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Understanding travelers' route choice behavior under uncertainty

Nikhil Sikka
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UNDERSTANDING TRAVELERS' ROUTE CHOICE BEHAVIOR UNDER UNCERTAINTY

by

Nikhil Sikka

An Abstract

Of a thesis submitted in partial fulfillment
of the requirements for the Doctor of
Philosophy degree in Civil and Environmental Engineering
in the Graduate College of
The University of Iowa

May 2012

Thesis Supervisor: Associate Professor Paul F. Hanley

ABSTRACT

The overall goal of this research is to measure drivers' attitudes towards uncertain and unreliable routes. The route choice modeling is done within the discrete choice modeling framework and involved use of stated preference data. The first set of analysis elicits travelers' attitudes towards unreliable routes. The results of the analysis provide useful information in relation to how commuters value the occurrence/chances of experiencing delay days on their routes. The frequency of days with unexpected delays also measures the travel time reliability in a way that is easy to understand by day-to-day commuters. As such, behaviorally more realistic values are obtained from this analysis in order to capture travelers' attitudes towards reliability. Then, we model attitudes toward travel time uncertainty using non-expected utility theories within the random utility framework. Unlike previous studies that only include risk attitudes, we incorporate attitudes toward ambiguity too, where drivers are assumed to have imperfect knowledge of travel times. To this end, we formulate non-linear logit models capable of embedding probability weighting, and risk/ambiguity attitudes. A more realistic willingness to pay structure is then derived which takes into account travel time uncertainty and behavioral attitudes. Finally, we present a conceptual framework to use a descriptive utility theory, i.e. cumulative prospect theory in forecasting the demand for a variable tolled lane. We have highlighted the issues that arise when a prescriptive model of behavior is applied to forecast demand for a tolled lane.

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Iowa City, Iowa

CERTIFICATE OF APPROVAL

PH.D. THESIS

This is to certify that the Ph.D. thesis of

Nikhil Sikka

has been approved by the Examining Committee
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To my parents Suraj and Sushma Sikka and my sister Deepika Ranjan

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TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

CHAPTER I.

INTRODUCTION

Understanding human behavior and what drives people's choices has been a subject of research in the field of economics, psychology, transport, and beyond. Many mathematical tools and analytical frameworks are used to model people's existing behavior and predict likely choice outcomes in varying settings. Analysis of travel behavior is no different. Traveling is one of the most important activities people engage in to serve various purposes of everyday life. People travel for going to work, shopping, recreation, tourism, and so on and choose different modes to get to the places they want. However, the dependence on automobiles, especially in United States, in everyday travel has augmented in the last few decades. This has led to the problems related to congestion, lost man-hours, serious environmental and health consequences, and road safety. As such, understanding travelers' attitudes and their behavior is a key to developing sustainable transport policies that meet user needs and promote modal shifts.

The study of travel behavior is a broad topic that provides insights into the choices that individuals and households make about their travel needs. Within this broad area lie various sub-categories like study of mode choice, destination choice, route choice, and so forth. The interplay of these different choice dimensions is what makes the analysis of travel behavior so complex and yet interesting. Over the years, travel behavior researchers have worked toward the development of increasingly sophisticated quantitative models, often used in conjunction with qualitative approaches, which could offer us powerful tools for helping us to understand those complexities.

The focus of this thesis is understating route choice behavior, especially from automobile drivers' viewpoint. Although, understanding route choice behavior is only a dimension to overall travel behavior analysis, it does provide very useful insights into travelers' decision making process which can eventually be tied back to broad travel behavior assessment. Route choice modeling is also essential in terms of transportation planning which requires predicting future traffic conditions on transportation networks and understanding travelers' response and adaptation to sources of information.

Route choice modeling involves evaluating travelers' perception of route characteristics that include travel time, cost, distance, safety, reliability, to name a few (Bekhor et al., 2001). These perceptions and preferences based on route characteristics are then tied to travelers' personal attributes such as income, age, gender, and other socio-economic characteristics. Modeling route choice is however, not as simple as it sounds, given the intricacies involved in representing human behavior, travelers' imperfect knowledge about the transportation network composition, and the uncertainty and heterogeneity associated with travelers' perceptions about route characteristics. Nevertheless, recent advancements in both quantitative and qualitative methodologies have made it possible to understand travelers' route choice behavior to a large extent.

Knowledge of travelers' route choice behavior can be applied in various areas of transportation: transportation forecasting, traffic management and control, design of road infrastructure, and development of road navigation technologies. The direct application of route choice modeling is in forecasting traffic flow on certain road networks. Understanding route choice behavior results in more realistic traffic forecasts would eventually lead to fewer traffic gridlocks and less congestion on roads. Thus, the results of this research are expected to contribute to the society in terms of reduction of air pollution, reduced man-hours in traffic, and effective use of road infrastructure.

In what follows, we first provide the need of this research followed by research objectives and scope. Finally, we highlight the contribution of this research to the existing literature. The last section gives the structure of the thesis.

Need of the Study

The transportation network consists of various links and nodes. As a driver, the traveler has a number of paths/routes available to make a trip. The results of route choice analysis, however, answer a simple question: *Under given conditions (that may include a plethora of variables), what route a traveler would take to get to the place he/she wants to?*

As mentioned earlier, travelers' route choice depends on the attributes of the route, such as travel time, cost, type of roadway and on the characteristics and perceptions of the travelers themselves. Now, several aspects of the route choice problem make it rather complex. Nevertheless, previous studies have shown that the most important factor that influences route choice is expected travel time (Bekhor et al., 2001; Outram and Thompson, 1977). However, traffic networks are inherently uncertain and what makes them more so are random disruptions. An unexpected and prolonged traffic disruption in travelers' commuting route is commonplace especially in areas with higher traffic density. The frequency of experiencing uncertain travel times can vary from one day in a week to several days in a week. These random disruptions can take any forms including planned activities or unplanned weather related events and other unforeseen emergencies. Travelers' route-choice behavior is difficult to gauge in this context because of increase in travel time uncertainty. An uncertain environment is referred as *risky* if the probability distribution of the outcomes is known, while it is called *ambiguous* if uncertainties cannot be reduced to simple probabilities or when the true probability distribution of outcomes is unknown. Apart from travel time uncertainty, several other sources of uncertainty exist in route choice context. Overall, traveler's preference among available routes depends on the utilities associated with each route and if the utilities are perceived to be uncertain then the decision making is influenced by travelers' attitude to that uncertainty (Avineri and Prashker, 2005).

Current route-choice models used in practice simplify the decision process such that uncertainty is assumed away by bestowing travelers with the ability to memorize travel times on all practical routes and constantly reassess this close-to-perfect information to a select route that maximize their utilities. Most often the models' underlying framework is economic rationality, which brings with it the adherence to the strictures of rational theory (Avineri and Prashker, 2004). Given the stochastic nature of the transportation networks, the assumption of a driver's close-to-perfect knowledge is, however, questionable. Common analytical non-behavioral route choice models, which are based on either network risk, to take into account randomness of network utilities, or perception errors, to account for imperfect information of travelers, or both, are as follows: deterministic network, deterministic user equilibrium model; deterministic network, stochastic user equilibrium model; stochastic network, deterministic user equilibrium; and stochastic network, stochastic user equilibrium model (Chen and Recker, 2001). However, these models lack psychological underpinnings and therefore, are not well suited to analyze drivers' cognitive decision making process. As a result, rule based models that are more representative of drivers' behavior are being used in understanding route-choice behavior from drivers' perspective. These models are based on the assumption that drivers follow latent decision rules for evaluating the attributes of available routes and decide on a specific route based on this evaluation. There is need to improve existing route choice models by adding more behavioral realism from travelers' viewpoint. Lacking in contemporary research efforts to model route choice under uncertainty is the inclusion of non-expected utility framework which incorporates some very important behavioral attributes. It is imperative to improve existing route-choice models by integrating the theory and empirical findings from fields of science, like psychology, where it has been repeatedly shown that decisions and behaviors are often determined by perceptions that may not be in accordance with traditional rational theories. Therefore, travelers' route choice attitudes toward *risk* and *ambiguity* add important dimension to the existing empirical methodologies (discrete choice framework in this case). The resulting specifications which add behavioral rigor to the existing discrete choice modeling framework would also fill the gap by providing more plausible willingness to pay values.

Objectives and Scope

The long range goal of this research is to measure travelers' attitudes towards uncertain and unreliable routes. More specifically, we aimed to understand drivers' attitudes to uncertainty in their commuting routes. The route choice modeling is done within the discrete choice modeling framework and involved use of stated preference data.

The objectives of this thesis are summarized under the following three paragraphs:

1. The stated preference (SP) surveys (also known as choice experiments) are based on responses to hypothetical choice situations and have been important survey instruments to understand behavioral responses and consumer preferences for various transportation services. Within SP surveys, travel time variability/uncertainty is usually presented in terms of statistical distributions and probabilities. Although it provides an efficient way of measuring travel time variability/uncertainty from an analyst's point of view, it is not easy to communicate statistical distributions to general public in order to get realistic behavioral responses. Therefore, one of the objectives of the study is to design SP surveys such that uncertainty in travel time is presented in easy to understand way for non-technical respondents.
2. Travelers' attitudes toward uncertainty in travel time are mostly modeled through the use of expected utility models. The use of non-expected utility behavioral theories that can be embedded within the traditional discrete choice modeling

framework to understand route choice behavior is almost non-existent. To the best of our knowledge, most route choice experimental studies consider only risky route choices, e.g., precise information on probability of delay. Therefore, an objective of this research is to simultaneously elicit people's attitude toward both *risky* and *ambiguous* routes and compare the results of both expected utility based models and non-expected utility based models. The specific hypothesis driving the proposed research is that drivers' do not always make rational decisions in route-choice situations and factors such as uncertainty in travel time and monetary cost play a significant role in route selection.

3. Willingness to pay (WTP) or marginal rate of substitution for travel time is an important output of studies based on discrete choice models. The other main objective of this research is to derive WTP measures that are more behaviorally appealing and take into account drivers' attitudes toward uncertainty and travel time variability.

Contributions

General

People make route-choice decisions on a daily basis. Knowledge of travelers' route choice behavior and related research methodologies can be applied in various areas of transportation: transportation planning, traffic management and control, design of road infrastructure, and development of road navigation technologies. This research would help in predicting travelers' behavior under travel time uncertainty which has a direct implication in forecasting traffic flow on certain road networks. More realistic traffic forecasts would eventually lead to fewer traffic gridlocks and less congestion on roads. Thus, the research would contribute to the society in terms of reduction of air pollution, reduced man-hours in traffic, effective use of road infrastructure, and so on.

Measurement of heterogeneity in WTP values that are more behaviorally sound would have direct influence on estimating toll roads' demand and revenue.

Specific

This study presents models to understand drivers' route choice attitudes under uncertainty. The research contributes to the existing knowledge of route choice behavior in three ways. First, we add behavior rigor to the existing random utility framework by incorporating important features of non-expected utility models such as probability weighting, and risk attitudes. Second, previous studies have mostly incorporated one aspect of uncertainty, risk that is, where drivers are assumed to have known the probability distribution of travel times. In this study, we study route choice attitudes towards ambiguity too, where drivers are assumed to have imperfect knowledge of travel times. Third, we derive WTP measures that are more behaviorally appealing and take into account drivers' attitudes toward uncertainty and travel time variability.

Thesis Structure

The thesis is divided into seven chapters. The first three chapters provide background material and a detailed SP survey methodology. Chapters 4, 5, and 6 contain analysis and main results. Chapter 7 concludes.

- Chapter 2 provides a review of literature related to use of behavioral theories in understanding travelers' route choice under uncertainty. We further review the theories that are well embedded within psychology and economics literature but are not yet incorporated within discrete choice modeling framework.
- Chapter 3 includes our SP survey methodology with detailed discussion on survey design and survey administration.

- Chapter 4 includes the first set of analyses focusing just on behavioral responses to travel time reliability and calculation of drivers' WTP values. The analysis is done using panel mixed logit modeling framework.
- Chapter 5 formulates non-linear logit models capable of embedding probability weighting, and risk and ambiguity attitudes (two aspects of uncertainty). Also, a willingness to pay structure is derived which takes into account travel time uncertainty and behavioral attitudes.
- Chapter 6 provides a potential application of a behavioral theory in the context of variable tolling. We illustrate the application of a behavioral choice model (Cumulative Prospect Theory) versus a rational choice model (Expected Utility Theory) in predicting the use of variable toll lanes.
- Chapter 7 concludes and highlight future research needs.

CHAPTER II.

LITERATURE REVIEW

Over the last few years there has been a growing recognition that traditional models of travelers' decision making need to be broadened to include situations involving uncertain travel time outcomes. Therefore, a natural extension of this field is analysis of choices under uncertainty. An uncertain environment is referred as *risky* if the set of outcomes and probability distribution of the outcomes is known, while it is called *ambiguous* if uncertainties cannot be reduced to simple probabilities or when the true probability distribution of outcomes is unknown. The application of these uncertainty models in transportation decision analysis is rare, though drivers and travelers face risky and ambiguous situations in their travel quite often. Travelers make route choice decisions on a daily basis and random disruptions like accidents, vehicle break-downs, weather closures, maintenance activities, community and social events, etc. make traffic networks inherently uncertain (Gao et al., 2010). Travelers' route-choice behavior is difficult to gauge in this context because of increase in travel time variability. Traveler's decision to take particular routes depends on the utilities associated with these routes and in case of uncertain travel conditions, the utilities can be affected based on travelers' attitude to that uncertainty (Avineri and Prashker, 2005).

After an extensive application of the conventional expected utility (EU) model of von Neumann and Morgenstern (1944) and the subjective expected utility model (SEU) of Savage (1954) in modeling uncertain behaviors, researchers have come to a conclusion that decision makers often do not make choices in a way consistent with the EU and SEU models. For example, the Allais paradox (overweighing high consequence low-probability cases) and the Ellsberg paradox (ambiguity aversion attitude) have challenged the underlying axioms of the EU and SEU models even in context of simple decision making situations. Consequently, researchers have resorted to more generalized models also known as non-expected utility models (and random utility models). A general trend in these studies now is the increasing use of behavioral theories that are already well established in economics and psychology literature, however still in early phases in transportation decision making. Therefore, the intent of this chapter is to provide a review of contemporary thinking in the use of these emerging behavioral theories in explaining travelers' route choice behavior. Some important theories are described, followed by a broad, but by no means exhaustive, discussion of pertinent studies.

Earlier Theories for Route Choice under Uncertainty

The most common analytical non-behavioral route choice models (Chen and Recker, 2001) which are based on either network uncertainty (to take into account randomness of network utilities) or perception errors (to account for imperfect information of travelers) or both are as follows: deterministic network, deterministic user equilibrium (DN-DUE) model, deterministic network, stochastic user equilibrium (DN-SUE) model, stochastic network, deterministic user equilibrium (SN-DUE), and stochastic network, stochastic user equilibrium (SN-SUE). However, these models lack psychological underpinnings and are not well suited to analyze travelers' cognitive decision making process. As a result, other rule-based models which are more suitable from travelers' behavioral point of view have been used over the years. The approach is based on the fact that decision makers follow certain decision rules to evaluate the attributes of various route choices available and then determine a choice. Earlier models in this realm used in gauging travelers' choice behavior were basically derived from Expected Utility Theory and Random Utility Theory (RUT). However, to accommodate rationality violations, other theories have been proposed, including elimination by aspects (Tversky, 1972), cumulative prospect theory (Tversky and Kahneman, 1992), fuzzy logic (Zadeh, 1965), and dynamic learning models.

Expected Utility Models

Expected Utility (EU) theory states that in situations involving uncertainty and risk, the decision maker (DM) chooses outcomes on the basis of their expected utility values, i.e., the weighted sums of the utility values of outcomes multiplied by their respective probabilities. Therefore, the DM selects the alternative with the maximum utility (Einhorn and Hogarth, 1981; von Neumann and Morgenstern, 1944). The three main assumptions about the decision making process under the EU theory include:

- Consistency of preferences for alternatives;
- Linear decision weights for alternatives; and
- Judgment in reference to a fixed frame of reference (Kahneman and Tversky, 1979).

Assume *Ej*, *j* = 1,…., *n* denote possible events, each with a probability of occurring of *P*(*Ej*), such that *P*(*Ej*) ≥ 0, and $\sum_j P(E_j) = 1$. Let x_j designate be the realization of some random variable (or any similar source of utility), which is the *outcome* of the event E_j , *j* = 1,…,*n*. For example, in Lam and Small (2001) and in de Palma and Picard (2006), the *Ej* denote traffic conditions and the *xj* refer to travel times. The utility of an outcome is given by *u*(*xj*). Finally, the EU theory states that if DMs behave rationally and exhibit above-stated three criteria, then they will behave as if they maximize the expected value of their utility given as:

$$E[u(x)] = \sum_{j=1}^{n} P(E_j)u(x_j) \qquad \text{Equation II-1}$$

The probabilities need not be objective, but may instead reflect subjective judgments of the decision maker. If objective probabilities are known we write p_j for $P(E_j)$. Application of EU and subjective expected utility model (SEU) models in route choice modeling is widespread. Travelers are assumed to behave as if they correctly assign probabilities to random travel times and choose a route that maximizes the expected value of their. However, after an extensive application of the conventional EU models in modeling uncertain behaviors, researchers have come to a conclusion that decision makers often do not make choices in a way consistent with the EU and SEU models. For example, the Allais paradox (overweighing high consequence low-probability cases) and the Ellsberg paradox (ambiguity aversion attitude) have challenged the underlying axioms of the EU and SEU models even in context of simple decision making situations. Avineri and Prashker (2004) conducted simple route-choice experiments and found two violations of EU theory. They found presence of certainty effect (Allais paradox) and the inflation of small probabilities in a stated-preference single-route experiment.

Discrete Choice Models and Random Utility

Random utility based discrete choice models extend the conventional expected utility models and provide a somewhat stronger econometric interpretation of travelers' behavior. Random utility models (RUMs) are based on the premise that decision-makers have incomplete knowledge of various alternatives and thus they have discrimination capabilities. Therefore, unlike utility maximization theory, the utility function of the alternative is divided into two components: i) deterministic part i.e. portion observed by the analyst, and ii) stochastic part which is the portion of the utility unknown to the analyst. The random utility equation is given by:

$$U_{in} = \beta_n x_{in} + \varepsilon_{in} \qquad \text{Equation II-2}$$

where:

- U_{in}: is the observed utility of the alternative i to the decision maker n,
- $\beta_n x_{in}$: is the deterministic or observable portion of the utility estimated by the analyst, and x_{in} represents a $(Q \times 1)$ vector of observed attributes along with

their interaction with other observable attributes. β_n is the parameter vector associated with x_{in}.

- ε_{in} : is the error or the portion of the utility unknown to the analyst.

Over the years, many other similar forms of choice modeling have been proposed based on different assumptions for error term, but the multinomial logit (MNL) and conditional logit (CL) models, proposed by McFadden (1974) are the most widely used tools for analyzing discrete dependent variables. The numerical expression for the probability of choosing an alternative '*i*' (*i = 1,2,.., J*) from a set of *J* alternatives is for a decision maker *n*:

$$P_{ni} = Prob\left(U_{ni} > U_{nj}\right) \forall j \neq i \qquad \text{Equation II-3}$$

The algebraic calculation of this probability results in a closed-form logit choice probability and can be written simple as (where V_{ni} is the deterministic part of the utility):

$$P_{ni} = \frac{exp\left(V_{ni}\right)}{\sum_{i=1}^{I} exp\left(V_{ni}\right)} \qquad \text{Equation II-4}$$

For more than a decade now, RUMs have been the front runners in behavioral analysis in transportation and especially in route choice modeling. A great deal of theoretical advancement has taken place over the years since the classic Multinomial Logit Model of Daganzo and Sheffi in1977. C-logit model and Path-Size logit followed and provided simple modifications to Multinomial Logit Models. A big breakthrough came with McFadden's General Extreme Value models that led to various flexible modeling structures including Nested Logit (Ben-Akiva and Lerman, 1985), Cross Nested Logit (Vovsha, 1997) and Paired-Combinatorial Logit (Chu, 1989; Koppelman and Wen, 2000). The other remarkable improvement providing greater flexibility within a random utility framework took place with the introduction of the Mixed Logit models (Ben-Akiva and Bolduc, 1996; Bhat, 2000; McFadden and Train, 2000). Several studies have used Mixed Logit specification in analyzing route choice behavior over the years now primarily due to its flexibility in accounting for correlation structure for repeated responses in panel settings (Bekhoret al., 2001; Jou et al., 2008; Srinivasan and Mahamassani, 2003).

