arrival times, on current and past experience and real-time information. These findings provide preliminary insight into the cognitive and decision processes underlying user behavior in the presence of ATIS and can guide the design of more detailed investigations.

Users are observed to adjust their route and departure time choices over time. Explicit models of these adjustment processes indicate that they are composed of heuristic mechanisms and search strategies. It is observed that users adjust their departure times from day-to-day primarily in increments of five minutes, and in a manner consistent with a heuristic greedy search procedure. The results suggest that users' evaluate alternatives in a sequential manner, with the alternatives closer to the current choice being considered preferentially ahead of other alternatives. Models of path choice adjustment highlight the significance of inertial and compliance mechanisms. The inertial mechanism reflects the tendency of a user to continue on the current path due to cognitive, information and physical costs of switching. The compliance mechanism represents a user's propensity to follow the 'best' (least trip time) path reported by the ATIS. The results suggest that both the mechanisms operate simultaneously and the actual choice

could result from a trade-off between the two. Both compliance and inertial mechanisms are found to vary with choice contexts, user characteristics, system performance measures, and network conditions.

10.3 SIGNIFICANCE OF FINDINGS

The substantive findings have significant applications in: 1) analyzing and forecasting traveler behavior, 2) traffic management, control and planning, and, 3) the design, deployment and evaluation of ATIS products and services.

The substantive findings on the effect of information quality and ATIS information strategies provide pointers for developing guidelines for the design and development of ATIS products and services. First, ATIS should provide information that is not only accurate but also reliable. Second, the quality of information supplied by ATIS jointly depends on the behavior of users' with access to ATIS information, the behavior of users' without access to information, and network conditions. Therefore, to ensure the quality of ATIS information supplied, it is necessary to have the capability to predict user behavior (in response to information) reliably. Besides accuracy, the extent of network coverage (whether information is available on all network links), scope of information supply (whether feedback is provided on actual trip choices) and timeliness of information (predicted information) are important design criteria that affect the credibility of the ATIS. Further, significant differences are observed in the manner in which ATIS influences the travel behavior of different market segments. Finally, the value of ATIS and its influence on choice behavior vary significantly with the magnitude of network loads and day-to-day evolution of traffic conditions on the network. The results indicate that ATIS can play an important role in alleviating users' uncertainty about trip-times under drastically fluctuating network conditions. Even though the effect of incidents is not modeled in this work, it is plausible that the presence of incidents could lead to dramatic fluctuations in network conditions from day-to-day, not unlike in the random treatment.

The behavioral and methodological findings presented here have significant implications in travel behavior analysis and demand forecasting. First, the applicability of the utility maximization framework (at least as currently implemented) to model trip-maker behavior under real-time information is questionable on the following theoretical and empirical grounds. This framework does not account for the cost associated with implementing alternative choices, the presence of inertia and habit persistence, evidence of learning about information, network conditions, and past choices, and the presence of heuristic search strategies. While a utility specification that incorporates all these effects may be mathematically possible, its empirical realization would be difficult at best. Furthermore, the utility maximization paradigm would not have provided to discover and uncover the cognitive and behavioral processes underlying user decision dynamics under real-time information. Second, complex dynamic and stochastic patterns are observed in trip-maker behavior in the dynamic traffic environment. Empirical evidence observed in the simulator-based experiments includes significant within-day and day-to-day correlations and variances of unobservables. Furthermore, observed choices also exhibit habit persistence state dependence, observed and unobserved heterogeneity. Third, it appears that trip-maker decisions are based on several underlying cognitive processes. Evidence of learning, adjustment, perception, judgment, and updating

processes are observed empirically in this study. Modeling the underlying processes and their interactions with observed choice is a promising area for future research, which can lead to richer insights into behavior and more robust model specifications.