The conventional RUM assumes that travelers have perfect information and show rational behavior to maximize their utility (or satisfaction). Rationality of travelers has been challenged in many recent studies (Avineri and Prashker, 2004; Bogers et al.,2007; Fujii and Kitamura, 2000). Moreover, the theory is concerned with the valuation of certain and riskless outcomes (i.e. V_{ij} is riskless). However, recent developments in the RUM framework have incorporated EU principles to model individual travel choice under risk (Noland and Small, 1995; Polak et al., 2008). Maximum Expected Utility Theory was introduced as a way to take into account travel time variability in which it was assumed that drivers select the alternative with the highest value of expected utility. This approach became one of the standard approaches to account for travel time uncertainty in terms of risk for quite some time (Bateset al., 2001; Small et al., 1999). Furthermore, although EU has been extensively used within RUM, a linear utility specification has been the dominant approach to account for risk in travel time occurrences (see Hensher et al., 2011 for a review). Recent developments in route choice modeling are now acknowledging non-linearities in both utility specification and probability weighting under uncertain travel times.

Behavioral Theories for Route Choice Modeling

Over the last few years a great deal of advancement has taken place in behavioral theories explaining what drives people's choices. The roots of behavioral research lie in psychology and neighboring social sciences. The results of various practical experiments conducted in these realms have shown that assumptions about the absolute rationality of individuals often get violated in real-life situations (Camerer, 1998). The following are some of the important behavioral theories that have been used in route choice studies.

Elimination by Aspects

This paradigm was first underlined by Kahneman and Tversky (1979) and hypothesizes that in uncertain and complex choice situations, instead of maximizing utility, individuals are more inclined to use *heuristics*. They are simple principles of reasoning individuals use to arrive at an ‘approximate’ solution without any complex computational effort. The elimination by aspect (EBA) procedure proposed by Tversky (1972) is one of these heuristics. In this case, the decision making process is seen as a sequential elimination process in which: (a) the common aspects of the choices set are first eliminated, (b) an aspect (attribute) is randomly selected and all alternatives not possessing the aspect are eliminated. The probability of selecting this characteristic is based on its utility to the decision maker, and (c) first two steps are performed till the residual alternatives have the same characteristics. In case, only single choice is left, it is selected; otherwise, all remaining choices have the same chances of getting selected. The order in which various aspects are considered and eliminated is the main driver of decision making. However, since a person’s ordering of attributes depends on the individual and is essentially unobserved, the model itself selects attributes randomly with probabilities of being selected proportional to weights. A quick review of the formal decision process discussed above in econometric terms is given in (Manrai, 1995). Several links exist between the EBA and random utility models (Laurent, 2006). Batley and Daly (2003) established formal mathematical conditions under which a hierarchical EBA model is equivalent to a nested logit model. The authors did not come across any route choice study that explicitly considered EBA modeling strategy. Takao and Asakura (2006), however, relied on EBA principles to some extent in analyzing route choice behavior using open-ended questionnaire texts.

In spite of the fact that EBA was one of the first few behavioral theories to come into the picture, it remained unexploited for a long period of time. Part of the reason was the influx of well entrenched alternative models. Also, lack of recognition of the tractability of more sophisticated forms of EBA led to decline in its use and popularity. Overall, the applicability of EBA models in route choice deem more research and they might have potential of opening interesting prospects for research in route choice modeling, both on theoretical and empirical levels. As highlighted in previous research, EBA models allow for the construction of discrete choice models and may offer more flexibility as compare to probit or nested logit models.

Fuzzy Logic

First introduced in Zadeh (1965), the idea of fuzzy sets relies on the degree of membership instead of dealing with some simple *black* and *white* answers. A fuzzy set is defined by its membership function and the elements of the set have degrees of membership that ranges from 0% to 100%. Therefore, membership value assigned to an element is no longer restricted to just two values, but can be 0, 1 or any value in-between. A major advantage of this theory is that uncertainty can be presented in linguistic terms rather than describing a problem in terms of precise numerical values (i.e. probabilities). An important distinction between membership function and probability distribution function is that the membership function is not based on some repeatable observations but rather on the judgment of the domain expert. Following are a couple of examples of how rules can be expressed:

IF *travel time on route 1 is very short and travel time on route 2 is intermediate* ***THEN*** *I will certainly choose route 1* (Henn and Ottomanelli, 2006)

IF *times on route 1 and 2 are very high* ***THEN*** *I will probably take route 3* (Lotan and Koutsopoulos, 1993)

In route choice modeling arena, Teodorovic and Kikuchi (1990) were first to design a set of fuzzy rules in a binary route choice problem. A plethora of studies have been done since then using these principles in order to account for uncertainty and imprecision in route choice modeling. Overall, the fuzzy logic approaches in route choice modeling can be broadly categorized into: fuzzy rule base and fuzzy arithmetic assignment models. Examples of studies based on fuzzy rules are Lotan (1992), Lotan and Koutsopoulos (1993), and Murat and Uludag (2008). The route choice modeling based on fuzzy assignment can be found in Chang and Chen (2000), Henn (2000), and Wang and Liao (1999). More recent studies combining other uncertainty theories with fuzzy logic are done by Quattrone and Vitetta (2011) and Ramazani, Shafahi and Seyedabrishami (2011). Although fuzzy logic has been used in route choice modeling over a decade now, it is still a young field. Fuzzy logic field itself was not very well accepted among academics circles when it was first implemented. The main reasons were under-developed mathematics and a somewhat vague construction of membership functions. Henn and Ottomanelli (2006) argued that fuzzy logic based models though easy to construct, and robust to small variations are not helpful in understanding the actual behavioral and decision making process of drivers. They also mention that the proposed models are only problem specific and are only applicable in a particular network. Xu and Akiva (2009, unpublished) conclude that these models not only lack theoretical basis to simulate travelers' actual behavior but it can be hard to explain drivers' route choice behavior from the results. They also agree that implementation of fuzzy logic in complex networks is non-existent and thus the applicability in real network is still questionable.

Dynamic Models

Most of the above models can be categorized as static models. The dynamic models, however, assume that the route choice decision making process is a dynamic process, involving some sort of information acquisition mechanism and learning over time. Some of the simple learning models that can be found in route choice literature are weighted average (Horowitz, 1984) and myopic models (Mahamassani and Liu, 1999; Srinivasan and Guo, 2004) which state the perceived travel time is a function of weighted average of past travel times, Bayesian learning models (Jha et al., 1998; Nakayama, 2009) where it is assumed travelers' choices in current period may be based (and updated) on information related to utilities in previous time periods, and reinforcement learning models (Avineri and Prashker, 2005; Ben-Elia and Shiftan, 2010; Bogers et al., 2007; Roth and Erev, 1995) where a decision maker is an adaptive learner who makes choices with respect to rewards that were obtained for each alternative in the past.

Overall, the learning models confirm violations of rationality and suggest that uncertainty in route choice problems essentially results in *indifference* and more of random choice behavior. Interestingly none of above mentioned studies explicitly highlights any blatant issues with using dynamic learning models in understanding travelers' route choice behavior. However, the main limitation as noted by Nakayama, Kitamura and Fujii (2001) is that underlying assumptions in many of the learning models lack strong psychological underpinnings and are not always based on observed behavior. Also, this field of research is still in its early stages and lack empirical and experimental evidence to further bolster the claimed hypothesis that learning (both in short term and in long term) has significant effect on route choice behavior.

Cumulative Prospect Theory

The Cumulative Prospect Theory (CPT) of Tversky and Kahneman (1992) which was the extension to their original Prospect Theory (Kahneman and Tversky, 1979) provides empirical evidence from several choice experiments in which preferences violate the axioms (mostly three stated above) of expected utility theory. As per CPT, DMs prefer to simplify their choices cognitively whenever possible, satisficing rather than maximizing. DMs in this case consider choices from a personal reference point and tend to be risk averse with respect to gains, and risk seeking with respect to losses. Also, DMs tend to overweight unlikely events and underweight likely events when assigning probabilities. Therefore, the manner in which alternatives are presented can influence the choice made by DMs. Of the various non-expected utility theories, CPT has received the most attention in travel behavior research and especially in route choice modeling under uncertainty (Avineri and Prashker, 2004; Connors and Sumalee, 2009; Gao et al., 2010; Razo and Gao, 2010; Viti et al., 2005; Xu et al., 2011). Therefore, we think it deems a more detailed discussion.

A prospect f is represented as a sequence of pairs (x_j, p_j), where x_j is the *j*th outcome and p_j is the associated objective probability. A prospect can also be treated as a set of choices. Preferences are modeled jointly with a value function and a weighting function. The value function is given by:

$$v(x_j) = \begin{cases} x_j^{\alpha} & \text{if } x_j > 0 \quad \text{for gains} \\ -\lambda(-x_j)^{\beta} & \text{if } x_j \le 0 \quad \text{for losses} \end{cases} \qquad \text{Equation II-5}$$

The value function is concave for gains ($\alpha \le 1$) and convex for losses ($\beta \le 1$). Kahneman and Tversky (1979) proposed an inverted *S*-shaped specification of the weighting function which overweights small probabilities and underweights moderate and high probabilities. The functional form of this weighting function for gains and losses, are respectively given as:

$$w^{+}(p_j) = \frac{(p_j)^{\gamma}}{\left(p_j^{\gamma} + (1-p_j)^{\gamma}\right)^{1/\gamma}}, \text{ and} \qquad \text{Equation II-6}$$

$$w^{-}(p_j) = \frac{(p_j)^{\gamma}}{\left(p_j^{\gamma} + (1-p_j)^{\gamma}\right)^{1/\gamma}} \qquad \text{Equation II-7}$$

where $w^{+}(p_j)$ is the weighting function in case of gains and $w^{-}(p_j)$ is the weighting function in case of losses. Therefore, CPT allows for different attitudes towards probability depending on whether a DM is in gain frame or loss frame. Now, let us suppose the outcomes are such that $x_1 \le ... \le x_k \le 0 \le x_{k+1} \le ... \le x_n$. In other words, the outcomes $x_1 ... x_k$ are outcomes in loss frame and $x_{k+1} ... x_n$ are outcomes in gain frame. Then, the CPT value of the prospect $(x_1 p_1; ...; x_n p_n)$ is given as:

$$U = \sum_{i=1}^{k} \pi_i^- v(x_i) + \sum_{i=k+1}^{n} \pi_i^+ v(x_i) \qquad \text{Equation II-8}$$

where π_i^- *and* π_i^+ are the decision weights for losses and gains, respectively. They are defined as:

$$\pi_1^- = w^-(p_1), \qquad \pi_i^- = w^-(p_1 + \ldots + p_i) - w^-(p_1 + \ldots + p_{i-1}) \qquad 2 \le i \le k$$

$$\pi_n^+ = w^+(p_n), \qquad \pi_i^+ = w^+(p_i + \ldots + p_n) - w^+(p_{i+1} + \ldots + p_n) \qquad k + 1 \le i \le n - 1$$

Equation II-9

If the decision weights are not weighted or linear i.e. π_i are all equal to objective probabilities p_i, then CPT collapses to traditional EU theory. A common finding in route choice studies (cited above) using CPT is that travelers do show aversion to risk when confronted with the prospect of gains and risk seeking when choices are framed as losses. Also, they are more sensitive to losses than gains. Therefore, CPT confirmed that travelers' decision making has bounded rationality and CPT as a theory can add to the understanding of route choice behavior. Also, the concepts of reference points and loss aversion provide useful insights in decision making under risk. The application of CPT as a whole is still missing in all route choice studies. For example, none of the above mentioned studies include probability weighting functions and non-linearities in them (except Hensher et al., 2011). Part of the reason is limited scope of stated-preference surveys most of these studies rely on. Secondly, the fact that CPT was originally proposed to analyze choice situations that were framed as lotteries and gamble, its applicability in route choice scenarios where the environment of decision making is more complex is not easy. The other conceptual problems with the application of CPT are identification of reference points, it's limitation to allow only analysis of decision making under risk only i.e. it is assumed that travelers know the probabilistic distribution of travel times, and its applicability only in some areas of travel behavior. But we think that CPT has a lot to offer in understanding travelers' route choice behavior under uncertainty, and as a theory it is still undergoing various advancements so that it can be generalized to other fields of studies for which it was not initially proposed (like route choice). More research is needed in terms of designing experiments (like stated preference methods) that facilitate quantitative analysis of CPT in terms of estimation of CPT parameters and reference point values of attributes of interest.

The tables at the end of the chapter provide a synopsis of various behavioral theories that have been used over the years and their main advantages and limitations.

Behavioral Models for Ambiguity

Uncertainty usually takes two forms: *risk* or *ambiguity* (Knight, 1921). An uncertain environment is referred as 'risky' if the set of outcomes and probability distribution of the outcomes is known, while it is called 'ambiguous' if uncertainties cannot be reduced to simple probabilities or when the true probability distribution of outcomes is unknown. Now the problem arises of how to apply EU models (or even CPT models) if no objective (and even subjective) probabilities of the outcomes are available, say due to lack of information to establish these.

After the Ellsberg's experiment, the term *ambiguity* was used to refer to imprecisely specified probabilities. However, Budescu et al. (1988) promoted the use of *vagueness* or *imprecision* to capture the essence of ambiguous decision problem. Most experimental studies on ambiguity and risk aversion consider only cases involving no information or precise information of the probability distribution. There is no room for true ambiguity (or imprecision) in the standard EU models and therefore attitudes like ambiguous aversion or ambiguous neutral cannot be reconciled with the EU or SEU models efficiently. It is believed that non-expected utility models like CPT, Max-min expected utility models, and Choquet expected utility models are more efficient in modeling people's decision making under ambiguous situations.

Gilboa and Schmeidler (1989) developed the maxmin expected utility (MEU) model, also known as *multiple-prior* model, to address the Ellsberg paradox (Ellsberg, 1961) and generalize the axiomatic framework to explain ambiguous decision problems. The MEU assumes that DMs obtain probabilities based on their personal experience and replaces the classic independence axiom of the EU models with the introduction of an axiom of uncertainty aversion. Thus, MEU-rational agents make choices over a non-unique set of probability distributions, thereby yielding the utility representation:

$$MEU = \min_{P \in C} \int_S u(t)\,dP \qquad \text{Equation II-10}$$

where C is the set of probability measures on the set of possible states (similar to prospects in PT) S. Under MEU, the DM considers only the worst-case scenario. Ghirardato et al. (2004) proposed α-maxmin model for ambiguity in a very general context. The model nests many previously proposed models of ambiguity, including MEU, and Choquet expected utility models of Schmeidler (1989). The model allows DMs attitude to vary from extremely ambiguity averse to extremely ambiguity loving. That is,

$$\alpha - MEU = \alpha\left[\min_{P \in C} \int u(t)\,dP\right] + (1-\alpha)\left[\max_{P \in C} \int u(t)\,dP\right] \qquad \text{Equation II-11}$$

where α can vary from 0 to 1 and gives the ambiguity attitude index i.e., the weight that the DM put on the most *pessimistic* probability in C. When $\alpha = 1$, decisions are entirely determined by the worst-case scenario, and the α- MEU model coincides with MEU. In case of $\alpha = 0$, the DM is absolutely ambiguity loving. In general, for $\alpha > 0.5$, the DM is ambiguity averse, for $\alpha < 0.5$, he/she is ambiguity loving, and at $\alpha = 0.5$, the DM is ambiguity neutral.

Ambiguity attitudes (specifically in route choice) have been less researched in choice situations. This is due to the fact that the models which have been developed so far are still in emerging stages. Moreover, there are not many tractable models and theories that are well established to analyze ambiguity empirically (de Palma et al., 2008). However, this doesn't mean learning about ambiguity attitudes is irrelevant and these attitudes coincide with risk attitudes. The *multiple-priors* model by Gilboa and Schmeidler (1989), as explained above, can be a starting point to disentangling risk attitudes from ambiguity attitudes. Since the above-stated model also assumes utility based decision making, it possible to incorporate it within the RUM framework with, needless to say, additional assumptions.

Table II-1. Features of expected utility model

Theory	Main Assumptions	Advantages	Limitations
EU	Consistency of preferences for alternatives; Linear decision weights for alternatives; Judgment in reference to a fixed frame of reference	Most popular because of its completeness and strong axiomatic foundations; Easy to estimate	Limited usefulness as a descriptive model under uncertainty (e.g. Allais paradox and Ellsberg paradox)

Table II-2. Features of expected utility model

Theory	Main Assumptions	Advantages	Limitations
RUT	Decision makers are rational agents; Utility of each alternative based on both systematic and stochastic components; Other structural assumptions for different models within random utility	Flexible in terms of embedding various utility specifications; Mixed logit framework allowing for flexible correlation structures and preference heterogeneity	Rationality violations; Valuation of certain and riskless outcomes

Table II-3. Features of dynamic models

Theory	Main Assumptions	Advantages	Limitations
Dynamic Models	Decision making a dynamic process, involving information acquisition and learning over time; Relation between the travel utilities in previous time periods and travelers' current choices; decision maker is an adaptive learner	Addresses repeated decision tasks such as route-choice; Strong conceptual basis	Lack of empirical basis

Table II-4. Features of elimination by aspects

Theory	Main Assumptions	Advantages	Limitations
Elimination by Aspect	Decision making process a sequential elimination process based on simple *heuristics*; Individuals arrive at an 'approximate' solution without any complex computational effort	Assumptions are the main advantages	Lacking experimental and empirical evidence of its applicability in route choice modeling; Low levels of model awareness and convenience of use

Table II-5. Features of cumulative prospect theory

Theory	Main Assumptions	Advantages	Limitations
CPT	*Reference dependence*, i.e., separate value functions defined over gains and losses; *Diminishing sensitivity* (i.e., the curvatures of value functions suggesting decreasing marginal value of both gains and losses) and *loss aversion*; *Non-linear probability weighting*	Allows for non-linearities in both utility and probability weighting; Useful for choices involving time variability such as arrival and departure time, travel time, delay time, etc.	Identification of reference points; Limited to decision making under risk only (known probabilities)

CHAPTER III.
DATA COLLECTION

An important feature of any behavioral research is its dependence on experiments to carefully test basic assumptions and mechanisms underlying decision making. Understanding route choice behavior from travelers' perspective warrants similar experimental analysis. We use stated preference (SP) surveys (also known as choice experiments) which have been important survey instruments to understand behavioral responses and consumer preferences for various transportation services. The purpose behind conducting these experiments is to determine the independent influence of different variables (attributes or factors) on observed outcome and their willingness to pay (WTP) for specific attributes. More detailed discussion on SP experiments can be found in Bliemer and Rose (2006) and Hensher et al. (2005). Following sub-sections provide a detailed discussion of the survey management and design.

Survey Management

The SP surveys were conducted online. However, before publishing the survey online, a paper-based pilot survey was conducted. The pilot survey provided valuable input and feedback related to content, attributes, and design of the survey. The web-based survey was then carefully constructed using traditional programming languages. Since the surveys were conducted online without any supervision, they were kept as simple as possible by carefully removing any ambiguity in questions.

We used the University of Iowa Alumni e-mail list to send out a mass e-mail inviting people to complete a web survey. The e-mail contained a short description of the research and a link to the web-survey. The e-mail was sent to the alumni living in the following areas: Chicago-Naperville-Joliet Metropolitan Division (Illinois), Dallas-Fort-worth-Arlington Metropolitan area (Texas), Harris County (Texas), Miami Dade County (Florida), New York, and New Jersey. The reasons for selecting above-mentioned study areas were twofold. First, these regions included large metropolitan cities (like Chicago, Dallas, Houston, New York City, and Miami) where chances of commuters experiencing unexpected delays are high. Second, the study areas have some of the busiest toll roads in the nation. The e-mails were sent out to a pool of about 8,500 people and we had about 292 valid responses. Subjects had to be 18 years of age and had to drive to work at least three times a week.

Survey Design

Based on existing literature, our study objectives, and the fact that the web-survey was not supervised, only the most important route characteristics were included in the SP experimental design. The attributes included were:

- *Usual travel time*: It is the one-way travel time (in minutes) from home to work assuming no unexpected delays.
- *Frequency/Chances of delay*: Frequency of delay means number of days travelers can experience unexpected delays out of 10 travel days (10 days means two weeks assuming 5 working days in a week). For example, '5 days out of 10 days' means that one can experience delays on that route 5 times out of 10 times he/she decided to take that route. Therefore travel time reliability in experiencing delay is presented in a more familiar and contextual way rather than giving survey respondents a statistical value.
- *Average delay*: It is the mean delay (in minutes) on the days travelers experience any unexpected delays.
- *Toll cost*: Amount of tolls (if any) travelers pay for their one way commute to work.

Each participant was asked to fill out three sections. The first section had four questions (choice questions in the next section were pivoted off the responses to these questions) including their one-way travel time from home to work, the frequency and amount of unexpected traffic delays, and amount of tolls (if any) they pay for their commute to work. In the second section each respondent was given a series of 12 choice scenarios. Each scenario has two questions. In the first question they had to make a choice between three routes including their existing route (based on the information they entered in the first section) and two hypothetical routes. In the second question they were to make choices only between two hypothetical routes assuming that the existing route is no longer feasible due to some long term construction. Since we are interested in analyzing travelers' commuting behavior when they are forced to take a different route than usual, we only analyze the responses to the second question in this paper. Finally, the third section consisted of socio-demographic questions.

In order to maintain realism in the choice experiments the levels of the route attributes were based on (pivoted off) the respondent's current trip. Hypothetical routes are constructed with factors that are somewhat above and below those of the recent trip, and the respondent is then asked to choose among these hypothetical routes. The levels for each attribute are given in Table III-1. Note that, however, the frequency of the unexpected delay attribute is not pivoted off the respondents' current route attributes. This was done in order to measure people' attitudes toward different reliability measures (more discussion is available in the next section).

We created blocked fractional-factorial designs and randomly selected choice sets in such a way that none of the choice sets has a dominant alternative. Three different designs comprising of four questions were created and each design was blocked into six subsets of four questions each. For the first design, the levels for usual travel time and average delay are such that they only have higher values than their current times (i.e. +50%, +25%, and +10% for usual travel time and +50% and +20% for average delay). The frequency of delay attribute only consisted of levels with known chances i.e. ('1 out of 10 days' to '9 out of 10 days'). The toll cost had all five levels shown above. The second design was similar to the first one except that now the levels for usual travel time and average delay are such that they only have lower values than their current times (i.e. -50%, -25%, and -10% for usual travel time and -50% and -20% for average delay). In other words, the first design have the hypothetical routes that are worse than their existing routes in terms of travel times and in the second design the hypothetical routes are better than their existing routes. In the third design, the frequency of delay was fixed to 'Unknown' in one of the two hypothetical routes and had same levels as shown in the table for rest of the attributes. Finally, the four questions from each design were combined and the respondents were given 12 choice questions in all and the order of questions (from the three designs discussed above) is randomized in order to avoid any response bias. Appendix includes the details on the generated SP designs. Figure III-1 to Figure III-5 provide screenshots of the web-survey.

Finally, we want to highlight some of the caveats and limitation of this survey methodology. First, the survey was sent out to a group of University of Iowa's alumni which means the survey participants had at least a college degree. This results into a survey pool which may be biased toward medium to higher income groups. Secondly, we didn't collect the location information of the participants as per the Institutional Review Board's guidelines to protect the privacy of the participants. Therefore, in modeling exercises we couldn't control for effects with respect to participants' location. However, we assume that most of the participants belong to Chicago-Naperville-Joliet Metropolitan Division (Illinois) area. Because of these limitations, the results are applicable to our sample of employed, higher than median income, college graduates, and living in major urban metropolitan areas. The conclusions of the study are limited to this population and not statistically valid as generalizations to the population as a whole.

Table III-1. Attributes and levels in the survey design

Levels	Usual Travel Time	Frequency of Unexpected Delays	Average Delay if Occurs	Toll Cost
Level 1	-50%	1 out of 10 days	-50%	-100%
Level 2	-25%	3 out of 10 days	-20%	-50%
Level 3	-10%	5 out of 10 days	+50%	+ $1
Level 4	+50%	7 out of 10 days	+20%	+ $2
Level 5	+25%	9 out of 10 days		+ $3
Level 6	+10%	Unknown		

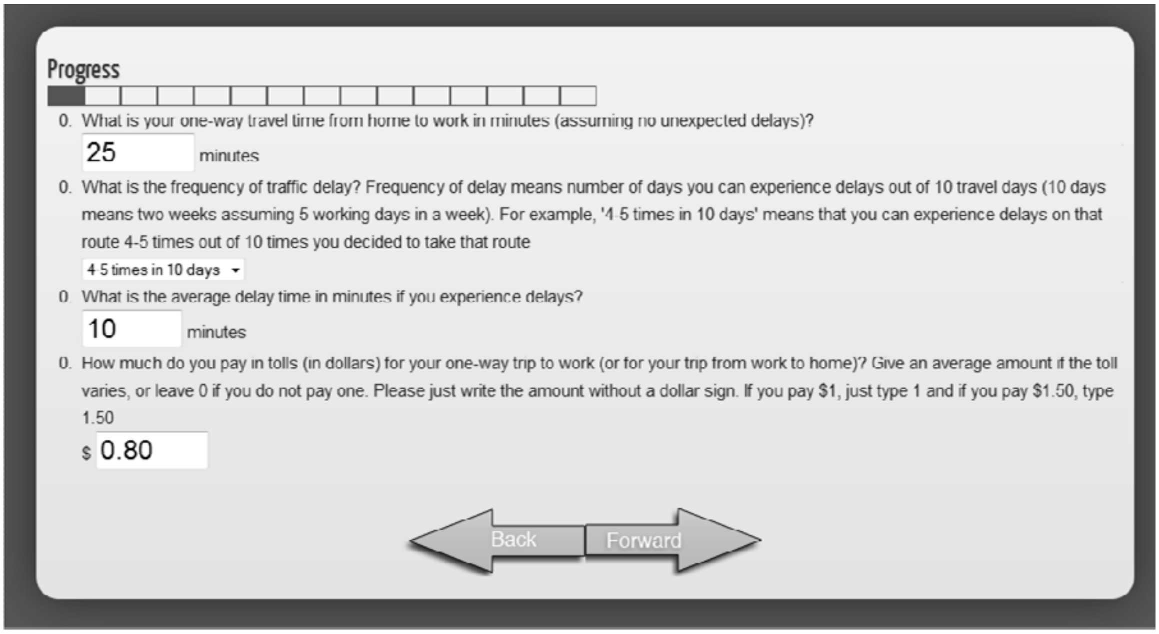

Figure III-1. Screenshot of the commuters' existing travel characteristics

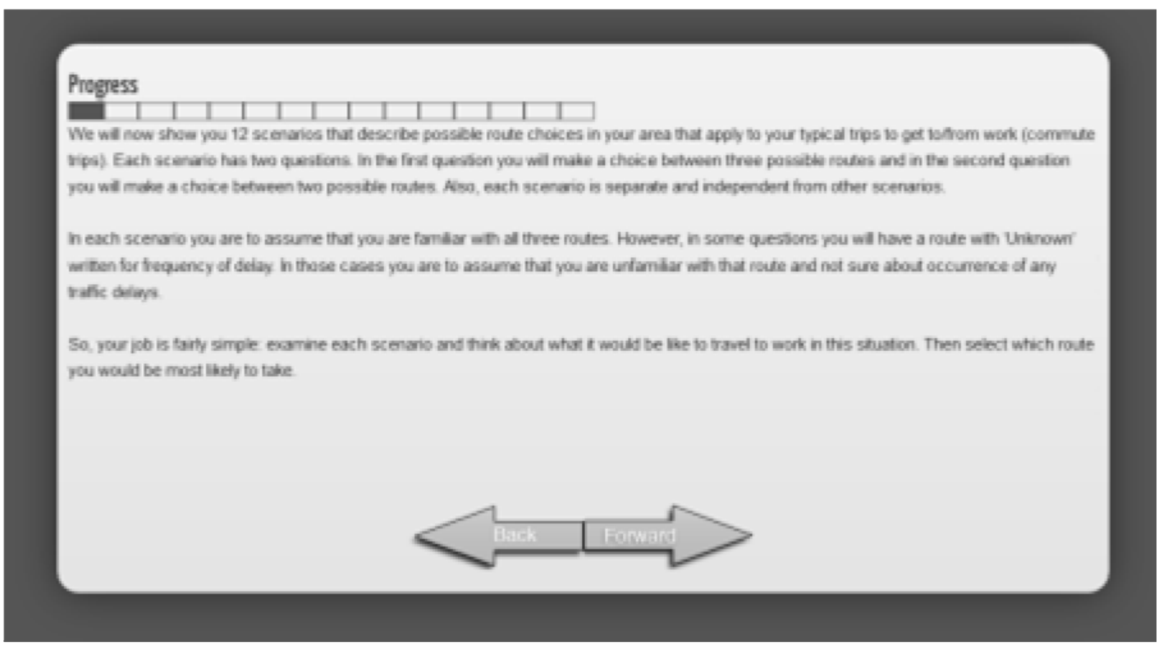

Figure III-2. Screenshot of instructions

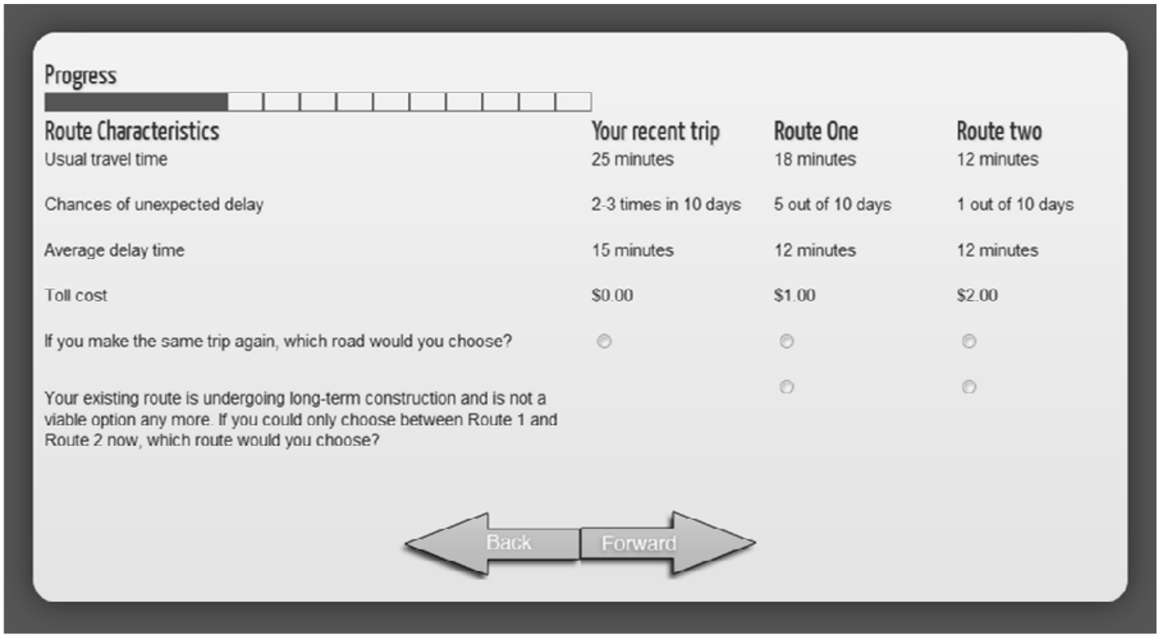

Figure III-3. Screenshot of the web-survey (risky routes only)

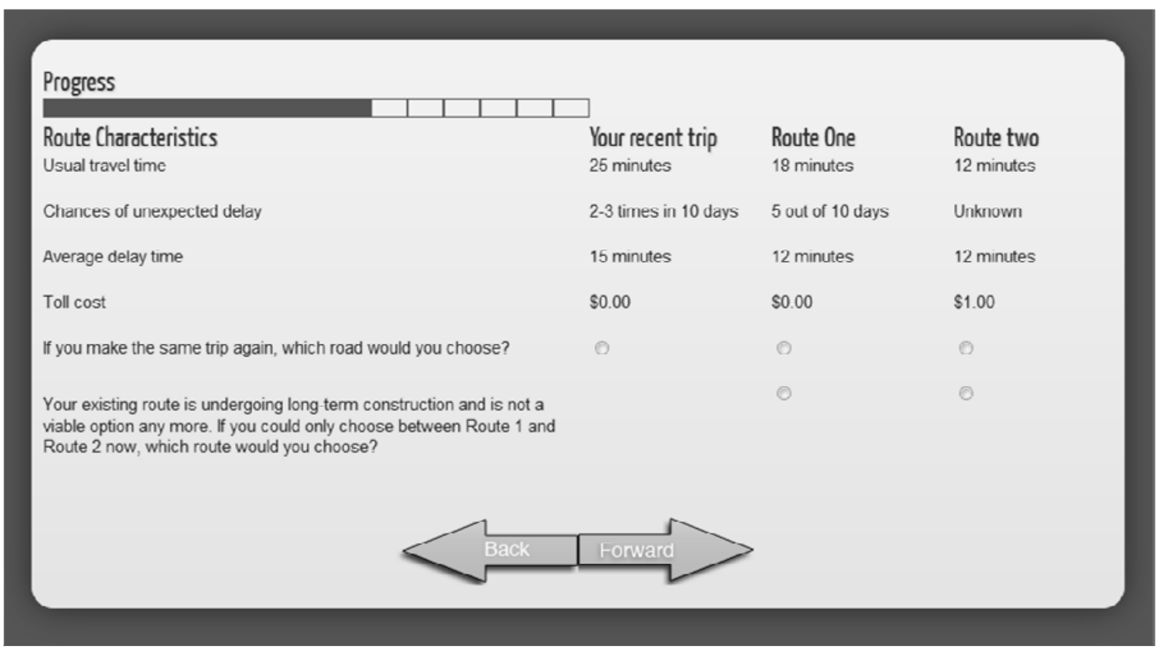

Figure III-4. Screenshot of the web-survey (with one of the routes as ambiguous)

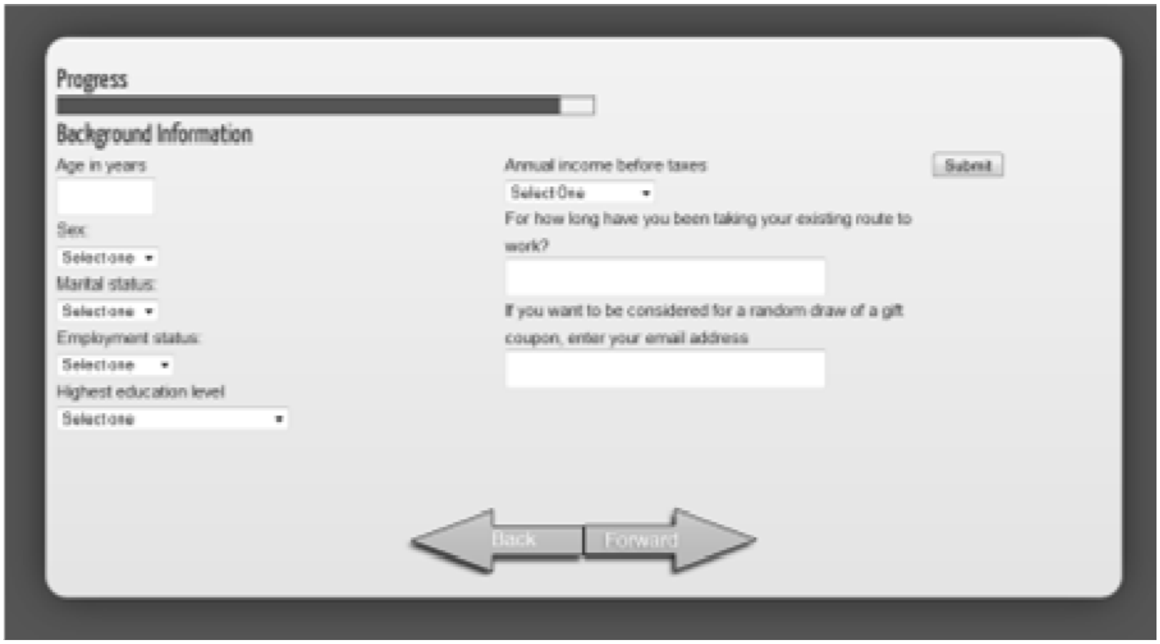

Figure III-5. Screenshot of the commuters' socio-economic characteristics

CHAPTER IV.
THE IMPACT OF DELAY OCCURRENCE AND DURATION AS A MEASURE OF RELIABILITY ON COMMUTER CHOICE

Behavioral responses to travel time reliability has become an important dimension of understating travelers' route choice attitudes. In simple words, travel time reliability can be regarded as the stability in travel time for a given trip. Several sources of disruption, both random and predictable, constitute variations in the traffic conditions leading to increased travel time unreliability. These random disruptions can take any form, including planned activities like construction and maintenance work, and community and social events or unplanned events such as weather closures, natural disasters, and other unforeseen emergencies. The result of these incidents is limited or a total loss of capacity on particular corridors and lead to poor transportation network performance. The spillover effects of inconsistent network performance can be seen in other sectors, including lost man-hours, air-pollution, and negative psychological effects on the drivers. Therefore, in the last two decades the measurement of transportation system reliability has become one of the central topics of travel demand studies. A more recent addition to this growing literature is the measurement of value of travel time reliability which provides a monetary cost of avoiding unpredictable travel time.

The first step to improve travel time reliability and to put a monetary value on it is to correctly measure it. The concept of travel time reliability has been historically linked with the concept of travel time variability where travel time is assumed to have a statistical distribution. The travel time reliability is then quantified in terms of the measure of spread of the assumed distribution. Although it provides an efficient way of measuring travel time reliability from an analyst's point of view, it is not easy to communicate statistical distributions to general public in order to get realistic behavioral responses to travel time reliability. Furthermore, using these methods to get travelers' willingness to pay measures can be challenging and may lead to biased estimates. Federal Highway Administration (FHWA) recommends using four possible measures of measure travel time reliability because of their technical merit and their simplicity to communicate to travelers. These measures are 90th or 95th percentile travel time, buffer index, planning time index, and frequency that congestion exceeds some expected threshold. The advantage of using these measures in eliciting traveler preferences for travel time reliability lies in the fact that these methods simply compare days with high delay to days with usual travel time. As such, it is easy to obtain travelers' attitudes toward travel time reliability by using methods similar to the ones recommended by the FHWA. In this study, we present travel time reliability as the frequency/chances that travel time exceeds commuters' usual travel time for a typical trip.

The goal of this chapter is to measure travelers' behavioral responses to travel time reliability and their willingness to pay to avoid unreliable routes. The route choice behavior is studied in the context of commuting trips. A typical person is unable to meaningfully understand numerical distributions and associated terms (like mean and variance). Therefore, we use the frequency of days with unexpected delays as a means of measuring people's attitudes to travel time reliability. The preferences are elicited through a stated preference (SP) survey technique where commuters were to choose between different routes with different levels of travel time reliability. The details on the data collection can be found in Chapter 3.

We divide our review of literature into two parts. The first part provides definitions of travel time reliability and how it is measured. The second part is on the value of travel time reliability and various empirical methodologies that have been used to put a monetary value on travel time reliability within route choice context.

Measurement of Travel Time Reliability

The definition of travel time reliability varies and different authors have used different definitions based on the study context. Lomax et al. (2003) define reliability in terms of consistency of transportation services for a given time period. As such, it can be defined for a mode, a trip, a route or a corridor. Emam and Al-Deek (2006) and Iida (1999) argue that travel time reliability can be expressed as the probability of completing a trip between a given origin-destination pair within a specified range of time interval. van Lint and van Zuylen (2005) extend the definition further and argue that travel time reliability for a route depends on the time of day, day of the week, month of year, and other external factors. In spite of differences in definitions, a well accepted notion is that travel time reliability considers the distribution of travel time probability and higher the variance is, the more unreliable is the route. From a behavioral perspective, travelers are more averse to higher variability in travel time than higher mean travel time (van Lint and van Zuylen, 2005).

In order to effectively communicate the idea of travel time reliability by avoiding statistical terms, FHWA measures travel time reliability in a more practical way. Following are the definitions/concepts used by the FHWA:

- *Percentile travel times*: It provides information on how bad delay will be on the busiest travel days. In most cases, a 95th percentile travel times is used, however, 85th, 90th, or 99th percentile travel times can be used depending upon the context.
- *Buffer index*: This is the extra time cushion travelers should take into account to ensure on-time arrival. The extra buffer time corresponds to any unexpected delays.
- *Planning time index*: The measure gives the total travel time including both typical delays and any unexpected delays. Therefore, it provides near-worst case travel time as compared to usual (or free flow) travel time.

- *Frequency that congestion exceeds some expected threshold*: This is presented as the percent of days or time that average (or usual) travel time (speed) exceeds (falls) a certain value.

In a nutshell, these methods simply compare days with high delay to days with usual travel time. For example, on typical weekdays the average travel time from an origin to a destination could be 15 minutes. However, when random disruptions like weather closures, accidents, or any other unforeseen emergencies cause unexpected delays, the travel time could be 25 minutes. The measures listed above essentially capture travel time reliability in an easy to understand (from a user's point of view) procedure. Agencies like FHWA, Minnesota Department of Transportation (Mn/DOT), and the Washington State Department of Transportation (WSDOT) have already used these measures in their travel demand studies as supplement to other congestion measures. A number of studies have been conducted to calculate these measures and have highlighted the importance of calculating travel time reliability. Chen, Skabardonis and Varaiya (2003) investigated the importance of measuring travel time reliability as a measure of freeway service quality. The study argued that the level of service (LOS) measure doesn't necessarily capture the variability in travel time and user's experience during the trip, rather just aids in ensuring proper geometric design of road networks. Lyman and Bertini (2008) proposed adding travel time reliability measures to the currently used measures of congestion. They calculated percentile travel times, buffer indices, and planning time indices for various interstate corridors in the Portland, Oregon metropolitan. The study used 20-second resolution count, speed and occupancy data from more than 500 freeway sensors to calculate these different measures. Susilawati et al. (2010) conducted a similar study and investigated the buffer time indices and planning indices for the ten corridors of the Adelaide Metropolitan road network. All these studies had a focus on traffic engineering aspects of improving network performance.