The methodological findings from this study indicate that the DKL formulation can be applied to model dynamics in large dimensional discrete choice panel data in several problem domains. The DKL formulation presented here provides a versatile tool (with a few exceptions) for modeling dynamics in various choice dimensions including mode, route, departure time, destination, and automobile ownership decisions. Furthermore, it can also be applied to estimate and test for the presence of very general dynamic and stochastic effects in activity and travel behavior. This formulation may be used to model ordered or unordered discrete choice data. Further, it is also possible to model several choice dimensions simultaneously using this framework.

The findings presented in this study also have implications for the operation and evaluation of traffic management strategies associated with ATMIS (Advanced Traffic Management and Information Systems). One of the key implications is that it is necessary to model time-dependent evolution of network flows both within-day and from one day to the next for an accurate analysis of network performance. The evolution of flows on the network is determined by dynamics of trip-maker decisions in response to ATIS information and experience and vice versa. Furthermore, trip-maker behavior, in turn, is affected by network dynamics. Therefore, it is necessary to incorporate realistic user behavior components in dynamic traffic assignment methodologies to develop robust and more accurate models of system performance. Analyzing the evolution of network flows from day-to-day flow is important from a tactical planning stand-point to assess the effectiveness of alternate control strategies, and to estimate the costs associated with alternative network states. The strong impact of information and its differential effect on various user segments suggests that real-time information may be used to manage and control traffic through Variable Message Signs (VMS) in-vehicle devices etc. A majority of studies investigating the impact of information have tended to rely on idealized user behavior assumptions. Relaxing these assumptions by integrating the user behavior models (similar to those calibrated here) would lead to more realistic estimates of the effectiveness of information as a traffic control strategy. Finally, the results suggest that it is essential to model the interactions between-route and departure time choices under real-time information, to accurately evaluate transportation demand management (TDM) measures.

10.4 DIRECTIONS FOR FUTURE RESEARCH

The models presented here can be extended and applied to pursue the following lines of further inquiry: 1) investigation of traveler behavior at a broader scope, 2) development of psychometric and measurement frameworks to model user decision processes in real-time, and 3) dynamic network analysis and applications to traffic management.

The scope of traveler behavior models presented here can be enhanced significantly by including in its ambit, consideration of various trip purposes, multiple travel choice dimensions, interactions between activity and travel patterns, and behavioral adjustments over the long-term. The analysis

presented here restricts its attention to commuting behavior. The behavior of trip-makers in other trip purposes such as non-commuting, recreational trips also need to be examined, as they contribute significantly to congestion in urban networks, particularly during the evening peak period. The behavioral framework can be extended to include the analysis of other trip dimensions of mode, destinations, and trip-chaining, particularly for non-commuting trips, in addition to the dimensions of route and departure time choices considered here. This increase in scope will translate to more realistic models of activity and travel patterns and their mutual inter-relationships. Another interesting direction of inquiry is the investigation of medium and longer term consequences of information technologies, internet, and traveler information services on not only traveler choices considered in this study, but on residential and work location choices as well.

Significant progress remains to be made in enhancing the psychometric and econometric frameworks to measure and quantify user decision processes in the presence of real-time information. Further investigations are desirable, particularly with regard to mechanisms in users' learning and adjustment behavior over time, reliable data collection on latent cognitive processes, insights into cognitive constraints, and the role of information acquisition, representation, and usage in choice decisions. Opportunities for econometric advances include, development of models based on alternative behavioral paradigms, specification of less restrictive non-parametric models, integration of revealed and stated preferences from diverse data sources, and applications of calibrated models for forecasting purposes.

The application of dynamic user behavior models to network analysis constitutes yet another promising area for future research. The integration of richer user behavior models proposed here with dynamic traffic modeling and ATIS components in a micro simulation framework will enable more realistic network performance analyses. The development of an integrated simulation framework has important applications to modeling and forecasting network flow evolution over time, dynamic traffic assignment methodologies, and decision support for traffic management. This framework will be valuable for the design and implementation of ATIS information strategies and the evaluation of alternative traffic control strategies aimed at achieving desired system objectives. The development of such a simulated network model would also have significant applications in supporting strategic and operational planning analyses.

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