However, lacking in these studies is the understanding of travelers' behavior from a user point of view. How do commuters assess these reliability measures and how do they decide which route to take when faced with different choice scenarios? We aim to fill this gap by analyzing commuters' route choice behavior in response to travel time reliability.

Value of Travel Time Reliability

Willingness to pay (WTP) or value of travel time (VOT) has been studied extensively from the viewpoint of consumer theory. Wardman (2004), and Small and Verhoef (2007) provide a good review of VOT estimates as applied in the field of transportation demand. WTP for travel time reliability is, however, still an emerging concept. Nevertheless, a fair amount of studies have been done that measure the VOT together with the value of travel time reliability. The empirical approaches followed by the researchers mostly interrelate the concept of travel time reliability with that of travel time variability where reliability (or variability) is assumed to be a function of the spread of the travel time distribution.

Various utility frameworks have been proposed and used over the past few years to account for and measure the value of travel time variability. The earlier efforts aimed to capture travel time variability (or unreliability) within utility maximization framework involved use of mean-variance approach which was first proposed by Markowitz (1952). The approach was primarily devised to measure the risk attitudes of decision makers within finance literature. Jackson and Jucker (1982) used the mean-variance models in route choice in which the utility value, $U(x)$ of a route is modeled as a trade-off between the expected travel time $\mathbb{E}(x)$ and the variability in time (risk) $Var(x)$, such that $U(x) = \mathbb{E}(x) - \theta Var(x)$. The parameter θ expresses the decision-maker's risk attitude. Similar methodology was adopted by Black and Towriss (1993), however they looked at the tradeoff between average travel time and standard deviation instead of variance. Like

Jackson and Jucker (1982), study, they also used a stated preference data and estimated a generalized traveled cost function with travel time, its standard deviation and travel cost in the utility function to capture the effect of travel time variability. These studies not only confirm the disutility associated with travel time variability but also indicate a considerable heterogeneity in travelers’ response to this variability. Despite its simplicity, the mean–variance approached is applicable only in cases where the random variables approximate normal distributions (Samuelson, 1970). de Palma and Picard (2006) further confirm the inconsistency in mean-variance models and suggested alternative utility specifications.

After the mean-variance approach, Expected Utility (EU) theory has been well recognized to capture uncertainty and travel time variability in route choice context. Maximum Expected Utility Theory was introduced as a way to take into account travel time variability in which it was assumed that drivers select the alternative with the highest value of expected utility. Various authors followed this methodology in the context of scheduling delays (Bates et al., 2001; Noland and Small, 1995; Small et al., 1999). Most of the studies based on expected utility theory relied on stated preference methods. On the other hand, Small, Winston and Yan (2005) successfully combined reveled preference (RP) data with SP data to measure the value of travel time reliability. The data was collected from morning commuters on California State Route 91 (CA-91) via telephone surveys and mail-back questionnaires. The authors used advanced random utility framework to estimate the value of time and value of reliability (VOR) where these measures were calculated as the marginal rates of substitution between travel cost, travel time and travel reliability. The unreliability of travel time was measured as the difference between the 80th and 50th percentiles of the travel time distributions. In order to get more accurate and realistic estimates, Carrion and Levinson (2011) used Global Positioning System (GPS) devices to collect travel data and to obtain VOR measures. Recent development in calculations of the VOT and VOR estimates have used advanced utility frameworks acknowledging non-linearities in utility specification within discrete choice modeling frameworks (see Hensher et al., 2011 and Carrion et al., 2011 for a detailed review).

However, there is a mismatch between how agencies like FHWA and state DOTs measure (or recommend to measure) travel time reliability and how existing literature measure the value of travel time reliability. The main issue with abovementioned empirical methodologies is that it is very difficult to elicit accurate behavioral responses from subjects (or non technical day-to-day commuters) when travel time reliability is presented in terms of statistical distributions and probabilities. The goal of this chapter is to present travel time reliability in a more simplified way so that more realistic WTP measures for travel time and reliability can be obtained. As such, travel time reliability is presented as the frequency of days with unexpected delays. Finally, we aim to calculate travelers' WTP measures that not only take travel time into account but also the frequency of experiencing unexpected delays on their routes. The WTP measures are calculated using a panel mixed logit formulation.

Empirical Framework

We used discrete choice modeling framework and in particular, a panel mixed logit model which is based on the fact that different agents behave differently and responses from the same individual are correlated. We formulate the mixed logit model in preference space. The utility function in preference space can be written as follows:

$$U_{nsi} = \beta_n x_{nsi} + \varepsilon_{nsi} \qquad \text{Equation IV-1}$$

where we use the index n ($n = 1, 2, \ldots, N$) for the respondents, s for the choice set, *i.e.* SP choice scenarios for a particular respondent, ($s = 1, 2, \ldots, S$). and i for the route alternative ($i = 1, 2, \ldots, I$). In our case $I = 2$ and $K = 8$. x_{nsi} is a $(Q \times 1)$ vector of route attributes, and their interaction with the traveler characteristics measuring the observable utility of individual n for alternative i at the s^{th} choice scenario. β_n is a corresponding

$(Q \times 1)$ parameter vector. We measure preference heterogeneity by allowing parameter vector β_n to vary over individuals according to both observed characteristics and unobserved influences. Thus β_n can be specified as:

$$\beta_n = \beta' + v_n' \qquad \text{Equation IV-2}$$

where β' is the $(Q \times 1)$ is the vector of the mean effects of the observed variables x_{nsi} and v_n' is another $(Q \times 1)$ randomly distributed vector which captures unobservable heterogeneity among individuals. In this analysis, we assume that the heterogeneity distribution from which v_n is drawn is a normal distribution with mean zero and variance σ_q^2. Finally, ε_{nsi} is the usual idiosyncratic random error term independently and independently distributed according to extreme-value distributions. Therefore, the probability of an individual *n* selecting alternative *i* (*i* = 1, 2,…, *I*) in choice scenario *s* (*s* = 1, 2, …, *S*) conditional on the unobservable vector v_n is:

$$P_{nsi} \mid v_n = \frac{exp\left(\beta' x_{nsi} + v_n x_{nsi}\right)}{\sum_{j=1}^{I} exp\left(\beta' x_{nsi} + v_n x_{nsi}\right)} \qquad \text{Equation IV-3}$$

Now, in order to take into account the probability of each respondent's sequence of observed choices in SP setting, we can write the likelihood function conditional on v_n as:

$$L_n(\beta \mid v_n) = \prod_{s=1}^{S}\left[\prod_{i=1}^{I} \frac{exp\left(\beta' x_{nsi} + v_n x_{nsi}\right)}{\sum_{j=1}^{I} exp\left(\beta' x_{nsi} + v_n x_{nsi}\right)}^{\,y_{nsi}}\right] \qquad \text{Equation IV-4}$$

where y_{nsi} is equal to one if respondent *n* chooses alternative *i* in choice situation *s* and 0 otherwise. However, in order to calculate the model parameters, we calculate the likelihood function unconditioned on the unobservable elements. Therefore, the unconditional likelihood function is given as:

$$L_n(\beta,\sigma) = \int_{v_n} L_n(\beta \mid v_n) f(v_n \mid \sigma) dv_n \qquad \text{Equation IV-5}$$

where f is the multivariate normal distribution and σ is a vector that populates the σ_q elements for all q. Therefore, the parameters to be estimated are the β and σ vectors. Finally, the log-likelihood function for all respondents is given as:

$$L(\beta,\sigma)=\sum_{i=1}^{n} log \int_{v_n} L_n(\beta \mid v_n) f(v_n \mid \sigma) dv_n \qquad \text{Equation IV-6}$$

Since the above integral does not have a closed form, we approximate it via simulated maximum likelihood and maximize its logarithm across all respondents to retrieve the parameters β and σ. More details related to maximum simulated likelihood estimators can be found in McFadden and Train (2000).

Results

Descriptive Analysis

A total of 292 respondents submitted the survey online. We only included the responses where the existing commute time was at least 5 minutes. The final sample used in the analysis consisted of 273 respondents with 2088 choice occasions. Table IV-1 shows the socio-economic characteristics of the respondents (who chose to provide that information) along with the characteristics of their existing commuting routes. We almost have an even distribution of males to females in our sample with an average age of respondents as 40 years. However, our sample is skewed towards the higher income groups. This is due to the fact that we sent out our survey to the alumni of the University of Iowa and almost all of them had at least four year college degree. The average travel time to work was calculated as 29.9 minutes with average delay time of 13.7 minutes (on days respondents experience unexpected delays on their commuting route). The other important piece of information we collected was the frequency/chances of commuters to experience days with unexpected delays. Some interesting results were obtained. About half of the respondents experience unexpected delays at least 4-5 times in two weeks with about 10 percent of them experiencing delays every day and about one-fourth of the respondents experience unexpected delays 2-3 times. Finally, about one-third of the respondents pay tolls for their commuting route and the average toll across our sample came out to be $0.45. We also asked respondents about how long they have been taking the existing route to work. As you can see in the table IV-1, travelers have strong tendency to take the same route to work. About three-fourth of the respondents have been taking the same route for more than a year. This also shows that travelers must have tried and formed mental representation of travel time distributions on other available routes in the network and stick to the one that potentially maximizes their utility.

Empirical Analysis

The mixed logit model estimated in this study included the four route attributes discussed earlier along with interaction effects. In order to have a parsimonious model we started with an elaborate model with various main and interaction effects and systematically eliminate the variables that deem highly insignificant. We assumed normal distributions for the random variables. Some researchers have used constrained distributions like log-normal or triangular distributions. However, the log-normally distributed parameters often have large tails and the constrained triangular distribution rely heavily on the mean. Therefore, we followed a more conservative approach by assuming normal distributions for the random parameters. The mixed logit model is estimated using BIOGEME software (Bierlaire, 2008) with DONLP2 as the optimization algorithm. Further, we used 500 pseudo random draws for randomly distributed parameters. Results of the estimation are shown in the table IV-2. The goodness-of-fit of the mixed logit model is good with an adjusted rho-square value of 0.14 (a value of 0.12 or higher is considered good for panel data).

As expected, the coefficients on the usual travel time attribute and the toll cost are both negative and statistically significant. The travel time reliability effects are measured by including both the frequency/chances of delay attribute as a separate categorical variable (main effects) and by interacting each of its level with the amount of unexpected delay. The category ‘1 day out of 10 days’ served as the base category. Therefore, the value of -0.741 in Table IV-2 shows that, on average, a route with chances of delay as ‘5 days out of 10 days’ is 0.741 utility units less attractive than a route with chances of delay as “1 day out of 10 days” for a given delay time. Additionally, a significant interaction term between the frequency of delay and the amount of delay shows that a route with higher delays and chances of delay as ‘5 days out of 10 days’ is even preferred less by 0.034 units. These coefficients related to the reliability of a route reveal some important results. First, travelers prefer a route with less occurrence/frequency of unexpected delay days which is intuitive since it provides more stability to drivers in terms of on-time arrivals to their workplace. Secondly, significant interaction between the frequency of delay days and the amount of unexpected delay means it’s not only the frequency but also the amount of unexpected delay attached to it predict the preference over a particular route. We also found significant standard deviation corresponding to the ‘5 days out of 10 days’ category.

Similar results are obtained when the frequency of experiencing delay was either ‘7 days out of 10 days’ or ‘9 days out of 10 days’ with significant negative estimates for these categories and their interaction with amount of delay. However, the main effects for the category ‘3 days out of 10 days’ is insignificant as compared to the base category but the interaction effect of this category with delay time is significant indicating frequency of experiencing delay alone is not significant as compared to the base category unless a route has a higher delay time too. This is also intuitive because these two categories are quite similar in terms of the frequency of delay and travelers’ preferences are governed by both the frequency and the amount of delay when making a selection between these two routes rather than just the frequency of delay. We do not find any significant standard deviation (or unobserved heterogeneity) in the categories '3 days out of 10 days', '7 days out of 10 days', and '9 days out of 10 days'.

Interaction effects of route characteristics with commuters' socio-economic characteristics, and travel characteristics were also considered, but to our surprise most of these other interaction effects were statistically insignificant. We initially hypothesize that commuters' existing frequency of experiencing delays would have some kind of relationship with time and cost but we didn't find any statistically significant coefficients for the same. However, we did find significant interaction effects between toll cost and whether a respondent pays tolls or not. A positive coefficient with magnitude 0.201 reveals that respondents who already pay tolls are more likely to pay higher tolls to save time than respondents who don't pay tolls. The interaction between income (we included only two income categories i.e. annual income above and below $60,000) and tolls was only significant at the 10% confidence level.

Willingness to Pay Estimates

In discrete choice models, the marginal rate of substitution expresses the willingness to pay (WTP) for various attributes. WTP estimates provide valuable information to transportation officials in terms of assessment of existing or proposed infrastructure facilities (tolls in our case) from a cost-benefit perspective. We calculate two different WTP measures. First, we calculate WTP for for travel time with respect to frequency of experiencing delay days. Second, we calculate WTP for travel time reliability expressed in terms of both the frequency of delay days and the amount of unexpected delay.

Previous studies have calculated WTP measures using a range of methods. The most widely used mechanisms to calculate WTP measures are a) if both cost and the attributes of interest for which the WTP need to be calculated are randomly distributed, one can simple take the ratio of the means of the assumed distributions, b) using simulation by taking random draws for each parameter from its assumed distribution and then computing the ratio. This method, however, can lead to a resulting distribution of the WTP measure which may have undefined population moments (Daly, Hess and Train, 2011), c) using constrained distributions like log-Normal or triangular distributions which constraint the signs to be consistent and thus giving analytically tractable estimates of WTP measures, d) calculating the model directly in WTP-space by dividing the coefficients of interest with cost coefficient before estimating the model (more discussion can be found in Train and Weeks (2005) and Scarpa, Theine and Train (2008), and e) assuming a fixed parameter for cost coefficient and letting the coefficients of interests for which the WTP measures need to be calculated vary randomly. We follow this last approach in this study because of several reasons. First, the estimation becomes easy and the shape of the WTP distribution is same as the shape of the parameters used in the numerator. Second, we can avoid issues related to infinite values being observed for WTP measures. Third, it is not trivial to select an appropriate distribution for the cost coefficient. Normal distribution for the cost coefficient may lead to positive estimates for WTP measures and other constrained distributions like mentioned above can mask data issues and lead to biased estimates.

Our final model takes following utility form:

$$U_{nsi} = (\beta_1 + v_1)UsualTravelTime + \beta_2 AverageDelayTime + (\beta_{3i} + v_2)FrequencyDelay + \beta_{4i} FrequencyDelay * AverageDelayTime + \beta_5 Toll + \beta_6 Toll * ExistingToll + \varepsilon_{nsi}$$

Equation IV-7

where β's are the corresponding coefficients for various attributes. v_1 and v_2 are the normally distributed random terms which capture unobservable heterogeneity in the usual travel time and frequency of delay parameters. Frequency of delay enters the equation as dummy variables for various categories ('1 day out 10 days', '3 days out of 10 days', and so on). β_{3i} are the corresponding coefficients for these dummy variables (for i = 1, 2,…,5). Similarly, β_{4i} are the dummy variable coefficients for the interaction effects between the frequency of delay and the amount of delay. The marginal utilities for time, cost and reliability are given by the partial derivatives of the utility function with respect to time (*T*), cost (*C*) and reliability (*R*).

$$\frac{\partial U}{\partial T} = (\beta_1 + v_1) + \beta_2 + \beta_{4i} FreqencyDelay \qquad \text{Equation IV-8}$$

$$\frac{\partial U}{\partial C} = \beta_5 + \beta_6 ExistingToll \qquad \text{Equation IV-9}$$

$$\frac{\partial U}{\partial R} = (\beta_{3i} + v_2) + \beta_{4i} AverageDelayTime \qquad \text{Equation IV-10}$$

And the WTP for travel time and the WTP for travel time reliability is given as follows:

$$w_{ti} = \frac{\partial U}{\partial T} \Big/ \frac{\partial U}{\partial C} = \frac{(\beta_1 + v_1) + \beta_2 + \beta_{4i} FreqencyDelay}{\beta_5 + \beta_6 ExistingToll} \quad for\ i = 1,....,5 \qquad \text{Equation IV-11}$$

$$w_{ri} = \frac{\partial U}{\partial R} \Big/ \frac{\partial U}{\partial C} = \frac{(\beta_{3i} + v_2) + \beta_{4i} AverageDelayTime}{\beta_5 + \beta_6 ExistingToll} \quad for\ i = 1,....,5 \qquad \text{Equation IV-12}$$

Therefore, for a commuter who already pays a toll has the following implied WTP distribution for time to avoid delay '5 days out of 10 days' is given by:

$$w_{t1} = \frac{(-0.083 + v_1) - 0.046 - 0.028}{-0.738 + 0.201} * 60 = \frac{(-0.083 + v_1) - 0.074}{-0.537} * 60 \qquad \text{Equation IV-13}$$

where, w_{t1} is expressed in dollar/hour and v_1 are randomly drawn values from a normal distribution with mean zero and standard deviation 0.082. Similarly, for a commuter who already pays a toll has the following implied WTP distribution for avoiding 10 minutes of delay possibly five times in 10 days as compared to 10 minutes of delay possibly once in 10 days:

$$w_{r1} = \frac{(-0.741 + v_2) - 0.028 * 10}{-0.738 + 0.201} = \frac{(-0.741 + v_2) - 0.28}{-0.537} \qquad \text{Equation IV-14}$$

where, w_{r1} is expressed in dollars and v_2 are randomly drawn values from a normal distribution with mean zero and standard deviation 0.623. Table IV-3 shows the WTP estimates for different categories. The confidence intervals for WTP measures are calculated using Krinsky and Robb (KR) method when the numerator has a normally distributed parameter and the delta method is used in case there are no randomly distributed coefficients. See Hole (2007) for a detailed discussion on these methods. The table provides measures for respondents who do not pay tolls for their existing commute trips and for respondents who pay tolls for their existing commute trips. As noted earlier, the standard deviation came out significant only for the usual travel time attribute and the "5 days out of 10 days" category. Therefore, the WTP measures are normally distributed involving only these attributes. As evident from the table IV-3, the mean WTP estimates are much higher for respondents who already pay tolls for their commute trips as compared to respondents who don't. Moreover, there is an increasing pattern for WTP measures as the reliability decreases. As evident from the marginal utilities, the WTP measures for travel time and reliability are both functions of the frequency of delay days. For respondents who do not pay tolls, the maximum estimate for the mean of WTP for travel time is observed when delay days could be '9 days out of 10 days' at \$17.14/hr. This mean value is about 1.7 times higher than the mean of the WTP corresponding to the base category i.e. '1 day out of 10 days'. Similarly, the WTP measures in terms of both the amount of delay and the frequency of delay are presented in the table. Respondents who don't pay tolls are likely to pay \$1.74 more to avoid 10 minutes of delay '9 days out of 10 days' as compared to 10 minutes of delay '1 day out of 10 days'. Similar but higher values of the WTP measures are obtained for respondents who already pay tolls.

Discussion and Conclusions

The study used a stated preference survey methodology to elicit travelers' attitudes towards unreliable routes. To circumvent the issue of presenting statistical distributions to day-to-day commuters, we use the frequency of days with unexpected delays as the means of measuring people's behavioral attitudes to travel time reliability. We calculated travelers' WTP measures that not only take travel time and its variability into account but also the frequency of experiencing unexpected delays on their routes. The results show that travelers prefer a route with less occurrence/frequency of days with unexpected delays. Moreover, it's not only the frequency but also the amount of unexpected delay attached to it that predicts the preference over a particular route. To our knowledge, no previous study has included frequency of days with unexpected delays as a means of eliciting behavioral response to travel time reliability. The study also contributes to the existing literature by calculating WTP measures that correspond to different levels of travel time reliability. The WTP measures for travel time and travel time reliability show significant heterogeneity and the mean WTP estimates are much higher for respondents who already pay tolls for their commute trips as compared to respondents who don't. The mean of WTP corresponding to highly unreliable routes (i.e. frequency of delay days is '9 days out of 10 days') ranges from \$17.14 to \$23.56 per hour as compared to \$10.56 to \$14.73 per hour for the reliable routes (i.e. frequency of delay days is '1 day out of 10 days').

Table IV-1. Descriptive socio-economic characteristics of the respondents

Female	54.1%
Male	45.9%
Age (Mean, Std. Deviation)	(39.75, 11.29)
Personal Income	
Up to $40,000	9.7%
$40,001 to $60,000	17.5%
$60,001 to $90,000	23.0%
$90,001 to $120,000	17.5%
Greater than $120,000	32.3%
Time at the current route to work	
Up to 1 month	2.7%
1 month to 6 months	14.4%
6 months to 1 year	8.9%
1 year to 5 years	40.5%
Greater than 5 years	33.5%
Usual Travel Time in Min. (Mean, Std. Deviation)	(29.90, 14.80)
Delay in Min. (Mean, Std. Deviation)	(13.71, 10.82)
Toll in $ (Mean, Std. Deviation)	(0.45, 0.97)
Frequency of Experiencing Unexpected Delay	
Never	4.7%
Once in 10 days	20.6%
2-3 times in 10 days	24.5%
4-5 times in 10 days	18.3%
6-7 times in 10 days	13.6%
8-9 times in 10 days	8.2%
Always	10.1%

Table IV-2. Panel mixed logit model

Attributes	Coefficient	|t-values|
Usual travel time	-0.083	4.42
Std. dev. usual travel time	0.082	2.55
Average delay time	-0.046	2.43
Frequency of delay		
1 day out of 10 days	ref.	-
3 days out of 10 days	0.098	0.66
Std. dev. 3 day out of 10 days	0.002	0.12
5 days out of 10 days	-0.741	3.7
Std. dev. 5 day out of 10 days	0.623	2.07
7 days out of 10 days	-0.749	3.75
Std. dev. 7 day out of 10 days	0.275	0.77
9 days out of 10 days	-0.496	1.93
Toll	-0.738	8.16
Interactions		
1 day out of 10 days * Delay	ref.	-
3 days out of 10 days * Delay	-0.021	2.01
5 days out of 10 days * Delay	-0.028	2.41
7 days out of 10 days * Delay	-0.056	3.61
9 days out of 10 days * Delay	-0.079	4.17
Toll * dummy for low to med income (<$60K)	-0.002	1.89
Toll * dummy for who already pay tolls	0.201	2.04
Final log-likelihood	-1226.15	
Likelihood ratio test	442.28	
Adjusted rho-square	0.141	
Number of choices	2088	
Number of individuals	273	

Table IV-3. Willingness to pay estimates

Categories	Mean	Lower and Upper 95%
For commuters who don't pay tolls		
WTP in terms of frequency (Value of Time)		
Avoid delay '1 day out of 10 days'	$10.72/hr	($10.17, $11.27)
Avoid delay '3 days out of 10 days'	$12.43/hr	($11.88, $12.98)
Avoid delay '5 days out of 10 days'	$13.00/hr	($12.45, $13.55)
Avoid delay '7 days out of 10 days'	$15.27/hr	($14.72, $15.82)
Avoid delay '9 days out of 10 days'	$17.14/hr	($16.59, $17.69)
WTP in terms of frequency and amount of delay (Value of Reliability)		
10 minutes of delay '1 day out of 10		ref.
10 minutes of delay '3 days out of 10		Not significant
10 minutes of delay '5 days out of 10	$1.40	($1.32, $1.48)
10 minutes of delay '7 days out of 10	$1.77	($0.79, $2.75)
10 minutes of delay '9 days out of 10	$1.74	($1.15, $2.33)
For commuters who pay tolls		
WTP in terms of Frequency (Value of Time)		
Avoid delay '1 day out of 10 days'	$14.73/hr	($14.18, $15.28)
Avoid delay '3 days out of 10 days'	$17.07/hr	($16.52, $17.62)
Avoid delay '5 days out of 10 days'	$17.86/hr	($17.31, $18.41)
Avoid delay '7 days out of 10 days'	$20.99/hr	($20.44, $21.54)
Avoid delay '9 days out of 10 days'	$23.56/hr	($23.01, $24.11)
WTP in terms of amount of delay and frequency (Value of Reliability)		
10 minutes of delay '1 day out of 10		ref.
10 minutes of delay '3 days out of 10		Not significant
10 minutes of delay '5 days out of 10	$1.93	($1.85, $2.01)
10 minutes of delay '7 days out of 10	$2.44	($0.85, $4.03)
10 minutes of delay '9 days out of 10	$2.39	($1.23, $3.55)

CHAPTER V.
UNDERSTANDING DRIVERS' ROUTE CHOICE BEHAVIORAL RESPONSE TO UNCERTAINTY IN THEIR COMMUTING ROUTES

Current route-choice models used in practice simplify the decision process such that uncertainty is assumed away by bestowing travelers with the ability to memorize travel times on all practical routes and constantly reassess this close-to-perfect information to a select route that maximize their utilities. Most often the models' underlying framework is economic rationality, which brings with it the adherence to the strictures of rational theory. Given the stochastic nature of the transportation networks, the assumption of a driver's close-to-perfect knowledge is, however, questionable. Therefore, it becomes imperative to improve existing route-choice models by integrating the theory and empirical findings from fields of science, like psychology, where it has been repeatedly shown that decisions and behaviors are often determined by perceptions that may not be in accordance with rational theories. Common analytical non-behavioral route choice models, which are based on either network risk, to take into account randomness of network utilities, or perception errors, to account for imperfect information of travelers, or both, are as follows: deterministic network, deterministic user equilibrium model; deterministic network, stochastic user equilibrium model; stochastic network, deterministic user equilibrium; and stochastic network, stochastic user equilibrium model (Chen and Recker, 2001). However, these models lack psychological underpinnings and therefore, are not well suited to analyze drivers' cognitive decision making process. As a result, rule based models that are more representative of drivers' behavior are being used in understanding route-choice behavior from drivers' perspective. These models are based on the assumption that drivers follow latent decision rules for evaluating the attributes of available routes and decide on a specific route based on this evaluation.

Lacking in contemporary research efforts to model the travel time uncertainty is the inclusion of non-expected utility framework which incorporates two very important behavioral attributes including risk/ambiguity attitudes and probability weighting. Therefore, the goal of this chapter is to understand people's attitudes towards uncertain situations when they make adjustments to their usual commuting route. To this end, we propose a non-linear logit model capable of embedding probability weighting, and risk/ambiguity attitudes. The model adds behavioral rigor to the existing random utility framework. Furthermore, a willingness to pay structure is derived which takes into account travel time variability and behavioral attitudes.

Empirical Approaches

Previous studies have shown that the most important factor that influences travelers' utilities and route choice is the expected travel time (Bekhor et al., 2001; Outram and Thompson, 1977). However, a number of recent studies (Bates et al., 2001; de Palma and Picard, 2005; Lam and Small, 2001) have shown that travelers have an aversion to uncertainty about travel time too and understanding drivers' attitudes towards travel time reliability has become an important aspect of travel demand studies (Madera and Levinson, 2010; Tilahun and Levinson, 2010). One aspect of travel time variability is the range and distribution of travel times on a particular trip. Usually drivers and especially daily commuters having repeated trips select a route that offers them least amount of variation around some mean time. The other aspect of travel time variability is how often commuters face unexpected traffic delays over a course of time. For example, a route may have a usual travel time of 15 minutes but has chances of experiencing an average delay of 10 minutes seven out of 10 days (this amounts to a 70% probability of delay). Whereas, there is another route available that has a usual travel time of 25 minutes but has chances of experiencing an average delay of 10 minutes only one out of 10 days (10% probability of delay). Moreover, when there is no reference time distribution for a route due to complete unfamiliarity and no prior experience in taking that route. How do drivers select routes under this kind of uncertainty when they make changes in their usual commuting patterns?

Most of the frameworks adopted by earlier studies to capture travel time uncertainty relied on utility maximization, in one way or the other. Mean-variance approach (Markowitz, 1952) was among the first ones that aimed to capture risky behavior within utility maximization framework. (Jackson and Jucker, 1982) studied route choice behavior by using a mean-variance model such that the utility of a route was given as $U(x) = \mathrm{E}(t) - \theta Var(t)$. $\mathrm{E}(t)$ represents the expected travel time on a particular route and the variability in time, $Var(t)$, is the measure of risk. The parameter θ captured travelers' attitudes toward risk. The used a stated preference survey methodology to elicit travelers' route choice behavior. Black and Towriss (1993), used a similar approach to study route choice behavior, however, used standard deviation as the measure of travel time variability instead of variance. These studies showed that travelers are, in general, averse to travel time variability; however, they found a considerable heterogeneity in travelers' responses.

Following the mean-variance approach, Expected Utility Theory (EUT) has been widely used to understand drivers' behavioral responses to travel time uncertainty. EUT states that in situations involving uncertainty, the decision maker (DM) chooses outcomes on the basis of their expected utility values, i.e., the weighted sums of the utility values of outcomes multiplied by their respective probabilities. As such, the DM selects the alternative with the maximum utility (Einhorn and Hogarth, 1981; von Neumann and Morgenstern, 1944). Application of expected utility (EU) in route choice modeling is widespread. Travelers are assumed to behave as if they correctly assign probabilities to random travel times and choose a route that maximizes the expected value of their utility. However, after an extensive application of the conventional EU models in modeling uncertain behaviors, researchers have come to the conclusion that decision makers often do not make choices in a way consistent with the EU models. For example, the Allais paradox (overweighing high consequence low-probability cases) and the Ellsberg paradox (ambiguity aversion attitude) have challenged the underlying axioms of the EU and subjected EU models even in context of simple decision making situations. Avineri and Prashker (2004) conducted simple route-choice experiments and found two violations of EU theory. They found presence of certainty effect (Allais paradox) and the inflation of small probabilities in a stated-preference single-route experiment.

Similarly, the conventional Random Utility Models (RUM) assume that travelers have perfect information and show rational behavior to maximize their utility (or satisfaction). Rationality of travelers have been challenged in many recent studies (Avineri and Prashker, 2004; Bogers et al., 2007; Fujii and Kitamura, 2000). Moreover, the theory is concerned with the valuation of certain and riskless outcomes. However, recent developments in the RUT framework have incorporated EU principles to model individual travel choice under risk (Noland and Small, 1995; Polak et al., 2008; Senna, 1994). Maximum Expected Utility Theory was introduced as a way to take into account travel time variability. This approach became one of the standard approaches to account for travel time uncertainty in terms of risk for quite some time (Bates et al., 2001; Small et al., 1999). Although EU has been extensively used within RUM, a linear utility specification has been the dominant approach to account for risk in travel time occurrences (see Hensher, Greene and Li, 2011 for a review). Recent developments in route choice modeling are now acknowledging non-linearities in both utility specification and probability weighting under uncertain travel times. For example, Hensher et al., (2011) investigated individual heterogeneity in value of travel time savings by incorporating non linear probability weights and risk attitudes, using a mixed multinomial model. We aim to further add behavioral realism in existing RUM framework by considering behavioral models available not only for risk analysis but also for ambiguity.

Behavioral Models for Risk and Ambiguity

As mentioned earlier, there are two aspects to uncertainty that we aim to capture in the route choice context: *risk* and *ambiguity*. When drivers' are operating in the risky space it is assumed that they have a prior knowledge of probabilities associated with possible outcomes. We rely on the principles of Prospect Theory, proposed by Kahneman and Tversky (1979), to capture the route choice attitudes in the risky space. Whereas, when drivers do not have knowledge of point probabilities, they operate in the ambiguity space. We use α-maxmin model, as proposed by Ghirardato et al. (2004), to untangle drivers' ambiguity attitudes. These two models fall under the umbrella of 'non-expected utility theories' and the name is primarily given due to the fact that they usually do not adhere to the principles of economic rationality and the standard choice axioms of EUT. Following subsections provide a brief overview of these behavioral theories.

Prospect Theory for Risk Analysis

The Prospect Theory (PT) relaxes the linear assumption on the probability of outcomes to include decision weights to allow for under or over weighting of point probabilities of possible outcomes. Another distinguishing feature of PT is the inclusion of risk attitudes via assigning non-linear utility function (also known as value function) to possible outcomes. A prospect (or a set of choices) is represented as a sequence of pairs (x_j, p_j), where x_j is the jth outcome and p_j is the associated objective probability. Preferences are modeled jointly with a value function and a weighting function. The value function is given by $v(x_j)$ and the weighting function is represented as $w(p_j)$, where w indicates the weighting of point probabilities. The utility under this framework can be written as:

$$U_j = \sum_j w(p_j) \times v(x_j) \qquad \text{Equation V-1}$$

A further advancement to PT, also known as Cumulative Prospect Theory (CPT), was proposed by Tversky and Kahneman (1992) and introduced the concept of reference dependence. Of the various non-expected utility theories, PT has received the most attention in travel behavior research and especially in route choice modeling under uncertainty (Connors and Sumalee, 2009; Gao et al., 2010; Razo and Gao, 2010; Viti et al., 2005; Xu et al. 2011).

Maxmin Expected Utility Theory for Ambiguity Analysis

Gilboa and Schmeidler (1989) developed maxmin expected utility (MEU) model, also known as *multiple-prior* model, to address the Ellsberg paradox (Ellsberg, 1961) and generalize the axiomatic framework to explain ambiguous decision problems. The MEU assumes that DMs obtain probabilities based on their personal experience and replaces the classic independence axiom of the EU models with the introduction of an axiom of uncertainty aversion. Thus, MEU-rational agents make choices over a non-unique set of probability distributions, thereby yielding the utility representation:

$$MEU = \min_{P \in C} \int_S u(t)\,dP \qquad \text{Equation V-2}$$

where C is the set of probability measures on the set of possible states (similar to prospects in PT) S. Under MEU, the DM considers only the worst-case scenario. Ghirardato et al. (2004) proposed α-maxmin model for ambiguity in a very general context. The model nests many previously proposed models of ambiguity, including MEU, and Choquet expected utility models of Schmeidler (1989). The model allows DMs attitude to vary from extremely ambiguity averse to extremely ambiguity loving. That is,

$$\alpha - MEU = \alpha \left[\min_{P \in C} \int u(t)\,dP \right] + (1-\alpha) \left[\max_{P \in C} \int u(t)\,dP \right] \qquad \text{Equation V-3}$$

where α can vary from 0 to 1 and gives the ambiguity attitude index i.e., the weight that the DM put on the most "pessimistic" probability in C. When $\alpha = 1$, decisions are entirely determined by the worst-case scenario, and the α- MEU model coincides with MEU. In case of $\alpha = 0$, the DM is absolutely ambiguity loving. In general, for $\alpha > 0.5$, the DM is ambiguity averse; for $\alpha < 0.5$, he/she is ambiguity loving; and at $\alpha = 0.5$, the DM is ambiguity neutral.

The use of abovementioned behavioral theories that can be embedded within the traditional RUM framework to understand route choice behavior is almost non-existent. To the best of our knowledge, most route choice experimental studies consider only risky route choices, e.g., precise information on probability of delay. In this research, we use a stated preference experimental protocol to simultaneously elicit people's attitude toward both risky and ambiguous routes. The specific hypothesis driving the proposed research is that drivers' do not always make rational decisions in route-choice situations and factors such as uncertainty in travel time and monetary cost play a significant role in route selection.

Empirical Framework

We use a random utility framework, specifically, a panel mixed logit model in order to account for correlated responses from the same individual and to include any unobserved heterogeneity in preferences. A simple utility function can be written as follows:

$$U_{nsi} = \beta_n x_{nsi} + \varepsilon_{nsi} \qquad \text{Equation V-4}$$

where n ($n = 1, 2,\ldots, N$) is used to denote respondents, s ($s = 1, 2, \ldots, S$) represents SP choice scenarios, and i indicates the route alternative ($i = 1, 2,\ldots, I$). Our analysis involves two alternatives only, therefore, $I = 2$ in this case. x_{nsi} represents a $(Q \times 1)$ vector of observed attributes along with their interaction with other observable attributes. β_n is the parameter vector associated with x_{nsi}. The unobserved term, ε_{nsi}, is assumed independently distributed according to extreme-value distributions. In order to account for any unobserved heterogeneity, we allow the parameter vector β_n to vary over individuals to follow a particular distribution. As such, β_n can be written as:

$$\beta_n = \beta' + v_n' \qquad \text{Equation V-5}$$

where β is the $(Q \times 1)$ vector that captures the mean effects of the observed variables x_{nsi} and the unobserved heterogeneity is given by the $(Q \times 1)$ randomly distributed vector, v_n.

For Risk Analysis

Eight of the 12 questions in our SP survey involve respondents making choices between two risky routes (i.e. the chances of experiencing any delay is known). As such, we extend the above stated utility function into probabilistic utility framework. First, consider an expected utility framework where the respondent chooses outcomes on the basis of their expected utility values, i.e., the weighted sums of the utility values of outcomes multiplied by their respective probabilities, given by $EU = \sum_j p_j \times U_j$. Therefore, a random utility function with linear probability function (based on EUT) can be written as:

$$U_{nsi} = \beta_n x_{nsi} + \beta_t \left[p_{nsi} T_{D,nsi} + (1 - p_{nsi}) T_{ND,nsi} \right] + \varepsilon_{nsi} \qquad \text{Equation V-6}$$

where β_n are the coefficients on deterministic attributes and include interaction terms too, β_t is the coefficient on travel time, T_D is the travel time if delay occurs, T_{ND} is the travel time in case of no delay (usual travel time), and p_{nsi} is the probability/frequency of delay. Now, as mentioned earlier, prospect theory posit that DMs tent to underweight or overweight probabilistic events when assigning probabilities. Therefore, we advance the EUT to include non-linear weights for objective probabilities. The utility under this framework can be written as $NEU = \sum_j w(p_j) \times U_j$, where NEU stands for non-expected utility, $w(p_j)$ is a probability weighting function, and U_j is a value function. The following equations adapt the standard EUT framework within RUM by incorporating a probability weighting function $w(p_j)$.

$$U_{nsi} = \beta_n x_{nsi} + \beta_t \left[w(p_{nsi}) T_{D,nsi} + (1 - w(p_{nsi})) T_{ND,nsi} \right] + \varepsilon_{nsi} \qquad \text{Equation V-7}$$

where

$$w(p_{nsi}) = \frac{(p_{nsi})^{\gamma}}{\left[(p_{nsi})^{\gamma} + (1 - (p_{nsi}))^{\gamma} \right]^{\frac{1}{\gamma}}} \qquad \text{Equation V-8}$$

The value of parameter γ signifies the non-linearity in the probability weighting. In case, $0 < \gamma < 1$ the probability function takes an inverted S-shape. This implies that when the function is concave low probabilities are over-weighted and when the function is convex high probabilities are under-weighted. On the other hand, all values $\gamma > 1$ imply the probability function is S-shaped, in which small probabilities are under-weighted and high probabilities are over-weighted. The probability equation presented above was first proposed by Tversky and Kahneman (1992) and is extensively used in other literature in various domains.[1] Several other probability functions have been proposed and used over the past few years and an application for various weighting functions within route choice can be found in Hensher et al. (2011). Finally, to include risk attitude parameters we specify a power function for the travel time attribute. The power function given by

[1] We also tried reference dependence model, cumulative prospect theory that is, as proposed by Tversky and Kahneman (1992). Under cumulative prospect theory, decision makers consider choices from a personal reference point and tend to be risk averse with respect to gains, and risk seeking with respect to losses. Also, DMs tend to overweight unlikely events and underweight likely events when assigning probabilities. We assumed drivers' existing travel characteristics as the reference points for usual travel time and average delay. However, we do not obtained results in accordance with cumulative prospect theory. The results are shown for both the gain frame and the loss frame in Tables V-6 and V-7 at the end of the chapter.

$U(x) = x^{\rho}$ belongs to the family of constant relative risk aversion (CRRA) and is widely used in the economic, psychological, and health domain (Wakker, 2008). The model now becomes:

$$U_{nsi} = \beta_n x_{nsi} + \beta_t \left[w(p_{nsi}) T_{D,nsi}{}^{\rho} + (1 - w(p_{nsi})) T_{ND,nsi}{}^{\rho} \right] + \varepsilon_{nsi} \qquad \text{Equation V-9}$$

The ρ parameter lies between 0 and 1 for risk seeking respondents and is greater than 1 for risk-averse respondents. The parameter also provides a measure of decreasing marginal utility of travel time, that is, travel times have decreasing effects as the amount of time increases. For, $\gamma = \rho = 1$, we have a standard linear expected utility model embedded within random utility framework. Now, the probability of an individual n selecting alternative i (i = 1, 2,…, I) in choice scenario s (s = 1, 2, …, S) is:

$$P_{nsi} = Pr\,ob\left(U_{nsi} > U_{nsj}\right) \forall j \neq i$$

$$P_{nsi} = Pr\,ob\begin{pmatrix} \beta_n x_{nsi} + \beta_t \left[w(p_{nsi}) T_{D,nsi}{}^{\rho} + (1 - w(p_{nsi})) T_{ND,nsi}{}^{\rho} \right] + \varepsilon_{nsi} > \\ \beta_n x_{nsj} + \beta_t \left[w(p_{nsj}) T_{D,nsj}{}^{\rho} + (1 - w(p_{nsj})) T_{ND,nsj}{}^{\rho} \right] + \varepsilon_{nsj} \end{pmatrix} \forall j \neq i$$

Equation V-10

The algebraic calculation of this probability results in a closed-form logit choice probability and can be written simple as (where V_{nsi} is the deterministic part of the utility):

$$P_{nsi} = \frac{exp\left(V_{nsi}\right)}{\sum_{i=1}^{I} exp\left(V_{nsi}\right)} \qquad \text{Equation V-11}$$

Let Δ is the parameter vector such that it contains the coefficients on various attributes, the probability weighting parameter, and the measure of decreasing marginal utility, i.e., $\Delta = \{\beta_n, \beta_t\, \gamma, \rho\}$ Now, in order to take into account the probability of each respondent's sequence of observed choices in SP setting, we can write the likelihood function conditional on knowing Δ as:

$$L_n(\Delta) = \prod_{s=1}^{S}\left[\prod_{i=1}^{I}\left(\frac{exp(V_{nsi})}{\sum_{j=1}^{I} exp(V_{nsi})}\right)^{y_{nsi}}\right] \qquad \text{Equation V-12}$$

where y_{nsi} is equal to one if respondent *n* chooses alternative *i* in choice situation *s* and 0 otherwise. In order to account for preference heterogeneity, we assume a normal distribution over subjects for the parameter vector Δ. The unconditional likelihood to calculate the model parameters is given by:

$$(L_n(\sigma) = \int_{\Delta} L_n(\Delta) f(\Delta \mid \sigma) d\Delta \qquad \text{Equation V-13}$$

where *f* is the multivariate normal distribution and σ is a vector that populates the σ_q elements for all *q*. The equation can also be seen as the weighted average of logit probabilities evaluated at different values of parameter vector Δ. The log-likelihood can be defined as:

$$LL(\sigma) = \sum_{i=1}^{n} log \int_{\Delta} L_n(\Delta) f(\Delta \mid \sigma) d\Delta \qquad \text{Equation V-14}$$

and is numerically calculated via simulated maximum likelihood estimation. The simulated log likelihood function is calculated by taking *r* =1,….,*R* draws from the assumed distribution $f(\Delta \mid \sigma)$. The simulated log likelihood is given as,

$$LL_s(\sigma) = \sum_{i=1}^{n} log \frac{1}{R} \sum_{r=1}^{R} L_n(\Delta^r) \qquad \text{Equation V-15}$$

More detailed discussion on retrieving parameters of interest via maximum likelihood estimation can be found in McFadden and Train (2000).

For Ambiguity

As mentioned earlier, four of the 12 questions asked in the SP survey involve a route where, the frequency of delay was fixed to ‘Unknown’ in one of the two hypothetical routes. In other words, one of the routes was ‘ambiguous’ and the other was ‘risky’ (see Figure 2). We use *α*-maxmin model to calculate the utility of the ambiguous route. We embed the α-maxmin framework within the RUM framework to calculate the parameters of interest. A utility function for an ambiguous route (with α-maxmin specification) can be written as:

$$\alpha - MEU = \alpha \min_{p\in[c_1,c_2]}\left[pU(T_D)+(1-p)U(T_{ND})\right]+(1-\alpha)\max_{p\in[c_1,c_2]}\left[pU(T_D)+(1-p)U(T_{ND})\right]$$

Equation V-16

where the respondent's perception of ambiguity is denoted by C such that $C = [c_1,c_2] = [0,1]$. The α parameter is the weight the respondent put on worst possible travel time (or worst possible prior) and 1 - α is the weight on the best possible travel time (or best possible prior). In our SP surveys, the frequency of delay for ambiguous route is 'Unknown' which means that the best possible prior is when $c_1 = 0$, and the worst possible prior is when $c_2 = 1$. Therefore, the respondent simply maximizes:

$$\alpha - MMEU = \alpha\, U(T_D)+(1-\alpha)\,U(T_{ND})$$ Equation V-17

We assign CRRA utility for travel time as we did in the case of risk analysis. The α-maxmin utility for travel time now becomes:

$$\alpha - MMEU = \alpha\,(T_D)^{\rho}+(1-\alpha)\,(T_{ND})^{\rho}$$ Equation V-18

where ρ is the estimate of the risk aversion coefficient from the risk analysis. Now, the probability of an individual n selecting the ambiguous alternative i over the risky alternative j in choice scenario s (s = 1, 2, …, S) is:

$$P_{nsi} = Prob\left(U_{nsi} > U_{nsj}\right)\ \forall j \neq i$$

Equation V-19

$$P_{nsi} = Prob\begin{pmatrix}\beta_n x_{nsi} + \beta_t\left[\alpha\, T_{D,nsi}{}^{\rho} + (1-\alpha)\,T_{ND,nsi}{}^{\rho}\right] + \varepsilon_{nsi} > \\ \beta_n x_{nsj} + \beta_t\left[w(p_{nsj})T_{D,nsj}{}^{\rho} + (1-w(p_{nsj}))T_{ND,nsj}{}^{\rho}\right] + \varepsilon_{nsj}\end{pmatrix}\forall j \neq i$$

The algebraic calculation of this probability results in a closed-form logit choice probability and can be written simple as:

$$P_{nsi} = \frac{exp\left(\beta_n x_{nsi} + \beta_t \left[\alpha\, T_{D,nsi}{}^{\rho} + (1-\alpha)\, T_{ND,nsi}{}^{\rho}\right]\right)}{exp\left(\beta_n x_{nsi} + \beta_t \left[\alpha\, T_{D,nsi}{}^{\rho} + (1-\alpha)\, T_{ND,nsi}{}^{\rho}\right]\right) + exp\left(\beta_n x_{nsj} + \beta_t \left[w(p_{nsj})T_{D,nsj}{}^{\rho} + (1-w(p_{nsj}))T_{ND,nsj}{}^{\rho}\right]\right)}$$

Equation V-20

Now, in order to take into account the probability of each respondent's sequence of observed choices in SP setting, we can write the likelihood function conditional on knowing Δ (the parameter vector) as:

$$L_n(\Delta) = \prod_{s=1}^{S}\left[\prod_{i=1}^{I}\left(\frac{exp\left(\beta_n x_{nsi} + \beta_t \left[\alpha\, T_{D,nsi}{}^{\rho} + (1-\alpha)\, T_{ND,nsi}{}^{\rho}\right]\right)}{exp\left(\beta_n x_{nsi} + \beta_t \left[\alpha\, T_{D,nsi}{}^{\rho} + (1-\alpha)\, T_{ND,nsi}{}^{\rho}\right]\right) + exp\left(\beta_n x_{nsj} + \beta_t \left[w(p_{nsj})T_{D,nsj}{}^{\rho} + (1-w(p_{nsj}))T_{ND,nsj}{}^{\rho}\right]\right)}\right)^{y_{nsi}}\right]$$

Equation V-21

The log-likelihood and the simulated log likelihood functions are calculated in a similar fashion as we did for Equations 13 to 15.

Results

Descriptive Analysis

A total of 292 respondents submitted the survey online. We only included the responses where the existing commute time was at least 5 minutes. The final sample used in the analysis consisted of 283 respondents with 3,259 choice occasions. Table V-1 shows the socio-economic characteristics of the respondents (who chose to provide that information) along with the characteristics of their existing commuting routes. We almost have an even distribution of males to females in our sample with an average age of respondents as 40 years. However, our sample is skewed towards the higher income groups. This is due to the fact that we sent out our survey to the alumni of the University of Iowa and almost all of them had at least four year college degree. The average travel time to work was calculated as 29.8 minutes with average delay time of 13.8 minutes (on days respondents experience delays on their commuting route). The other important piece of information we collected was the frequency/chances of commuters to experience days with unexpected delays. About half of the respondents experience unexpected delays at least 2-3 times in two weeks with about 10 percent of them experiencing delays every day. Finally, about one-third of the respondents pay tolls for their commuting route and the average toll across our sample came out to be $0.45.

Empirical Analysis

a) <u>Risk Analysis</u>

We first estimated panel multinomial logit and panel mixed logit models based on expected utility theory as per Equation V-6. The results are shown in Table V-2 under the column headings EUT-MNL and EUT-MMNL. The mixed logit model is estimated using BIOGEME software (Bierlaire, 2008) with DONLP2 as the optimization algorithm. More details on algorithm can be found in Spelluci (1999). Further, after testing various number of pseudo random draws for randomly distributed parameters, we selected 250 as a balance between accuracy and speed of solution. The coefficients on expected travel time and toll cost are both negative, as expected. However, the mixed logit specification provides a better fit (as evident from the higher adjusted rho-squared value of 0.229 for mixed logit specification) with significant heterogeneity in both the expected travel time and the toll cost.

The results based on cumulative prospect theory are presented in Table V-6 and Table V-7. However, the coefficient on travel time came out be insignificant. Therefore, we rejected the hypothesis that drivers operate differently in the gain domain as compared to the loss domain. We then estimated similar models based on prospect theory specification as per Equation V-9 (see Table V-3 under the column headings PT-MNL and PT-MMNL). The multinomial logit specification shows that coefficients on travel time and toll cost are both negative and statistically significant at 95% confidence level. The coefficient on risk parameter ρ (or marginal diminishing utility) is 0.84 meaning that, on average, drivers are risk seeking. The standard error associated with this estimate is 0.087, which means that the estimate is not statistically different than 1, at 95% confidence level. However, the multinomial specification does provide an evidence of risk seeking attitudes. The estimate of 1.41 for γ, confirms non-linearity in probability weighting, however, a value greater than one implies drivers under weigh small probabilities and over-weigh high probabilities. A value of 1.41 for γ, shows that drivers perceive a probability of 0.20 as 0.118, i.e. $w(0.2) = 0.118$, whereas a probability of 0.8 is perceived as 0.831, i.e. $w(0.8) = 0.831$. Surprisingly, we didn't find significant interaction effects between route characteristics and drivers' socio-economic and travel characteristics. The only statistically significant interaction effect is between toll cost and a dummy variable corresponding to whether a respondent pays tolls or not. We found a positive coefficient of 0.186 implying that respondents who already pay tolls for their commuting routes have a tendency to pay higher tolls than respondents who don't pay tolls.

PT-MMNL (Table V-3) shows results of the mixed logit model with same variables as we have for the MNL specification. The estimates from the MNL model entered as the starting values for the mixed logit model. The estimation of a non-linear mixed logit model incorporating unobserved heterogeneity in probability weighting parameter, risk attitudes, and other parameters is rather complex and time taking. Although it is possible to assume various distributions for the random variables, we decided to follow a more conservative approach by allowing the random parameters to be distributed normal. Researchers have used constrained distributions like log-normal or triangular distributions. However, the log-normally distributed parameters often have large tails and the constrained triangular distribution rely heavily on the mean. The goodness-of-fit of the mixed logit model is better as compared to the MNL model as evident from the higher adjusted rho-squared value of 0.238 for mixed logit specification. A lower value for the final log-likelihood of -1136.06 for mixed logit also implies a superior fit. As expected, the coefficients on the mean estimates of expected travel time and toll cost are both negative and statistically significant. We found significant unobserved heterogeneity in the toll cost parameter, though, not for the coefficient on expected travel time. The mean estimate of risk parameter, in this case, is found to be 0.75 and is statistically different than one. This confirms that, on an average, drivers have risk seeking behavior in the context of route choice. A significant measure of standard deviation confirms unobserved heterogeneity in risk attitudes. An estimate of 0.153 for the standard deviation suggests that about 94.5% of the respondents have ρ estimates less than one (risk taking) while 5.5% have estimates ρ greater than one (risk averse). Hensher et al. (2011) found similar results with their survey respondents showing risk seeking behavior on average, however, their study showed a higher proportion of risk averse drivers (34.3%). Another interpretation of this measure is in terms of diminishing marginal utility. An estimate less than one for ρ, indicate a significant decrease in sensitivity to travel time (in other words a delay of 2 min for a 20 min trip hurts more than a delay of 2 min for a 50 min trip). In our case, about 94.5% of respondents have decreasing sensitivity to travel times and only 5.5% of the respondents have increasing sensitivity to travel times. The estimation of probability weighting parameter γ in the mixed logit specification is similar to the MNL specification at 1.40. Figure V-1 further illustrates the probability weighting functions for $\gamma = 1.40$, $\gamma = 0.69$, and $\gamma =1$. This again confirms that drivers under-weigh small probabilities and over-weigh high probabilities. We tried including random effects for the probability weighting parameter but the standard deviation coefficient was not only insignificant but the model was also poorly identified.

Interesting conclusions can be drawn if we simultaneously consider the CRRA utility function (which turns out to be a convex function in our case with ρ less than one) and the probability weighting function. For example, when the probability of delay travel time is small, say 0.2, the drivers tend to under weigh this probability, $w(0.2) = 0.112$ and over weigh the probability of usual travel time, i.e. 1 – 0.112 = 0.888, meaning they show optimism in perceiving the chances of delay and thus may reflect risk seeking attitudes. On the other hand, if the probability of delay travel time is high, say 0.8, the drivers would over weight this probability, $w(0.8) = 0.831$, and under weigh the probability of usual travel time. This shows pessimism when the chances of delay are high, and drivers may act risk averse even with a convex CRRA utility function.

Comparing EUT based models with PT based models, we found that PT based models with probability weighting parameter and non-linear utility specification provide better fit and confirm that drivers do show behavior that departs away from rationality assumptions within traditional expected utility theory.

b) Ambiguity Analysis

Similar analysis is done for calculating drivers' ambiguity attitudes. The respondents answered up to four questions in the ambiguity domain where one of the routes had 'Unknown" for the frequency/chances of delay attribute and the other route was a risky route with known chances of delay. We again assumed CRRA utility for travel time for both the ambiguous route and the risky route. We used the fixed value for the risk attitude parameter and the probability weighting parameter calculated from the risk analysis. Table V-4 shows the results of ambiguity analysis based on the α-maxmin utility function for the ambiguous route. The results of MNL are shown under the column heading AMB-MNL. The negative coefficients on both the expected travel time and the toll cost are as expected. The ambiguity parameter is calculated as 0.57 and is statistically different than one, implying that drivers are ambiguous averse on average. However, the parameter is not statistically different than 0.50 (when alpha = 0.50, it means that drivers are ambiguity neutral). Also, the estimated parameter for the alternative specific constant is insignificant, indicating that after controlling for all the observed factors, drivers are indifferent between a risky route and an ambiguous route. We again found a significant interaction effect between toll cost and a dummy variable corresponding to whether a respondent pays tolls or not.

We finally extend the ambiguity analysis to the mixed logit framework (AMB-MMNL). We find significant unobserved heterogeneity in both the expected travel time and the toll cost. More importantly, we found significant standard deviation for the ambiguity parameter α. The mean estimate of ambiguity parameter is calculated as 0.574, which again shows ambiguity averse attitudes in general. As mentioned earlier, a value of 0.50 for the ambiguity parameter signifies ambiguity neutral attitudes and drivers put equal weight on their best and worst travel times. An estimate of 0.242 for the standard deviation for alpha parameter shows that about 37.9% drivers exhibit ambiguity seeking attitudes and about 62.1% exhibit ambiguity averse attitudes (given they are risk seeking in general).

c) Willingness to Pay Measures

Willingness to pay (WTP) or marginal rate of substitution for travel time is an important output of studies based on discrete choice models. The models presented in this study both in terms of risk and ambiguity can add behavioral rigor and sufficient travel time variability in the calculation of WTP measures. Equation V-22 gives the value of time or WTP equation for expected utility model.

$$WTP_{risky,EUT} = \frac{\beta_{time}}{\beta_{toll}} \qquad \text{Equation V-22}$$

where β_{time} and β_{toll} are the coefficients on expected travel time and toll cost, respectively. Based on our non-linear utility specification, the value of time for risky routes based on prospect theory is given as:

$$WTP_{risky} = \frac{\beta_{time}\rho\left[w(p)T_D^{\rho-1} + (1-w(p))T_{ND}^{\rho-1}\right]}{\beta_{toll}} \qquad \text{Equation V-23}$$

where β_{time} is the coefficient on expected travel time, ρ is the risk attitude measure (diminishing marginal utility), $w(p)$ is the weighting function parameterized by γ, T_D and T_{ND} are delayed and usual travel time respectively, and β_{toll} is the coefficient on toll cost. Similarly, WTP for an ambiguous route is given by:

$$WTP_{ambigous} = \frac{\beta_{time}\rho\left[\alpha T_D{}^{\rho-1} + (1-\alpha)T_{ND}{}^{\rho-1}\right]}{\beta_{toll}} \qquad \text{Equation V-23}$$

Table V-5 shows the measures of WTP for different scenarios based on Equation V-23 through V-24. Since, the WTP is a function of the probability of experiencing delays; we considered different cases ranging from 10% to 90% chances of delay occurrence. The table gives corresponding weighted measures as well, based on our estimated weighting parameter γ. We first calculated 'average' WTP estimates by taking only the means of the assumed distributions for various parameters involved in the calculation of WTP. We then calculated the WTP measures based on simulation which takes into account the distributions of various parameters involved[2]. The results show that simulation produced higher estimates for WTP than the average values. Nonetheless, based on these estimates, we can see a systematic decrease in WTP values (although not by much) as the chances of delay increase. For example, drivers' mean WTP when the chance of delay is 10% is \$12.18 per hour, on the other hand, their WTP is \$11.46 per hour when the chance of delay is 90%. However, the standard deviations associated with the distributed WTP measures are quite large. This is due to the fact that the cost parameter is distributed and drawing parameter values during simulation that may be close to zero lead to extremely large positive and negative values.

Similarly, we calculated WTP values in case of ambiguous routes. As can be see seen in Table V-5, the mean WTP for ambiguous route is \$9.36 per hour. This value is

[2] The mean, standard deviation, and median values are calculated after removing 5% from each tail of the resulting distribution (see Sillano and Ortuzar, 2005 for more details).

lower than the WTP values for risky routes. It shows that drivers are not only ambiguity averse, in general, but also are willing to pay less if they are not familiar with the route. Figure V-2-6 show WTP distributions for different probability values.

Discussion and Conclusions

This study presents models to understand drivers' route choice attitudes under uncertainty. The paper contributes to the existing knowledge of route choice behavior in three ways. First, we add behavior rigor to the existing random utility framework by incorporating important features of non-expected utility models such as probability weighting, and risk attitudes. Second, previous studies have mostly incorporated one aspect of uncertainty, risk that is, where drivers are assumed to have known the probability distribution of travel times. In this study, we study route choice attitudes towards ambiguity too, where drivers are assumed to have imperfect knowledge of travel times. Third, we derive WTP measures that are more behaviorally appealing and take into account drivers' attitudes toward uncertainty and travel time variability.

A stated preference methodology was used in this research using a web-based survey to collect behavioral data in the context of route choice. The main objective of the paper was to elicit drivers' attitudes toward 'risky' and 'ambiguous' routes. The results of the empirical analysis provide several valuable insights. It was found that when drivers are operating in risky domain, they tend to be risk seeking in general, with a small percentage of drivers showing risk averse behavior. Results also show that drivers tend to under weigh small probabilities of experiencing traffic delays and over-weigh high probabilities of experiencing traffic delays. The empirical findings from models capturing ambiguity attitudes further offer important insights. Assuming drivers are risk seeking in general, the estimation of ambiguity parameter shows that drivers are ambiguity averse, in general. This means that drivers tend to avoid taking routes about which they don't have prior knowledge of experiencing delays. However, significant heterogeneity is found in ambiguity attitudes. About 62.1% drivers exhibit ambiguity averse attitudes and about 37.9% exhibit ambiguity seeking attitudes. Finally, WTP measures are calculated that are based on drivers' behavioral attitudes and possible chances of experiencing delays. The mean WTP measures for routes with known probability distribution range from $11.46 to $12.18. In case of ambiguous routes, drivers' WTP for tolls is $9.36 per hour.

Table V-1. Descriptives of survey participant

Female	54.95%
Male	45.05%
Age (Mean, Std. Deviation)	(40.18, 11.23)
Personal Income	
Up to $40,000	10.0%
$40,001 to $60,000	16.9%
$60,001 to $90,000	21.4%
$90,001 to $120,000	18.4%
Greater than $120,000	33.2%
Usual Travel Time in Min. (Mean, Std. Deviation)	(29.78, 14.63)
Delay in Min. (Mean, Std. Deviation)	(13.77, 10.64)
Toll in $ (Mean, Std. Deviation)	(0.42, 0.95)
Frequency of Experiencing Unexpected Delay	
Never	4.4%
Once in 10 days	20.8%
2-3 times in 10 days	25.1%
4-5 times in 10 days	18.6%
6-7 times in 10 days	13.7%
8-9 times in 10 days	8.2%

Table V-2. Model results based on EUT

	EUT-MNL		EUT-MMNL	
Attributes	Coefficient	S.E	Coefficient	S.E
Risk parameter (Rho)	-	-	-	-
Std. dev. risk parameter	-	-	-	-
Probability weighting parameter (lambda)	-	-	-	-
Travel time	-0.121	0.009	-0.266	0.023
Std. dev. travel time	-	-	0.163	0.022
Toll cost	-0.670	0.044	-1.380	0.120
Std. dev. toll cost	-	-	1.020	0.099
Toll * dummy for who already pay tolls	0.170	0.052	0.305*	0.160
Final log-likelihood	-1317.59		-1153.61	
Likelihood ratio test	368.93		696.73	
Adjusted rho-square	0.121		0.229	
Number of choices	2167		2167	
Number of individuals	283		283	

All estimates are significant at 5% significance level.

*Not significant

Table V-3. Model results based on PT

	PT-MNL		PT-MMNL	
Attributes	Coefficient	S.E	Coefficient	S.E
Risk parameter (Rho)	0.845	0.087	0.755	0.097
Std. dev. risk parameter	-	-	0.153	0.022
Probability weighting parameter (lambda)	1.41	0.152	1.40	0.112
Travel time	-0.239	0.103	-0.712	0.335
Std. dev. travel time	-	-	0.107*	0.183
Toll cost	-0.700	0.047	-1.51	0.127
Std. dev. toll cost	-	-	1.02	0.104
Toll * dummy for who already pay tolls	0.186	0.0537	0.268*	0.163
Final log-likelihood	-1311.61		-1136.06	
Likelihood ratio test	380.88		731.98	
Adjusted rho-square	0.123		0.238	
Number of choices	2167		2167	
Number of individuals	283		283	

All estimates are significant at 5% significance level.

*Not significant

Table V-4. Model results based on alpha-maxmin

	AMB-MNL		AMB-MMNL	
Attributes	Coefficient	S.E	Coefficient	S.E
Alternative Specific Constant	0.139*	0.136	0.286*	0.251
Travel time	-0.607	0.069	-1.12	0.169
Std. dev. travel time	-	-	0.805	0.187
Toll cost	-1.37	0.096	-2.48	0.283
Std. dev. toll cost	-	-	1.20	1.20
Ambiguity parameter (Alpha)	0.567	0.041	0.574	0.057
Std. dev. ambiguity parameter	-	-	0.242	0.05
Toll * dummy for who already pay tolls	0.561	0.109	0.571	0.239
Final log-likelihood	-537.28		-503.32	
Likelihood ratio test	439.28		507.2	
Adjusted rho-square	0.284		0.324	
Number of choices	1092		1092	
Number of individuals	283		283	

All estimates are significant at 5% significance level.

*Not significant

Table V-5. Willingness to pay measures

Probability of Delayed Travel Time	Probability of Usual Travel Time	Weighted Probability of Delayed Travel Time	Weighted Probability of Usual Travel Time	WTP (per hour)	Mean WTP (per hour)	S.D. WTP (per hour)	Median WTP (per hour)
				Average		Simulation	
10%	90%	7.17%	92.83%	$9.25	$12.18	$11.36	$8.83
30%	70%	28.32%	71.68%	$9.10	$12.01	$11.27	$9.10
50%	50%	53.81%	46.19%	$8.90	$11.81	$11.17	$8.61
70%	30%	78.11%	21.89%	$8.69	$11.61	$11.01	$8.43
90%	10%	95.72%	4.28%	$8.51	$11.46	$10.99	$8.30
Unknown	Unknown	42.60%	57.40%	$8.55	$9.36	$7.27	$8.00
50%	50%	50%	50%	$11.57	$11.65	$13.07	$9.23

Table V-6. Risk analysis in gain frame

	Model 1		Model 2	
Attributes	Coefficient	S.E	Coefficient	S.E
Risk parameter (Rho)	0.663	0.145	0.738	0.191
Std. dev. risk parameter	-	-	0.104	0.047
Probability weighting parameter (lambda)	1.410	0.242	1.530	0.199
Travel time	-0.602*	0.418	-1.130*	0.980
Std. dev. travel time	-	-	0.752*	0.658
Toll cost	-0.890	0.074	-1.97	0.229
Std. dev. toll cost	-	-	1.31	0.177
Toll * dummy for who already pay tolls	0.320	0.083	0.413*	0.222
Final log-likelihood	-648.87		-603.54	
Likelihood ratio test	227.18		380.89	
Adjusted rho-square	0.142		0.250	
Number of choices	1100		1100	
Number of individuals	282		282	

All estimates are significant at 5% significance level.

*Not significant

Table V-7. Risk analysis in loss frame

	Model 1		Model 2	
Attributes	Coefficient	S.E	Coefficient	S.E
Risk parameter (Rho)	0.764	0.142	0.799	0.189
Std. dev. risk parameter	-	-	0.126	0.033
Probability weighting parameter (lambda)	1.410	0.207	1.390	0.156
Travel time	-0.344*	0.261	-0.500*	0.488
Std. dev. travel time	-	-	0.137*	0.137
Toll cost	-0.575	0.060	-1.08	0.133
Std. dev. toll cost	-	-	0.753	0.134
Toll * dummy for who already pay tolls	0.118*	0.072	0.065*	0.170
Final log-likelihood	-655.25		-607.89	
Likelihood ratio test	168.69		263.44	
Adjusted rho-square	0.107		0.167	
Number of choices	1067		1067	
Number of individuals	276		276	

All estimates are significant at 5% significance level.

*Not significant

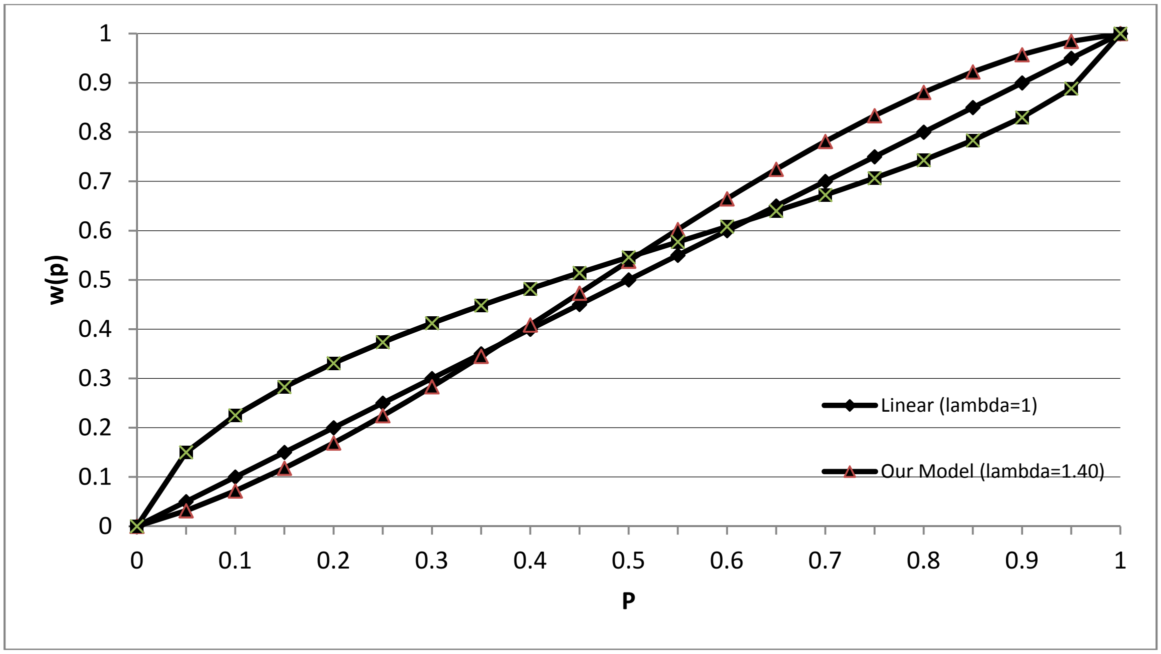

Figure V-1. Probability weighting function

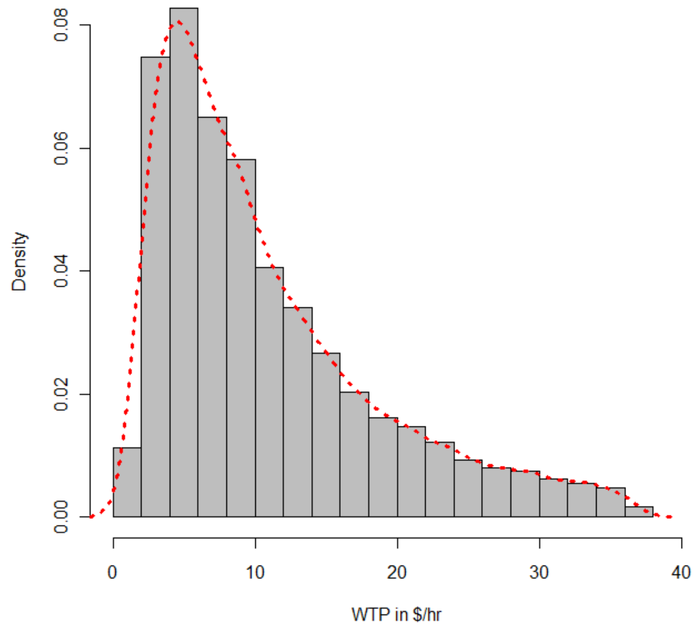

Figure V-2. WTP distribution with 10% chances of delay

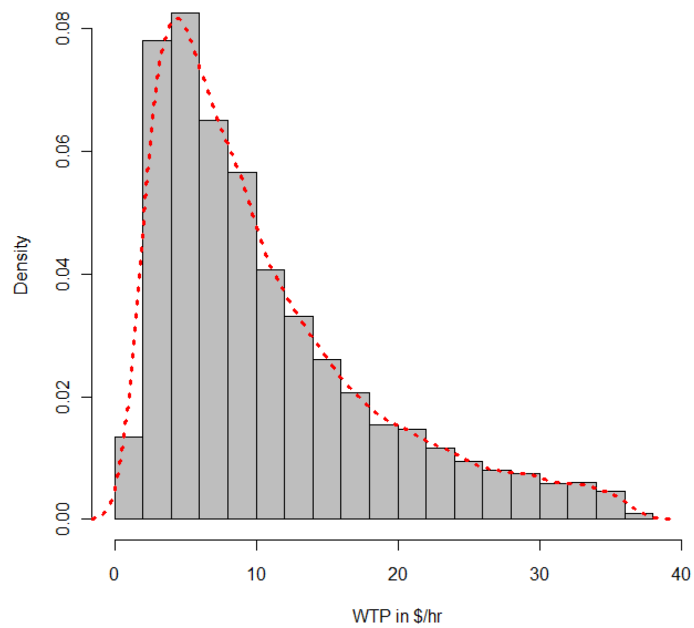

Figure V-3. WTP distribution with 30% chances of delay

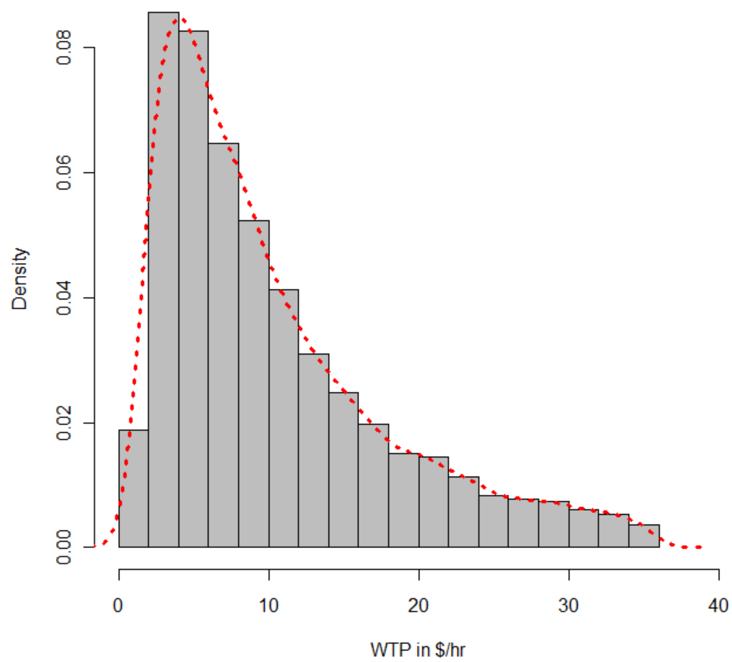

Figure V-4. WTP distribution with 70% chances of delay

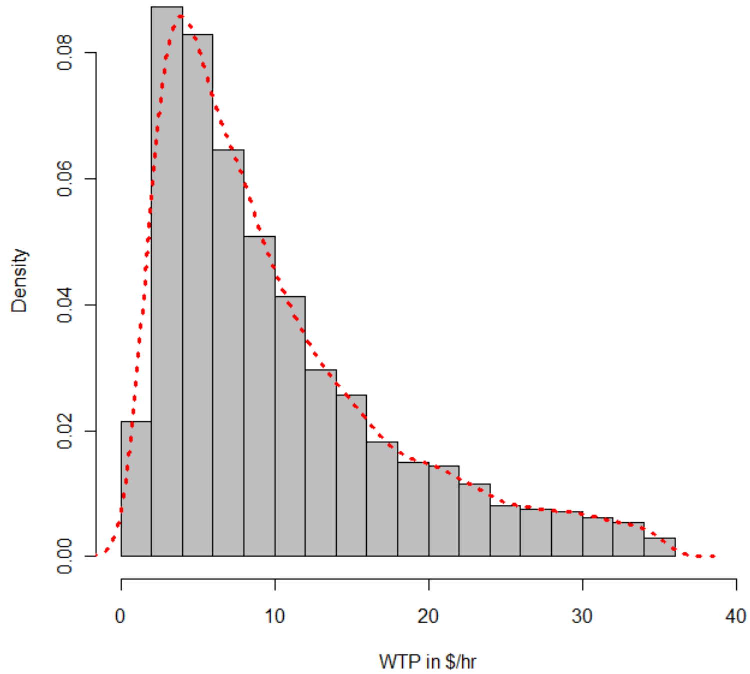

Figure V-5. WTP distribution with 90% chances of delay

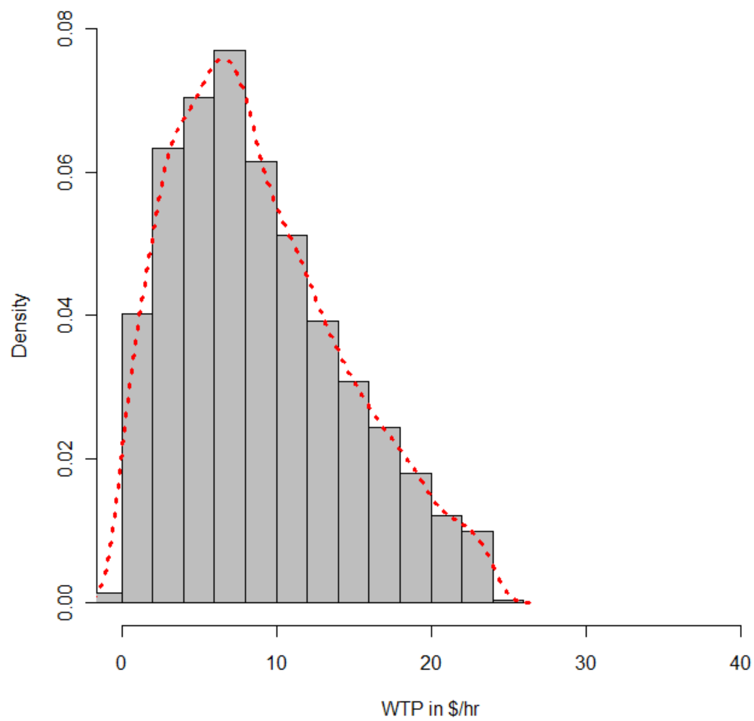

Figure V-6. WTP distribution with unknown chances of delay

CHAPTER VI.

BEHAVIORAL ANALYSIS FOR VARIABLE TOLL LANES

A variable toll provides information that is used by drivers to reduce travel time uncertainty. The information signaled by the toll amount is either perceived as a gain or loss; a gain if the drivers believe the information costs less than the travel time savings and as a loss if they believe that using the tolled lane will not save them time. Additionally, in the case of a gain the driver must value the travel time savings as being in excess of the information cost, whereas, it would be viewed as a loss if the travel time savings does not exceed the cost of information.

Complicating the decision processes is the quality of the information, as perceived by the driver, conveyed by the toll in reducing the travel time uncertainty. A perfect signal would require the toll to flawlessly correlate with travel speed —assuming every driver values monetary amounts identically, the chosen increment that the toll increases would map precisely to the increase in travel speed, for example, every one dollar increase guarantees an increase of one mile per hour. Should the information perfectly signal travel time savings, that is reducing uncertainty to zero, and the drivers are rational then expected or random utility theory could be applied using fixed risk averse, risk seeking or risk neutral utility functions. However, when the information is imperfect, containing uncertainty, the drivers will react differently based on the level of imperfection.

Application of Cumulative Prospect Theory in Variable Tolling

Information uncertainty occurs when drivers either do not understand the exact relationship between the toll and speed, assuming it exists, do not trust that the relationship holds, perhaps based on experience using the tolled lanes, or do not have experience with the given toll lanes. Under this condition, traditional utility theory does not model actual choice behavior sufficiently. Cumulative prospect theory, the theory descriptive of actual choice behavior, posit that drivers will react to uncertainty differently based on their current condition and perceived likelihood of improving their situation. Under cumulative prospect theory, there is a mid-range of uncertainty, taken as a range 25 to 75 percent, within which drivers will react with risk aversion to perceived improvements, whereas if the drivers view the toll a loss, they will react with risk seeking behavior (Tversky and Kahneman, 1992). Under extreme uncertainty in the information, the drivers would swap their reactions to risk. That is when the toll is signaling a travel time savings relative to the general purpose lanes with a chance above or below 25%, drivers will be risk seeking and if the toll signals slower travel times they will be risk averse. Table VI-1 summarizes the reactions of drivers to possible outcomes, both gains and losses, to tolled lanes for given ranges of probabilities. The following discussion expands the summary.

Why would drivers be <u>risk averse</u> under <u>mid-range</u> levels of uncertainty of improving their travel speed by switching to the tolled lane from the general purpose lane? When drivers are in the general purpose lanes, according to cumulative prospect theory they will react in a risk adverse manner towards switching into the tolled lane if they perceive they will be traveling near an acceptable speed, gauged by past experience or relative to the posted speed limit. Typically, consumers will tend not to gamble on improving their situation when the gamble has a moderate chance of producing a gain because they shy away from the chance of decreasing their positive situation. People like the known and are content when we are pleased.

Why would a driver be <u>risk averse</u> under <u>extreme</u> uncertainty of improving their travel speed by switching to the tolled lane? When drivers view that staying within the general purpose lane will be much slower than the tolled lane, as measured by travel speed, switching into the tolled lane would be appealing because they seek to reduce a large perceived loss if they stay in the general lane. They are willing to pay the toll price with the hope, although small, that switching into the toll lane will be faster and protect them from a larger loss of the general lane. This parallels consumers' choice of purchasing insurance to safeguard a large loss even though there is an extremely small probability that the loss will occur.

Why would a driver be risk seeking under mid-range levels of uncertainty of improving their travel speed by switching to the tolled lane? When drivers view the general purpose lanes as moving slower than they desire, could be based on their experience or based on the rate of speed related to the posted speed limit, they will be more likely to switch into the tolled lane if they believe there is a mid-range chance that the tolled lane will be faster. In this case, the drivers are saying that they are already losing by staying in the general lane and will continue to lose if they stay in the lane, so why not take a chance by paying the toll and switching lanes. People tend to look for a way to reduce known losses by taking more chances at improving their situation even though it is possible to increase their loss (optimism bias).

Why would a driver be risk seeking under extreme levels of uncertainty of improving their travel speed by switching to the tolled lane? Drivers will tend to select the tolled lane when they believe they will gain much higher travel speeds by switching into the tolled lane than staying within the general purpose lane. Similar to the tendency for consumers to ignore the purchase price of a lottery tickets even though the ticket has a very low probability of winning, the drivers will select the tolled lane hoping for the larger pay-off of fast speeds.

Numerical Illustration

Using cumulative prospect theory as the theoretical underpinning of actual choice behaviors, we would need to apply (Hens and Rieger, 2010)

$$CPT(\,) = \sum_{i=1}^{n} v(x)\, w\big(F(p)\big) \qquad \text{Equation VI-1}$$

where:

CPT = subjective utility

x = outcome value of selecting route

$v(x)$ = value function evaluated at x

$w(\ \ )$ = probabilty weighting function

$F(p)$ = cumulative probability function evaluated at p.

Multiple value function formulations have been suggested in the literature, which represents a person's utility for a given outcome. The advancement of cumulative prospect theory is the ability of the value function to model choices when the person is in either a gain or loss frame. That is when a driver perceives switching into the tolled lane will improve or decrease their current speed. Increasing the fidelity to actual decision making, cumulative prospect theory allows for the subjective weighting of probabilities to correlate to the driver's perceived probability. This allows for the underweighting of large probabilities and the overweighting of small probabilities of outcome occurrence. For this illustration, we have chosen common functional forms and parameter values given by Tversky and Kahneman (1992).

$$w(p) = \frac{p^{\gamma}}{(p^{\gamma}+(1-p)^{\gamma})^{1/\gamma}} \qquad \text{Equation VI-2}$$

$$v(x_i) = x^{\alpha} \text{ when } x \geq 0, \qquad \text{Equation VI-3}$$

$$v(x_i) = -\lambda(-x)^{\beta} \text{ when } x < 0. \qquad \text{Equation VI-4}$$

Three scenarios (Figure VI-1-VI-3) are shown below to illustrate the impact of using cumulative prospect theory versus expected utility theory in modeling drivers' choice between a general purpose and a tolled lane. Scenario 1 consists of a hypothetical choice between general purpose lane and a toll lane where there is an equal probability of a 10 minute delay in either type of lane and a possibility of a 10 minute improvement in the tolled lane that occurs with equal probability as the delay previously stated. All the scenarios use a \$1.50 toll. The expected utility is calculated as the sum of the probability multiplied by the outcome. For the three scenarios, a constant value of \$16.31 is used for the dollar value of travel time per hour. A logit formulation is used to calculate the probability of a driver staying in the general purpose lane separately for the cumulative prospect utility value and expected utility values.

Comparing the modeled results reveal that the expected utility method over estimates the probability of a driver switching to a tolled lane. Expected utility would forecast more than a 0.27 point increase in those opting for the tolled lane and it grows in scenario 2 to an increase of 0.40. The striking difference between the applications of the two theories is the result of drivers overweighting the extreme probabilities for losses. If the cumulative prospect theory is correct, it reflects drivers' hesitancy of changing from a known state—general purpose lane—even if they are likely to sustain a loss by not switching. The third scenario reveals a closing of the difference between the forecasted probabilities of switching into a tolled lane. The gap is 0.06, which is the result of increasing the positive outcome of the tolled lane—the possible gain in travel time savings doubles from scenario 2 to 3 with the other attributes held constant.

Discussion and Conclusions

The introduction of tolled lanes as a means to reduce congestion, thereby, functionally increase capacity and its ability to supplement the fuel tax revenue highlights the need to move from proscriptive theories, such as expected and random utility theory, that detail how rational drivers should decide, to a behavioral model. The move should be towards a descriptive behavioral theory, such as cumulative prospect theory that will allow for improved lane usage and revenue forecasts. Today, the most popular descriptive theory of decision making under risk and uncertainty is cumulative prospect theory. Its advantages over standard expected utility and random utility theories is in its ability to forecast decisions based on observed outcomes that are grounded in actual psychological behavior. Cumulative prospect theory encompasses our risk aversion and risk seeking, our differing actions depending on perceived negative or positive outcome, and our miss-application of extreme probabilities—it accounts for framing effects and over and underweighting of extreme probabilities. The cumulative prospect theory now has a firm axiomatic foundation and its formulation makes it tractable.

As illustrate in the simple scenarios presented in the previous section, ignoring the tendency to overweight low probabilities when negative outcomes are possible greatly impacts forecasts. The examples show that when drivers perceive a delay is equally as likely as a travel time savings, the behavioral models shows we would greatly overestimate the probability drivers will switch from a general purpose to a tolled lane. The overestimation is the result of the traditional models that reveal how a rational driver ought to act. Congestion and revenue forecast would suffer. Granted, the illustrations above are simplified in the sense that the model parameters are those accepted in the literature, but are not specifically derived for the context of lane tolling.

To overcome the limitations of using existing parameters, we are proposing in future work to estimate parameters within the context of variable tolling. The purpose behind conducting these experiments is to determine the independent influences on observed behavior and their use of varying tolls as information regarding likely outcomes—delays or travel time savings.

This chapter provided a review of traditional decision theories based in rationality—expected and random utility and their extensions—along with contemporary thinking on the use of emerging behavioral theories as applied to travelers' route-choice behavior. We have highlighted the issues that arise when a prescriptive model of behavior is applied to forecast demand for a tolled lane. Mostly, when actual behavior is ignored in route-choice estimates of demand for tolled lanes, the estimates will be extremely misleading. As shown, the application of cumulative prospect theory, the leading descriptive behavioral model, better forecasts demand when the probability for a loss or gain is extreme. Using accepted model parameters, when drivers are facing low probabilities of experiencing delays or travel time savings on a tolled lane, it is more likely that the drivers will not opt to use such lanes. Finally, we proposed that cumulative prospect theory could be one of the more useful analytic frameworks in analyzing route-choice behavior since it corrects for the errors of applying traditional prescriptive models.

Table VI-1. Travel behavior based on CPT

		Outcome	
		Slower travel speed (loss)	Faster travel speeds (gain)
Probability of Outcome Occurring	Mid-range of perceived information uncertainty (25% to 75%)	Risk seeking – more likely to select the toll lane if they are currently in a general purpose lane and traveling at a slower than desired speed. They will gamble on switching lanes, paying the toll for the potential improving their travel speed.	Risk averse – more likely to stay in the general purpose lane when traveling at a desired speed even if they could travel faster in the tolled lane. They will not gamble on switching lanes, paying the toll for the potential improving their travel speed.
	Extreme range of perceived information uncertainty (above or below 25%)	Risk averse – more likely to stay in the general purpose lane even if they are traveling at a slower than desired speed. They will not gamble on switching lanes, paying the toll for the potential improving their travel speed.	Risk seeking – more likely to select the toll lane if they are currently in a general purpose lane. They will gamble on switching lanes, paying the toll for the potential improving their travel speed.

Table VI-2. Assumed CPT parameters

Power of gain	0.88
Power of loss	0.88
Loss aversion	2.25
Probability weighting parameter for gains	0.61
Probability weighting parameter for losses	0.69

Scenario 1						
Probability of delay of			10	mins	equally likely in toll or general purpose lanes	
Probability of improving by			10	mins	equally likely in the toll lane as a delay in toll lane	
Toll cost				1.5	dollars	
Outcomes				Probabilities	Weighted Probabilities	
Gain of	0	mins	general purpose lane	0.25	0.291	
Loss of	10	mins	general purpose lane	0.25	0.294	
Gain of	10	mins	tolled lane	0.25	0.291	
Loss of	10	mins	tolled lane	0.25	0.294	
				Values	CPT( )	EUT( )
Gain, staying in general lane			(null)	$0.00	0.000	0.000
Loss, staying in general lane			(delay time)	-$2.72	-5.425	-0.680
Gain, moving to tolled lane			(time saved - toll)	$1.22	1.190	0.305
Loss, moving to tolled lane			(delay time + toll)	-$4.22	-7.986	-1.055
Probability of staying in general purpose lane					0.798	0.518

Figure VI-1. Illustration 1

Scenario 2					
Probability of delay of	10	mins	twice as likely in general purpose lane than toll lane		
Probability of improving by	10	mins	equally likely in the toll lane as a delay in toll lane		
Toll cost			1.5	dollars	
Outcomes			Probabilities	Weighted Probabilities	
Gain of 0 mins	general purpose lane		0.125	0.208	
Loss of 10 mins	general purpose lane		0.500	0.454	
Gain of 10 mins	tolled lane		0.125	0.194	
Loss of 10 mins	tolled lane		0.250	0.294	
			Values	CPT( )	EUT( )
Gain, staying in general lane	(null)		$0.00	0.000	0.000
Loss, staying in general lane	(delay time)		-$2.72	-5.425	-1.359
Gain, moving to tolled lane	(time saved - toll)		$1.22	1.190	0.152
Loss, moving to tolled lane	(delay time + toll)		-$4.22	-7.986	-1.055
Probability of staying in general purpose lane				0.798	0.388

Figure VI-2. Illustration 2

Scenario 3						
Probability of delay of			10	mins	twice as likely in general purpose lane than toll lane	
Probability of improving by			20	mins	equally likely in the toll lane as a delay in toll lane	
Toll cost					1.5	dollars
Outcomes				Probabilities	Weighted Probabilities	
Gain of	0	mins	general purpose lane	0.150	0.227	
Loss of	10	mins	general purpose lane	0.425	0.407	
Gain of	20	mins	tolled lane	0.213	0.266	
Loss of	10	mins	tolled lane	0.213	0.266	
				Values	CPT( )	EUT( )
Gain, staying in general lane			(null)	$0.00	0.000	0.000
Loss, staying in general lane			(delay time)	-$2.72	-5.425	-1.155
Gain, moving to tolled lane			(time saved - toll)	$3.94	3.340	0.837
Loss, moving to tolled lane			(delay time + toll)	-$4.22	-7.986	-0.896
Probability of staying in general purpose lane					0.315	0.251

Figure VI-3. Illustration 3

CHAPTER VII.

CONCLUSIONS

The overall goal of this research is to measure drivers' attitudes towards uncertain and unreliable routes. The route choice modeling is done within the discrete choice modeling framework and involved use of stated preference data. This chapter highlights the main results from the analysis and possible directions for future research.

Chapter 3 presents the stated preference survey methodology we used in this research. The stated preference surveys were conducted online. The advantages to publishing a survey online are many. The greatest benefit from a researcher's viewpoint is that they are quite inexpensive to conduct and the turn-around time is quick since it can be disseminated to a large group via single e-mail. The data can also be readily available in electronic format for the analysis purposes. Moreover, it saves time for respondents who can do the survey at their convenience without having to travel to a centralized location or having to fill them out manually and sending through mail. We created pivoted blocked fractional-factorial designs and randomly selected choice sets in such a way that none of the choice sets has a dominant alternative. Three different designs comprising of four questions were created and each design was blocked into six subsets of four questions each. Apart from some background information, each respondent was given a series of 12 choice scenarios. Each choice scenario has four attributes, including usual travel time, chances/frequency of delay, average delay, and toll cost. The e-mails were sent out to a pool of about 8,500 people and we had about 292 valid responses. Subjects had to be 18 years of age and had to drive to work at least three times a week. We only included the responses where the existing commute time was at least 5 minutes. The final sample used in the analysis consisted of 283 respondents with 3,259 choice occasions.

We almost have an even distribution of males to females in our sample with an average age of respondents as 40 years. However, our sample is skewed towards the higher income groups. This is due to the fact that we sent out our survey to the alumni of the University of Iowa and almost all of them had at least four year college degree. The average travel time to work was calculated as 29.8 minutes with average delay time of 13.8 minutes (on days respondents experience delays on their commuting route). The other important piece of information we collected was the frequency/chances of commuters to experience days with unexpected delays. About half of the respondents experience unexpected delays at least 2-3 times in two weeks with about 10 percent of them experiencing delays every day. Finally, about one-third of the respondents pay tolls for their commuting route and the average toll across our sample came out to be $0.45. Finally, it should be noted that that there are some caveats and limitations related to our survey methodology. Because of these limitations, the results are applicable to our sample of employed, higher than median income, college graduates, and living in major urban metropolitan areas. The conclusions of the study are limited to this population and not statistically valid as generalizations to the population as a whole.

Chapter 4 includes the first set of analysis for the stated preference data we collected. The aim of this chapter is to elicit travelers' attitudes towards unreliable routes. The results of the analysis provide very useful information in relation to how commuters value the occurrence/chances of experiencing delay days on their routes. The frequency of days with unexpected delays also measures the travel time reliability in a way that is easy to understand by day-to-day commuters. As such, behaviorally more realistic values are obtained from this analysis in order to capture travelers' attitudes towards reliability. The results provide a valuable input to cost-benefit analysis of roadway pricing tools like tolling facilities. Results show that travelers' are not only averse to how likely they are to experience delays on their commuting routes but also to the amount of unexpected delay on those days. The goal of pricing the roadway system should not only be reducing the average travel time but also to reduce the occurrence of worst few days. From a viewpoint of supply side agencies, this would increase the expected revenue from the tolling facilities and from the travelers' viewpoint they will have more on-time arrivals to their work and fewer unexpected delays.

The other valuable output from this analysis is travelers' WTP for travel time reliability. We measured travelers' WTP not only for travel time but also in terms of frequency of experiencing unexpected delays. We found that travelers' mean estimation of WTP increases with increasing unreliability. Higher the chances of unexpected delays, higher are the WTP values for travel time and reliability. We also found significant differences between the mean WTP estimates for travelers who already pay tolls for their commute and the mean WTP estimates for travelers' who don't. People in the latter category have noteworthy lower WTP for travel time and reliability. This can be attributed to the fact that commuters who already pay tolls value on-time arrivals more and that's why they chose to take toll roads in the first place. Moreover, they become aware of the benefits of using tolls in a long-term.

In Chapter 5, we model attitudes toward travel time uncertainty using expected and non-expected utility theories within the random utility framework. Unlike previous studies that only include risk attitudes, we incorporate attitudes toward ambiguity too, where drivers are assumed to have imperfect knowledge of travel times. To this end, we formulated non-linear logit models capable of embedding probability weighting, and risk/ambiguity attitudes. Finally, a more realistic willingness to pay structure is derived which takes into account travel time uncertainty and behavioral attitudes.

The results of the empirical analysis from this chapter provide several valuable insights. It was found that when drivers are operating in risky domain, they tend to be risk seeking in general, with a small percentage of drivers showing risk averse behavior. Results also show that drivers tend to under weigh small probabilities of experiencing traffic delays and over-weigh high probabilities of experiencing traffic delays. The empirical findings from models capturing ambiguity attitudes further offer important insights. Assuming drivers are risk seeking in general, the estimation of ambiguity parameter shows that drivers are ambiguity averse, in general. This means that drivers tend to avoid taking routes about which they don't have prior knowledge of experiencing delays. However, significant heterogeneity is found in ambiguity attitudes. About 62.1% drivers exhibit ambiguity averse attitudes and about 37.9% exhibit ambiguity seeking attitudes. Finally, WTP measures are calculated that are based on drivers' behavioral attitudes and possible chances of experiencing delays. The mean WTP measures for routes with known probability distribution range from $11.46 to $12.18. In case of ambiguous routes, drivers' WTP for tolls is $9.36 per hour.

Chapter 6 presents a conceptual framework to use a descriptive utility theory, i.e. cumulative prospect theory in forecasting the demand for a variable tolled lane. We have highlighted the issues that arise when a prescriptive model of behavior is applied to forecast demand for a tolled lane. Mostly, when actual behavior is ignored in route-choice estimates of demand for tolled lanes, the estimates will be extremely misleading. As shown in the chapter, the application of cumulative prospect theory, the leading descriptive behavioral model, better forecasts demand when the probability for a loss or gain is extreme. Using accepted model parameters, when drivers are facing low probabilities of experiencing delays or travel time savings on a tolled lane, it is more likely that the drivers will not opt to use such lanes. Finally, we proposed that cumulative prospect theory could be one of the more useful analytic frameworks in analyzing route-choice behavior since it corrects for the errors of applying traditional prescriptive models.

Tractable models measuring behavioral attitudes where uncertainty extends beyond risk and known probabilities is the most investigated topic in behavioral analysis today (Wakker, 2010). Because probabilities are rarely known in real life, looking for pragmatic ways of measuring uncertainty should indeed be of most interest in drivers' behavioral analysis too (specifically in case of route choice modeling). In this research, an effort has been made to cross-fertilize state-of-the art behavioral theories and RUM-based route choice models. One of the lasting contributions of behavioral economics is that we now have an affluent set of competing models of behavior in many settings. At the same time recent developments in discrete choice modeling with widespread use of mixed logit models offer researchers greater flexibility in terms of including behavioral and psychological factors like risk/ambiguity preferences, probability weighting, learning, and so on. Different structural forms of utility functions based on behavioral theories can be embedded within discrete choice RUM models. Moreover, mixed logit specifications can incorporate correlations of repeated choice sequences allowing for participant heterogeneity. This study is a first attempt to understand drivers' ambiguity attitudes. More research is needed in terms of including models that can include drivers' attitudes toward imperfect knowledge. We also recommend designing new and better choice experiments that provide flexibility and add behavioral realism in understanding drivers' attitudes. In terms of policy implications, the results of this study would provide help policy makers to make correct decisions in terms of pricing the user costs for transport infrastructure. For the evaluation of any transportation infrastructure project (like road tolling) that may lead to heterogeneous impacts across the relevant population, economic assessment should ideally control for behavioral attitudes to any changes proposed.

Future Research Directions

This research is expected to impact the future research efforts in two ways. First, advancing the applicability of tractable models, measuring behavioral attitudes where uncertainty extends beyond risk and known probabilities, into discrete choice modeling framework. Second, instigating national interest in strengthening behavioral based forecasts that pertain to sustainable funding of our transportations systems. Moreover, the introduction of managed lanes as a means to reduce congestion and increase funding for road infrastructure improvements, highlights the need to move from proscriptive theories, such as expected and random utility theory, to descriptive behavioral models, such as cumulative prospect theory. The move should be towards a descriptive behavioral theory that will allow the introduction of ambiguity alongside risk for the purpose of improving lane usage and revenue forecasts.

This research is based on stated preference survey data to elicit travelers' attitudes, however, in future research efforts we propose to use real-time, and real-consequence choice data. This can be done using custom designed application in traditional smart phones. The application can be designed to record data related to route choice, particularly in relation to switching to a managed lane. The dynamic data will include time and location of choice to switch or not into the managed lane, price of the toll at that time, and verbal response to prompts regarding the thought of why they did or did not switched. In prompting the driver, one can request their guess at the expected delay—or expected time savings—and if they think the current toll is a bargain for the conditions. The dynamic data can be merged with drivers' socio-economic attributes along with other known attributes of the trip underway, such as trip type and passengers. Additional traffic data, such as vehicle volume by location and time of day, can be obtained via the web portals administered by state departments of transportation.

There is also a need to improve the vehicle monitoring and navigation systems, and design new smart phone applications that can assist drivers with up-to-date real time information about possible travel times on various route networks. The goal of these navigations systems and applications should be to decrease the uncertainty in travel time as much as possible so that drivers can make more informed decisions.

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APPENDIX

This appendix contains the blocked fractional factorial designs generated for the Stated Preference surveys. In total, there are six blocks with 12 questions in each.

Table A- 1: Block 1 Scenario 1

Attributes	Route 1	Route 2
Usual Travel Time (min)	-10%	-10%
Frequency of Delay	1 out of 10 days	3 out of 10 days
Average Delay Time (min)	-20%	-50%
Toll Cost ($)	$1	-50%

Table A- 2: Block 1 Scenario 2

Attributes	Route 1	Route 2
Usual Travel Time (min)	+25%	+25%
Frequency of Delay	3 out of 10 days	7 out of 10 days
Average Delay Time (min)	+50%	+50%
Toll Cost ($)	$2	-50%

Table A- 3: Block 1 Scenario 3

Attributes	Route 1	Route 2
Usual Travel Time (min)	-10%	-25%
Frequency of Delay	1 out of 10 days	9 out of 10 days
Average Delay Time (min)	-20%	-20%
Toll Cost ($)	$2	-50%

Table A- 4: Block 1 Scenario 4

Attributes	Route 1	Route 2
Usual Travel Time (min)	+10%	+25%
Frequency of Delay	5 out of 10 days	3 out of 10 days
Average Delay Time (min)	+50%	+20%
Toll Cost ($)	$1	$1

Table A- 5. Block 1 Scenario 5

Attributes	Route 1	Route 2
Usual Travel Time (min)	+25%	+25%
Frequency of Delay	7 out of 10 days	3 out of 10 days
Average Delay Time (min)	+20%	+50%
Toll Cost ($)	-50%	$3

Table A- 6. Block 1 Scenario 6

Attributes	Route 1	Route 2
Usual Travel Time (min)	-25%	-10%
Frequency of Delay	5 out of 10 days	Unknown
Average Delay Time (min)	-20%	-20%
Toll Cost ($)	$3	-50%

Table A- 7. Block 1 Scenario 7

Attributes	Route 1	Route 2
Usual Travel Time (min)	-10%	-10%
Frequency of Delay	1 out of 10 days	3 out of 10 days
Average Delay Time (min)	-20%	-50%
Toll Cost ($)	$1	-50%

Table A- 8. Block 1 Scenario 8

Attributes	Route 1	Route 2
Usual Travel Time (min)	+25%	+50%
Frequency of Delay	Unknown	3 out of 10 days
Average Delay Time (min)	+20%	+20%
Toll Cost ($)	$1	$1

Table A- 9. Block 1 Scenario 9

Attributes	Route 1	Route 2
Usual Travel Time (min)	+25%	+25%
Frequency of Delay	5 out of 10 days	1 out of 10 days
Average Delay Time (min)	+50%	+50%
Toll Cost ($)	-50%	$3

Table A- 10. Block 1 Scenario 10

Attributes	Route 1	Route 2
Usual Travel Time (min)	-25%	-50%
Frequency of Delay	7 out of 10 days	1 out of 10 days
Average Delay Time (min)	-20%	-20%
Toll Cost ($)	-50%	$2

Table A- 11. Block 1 Scenario 11

Attributes	Route 1	Route 2
Usual Travel Time (min)	+10%	+10%
Frequency of Delay	5 out of 10 days	Unknown
Average Delay Time (min)	+20%	+20%
Toll Cost ($)	$1	-100%

Table A- 12. Block 1 Scenario 12

Attributes	Route 1	Route 2
Usual Travel Time (min)	-25%	-25%
Frequency of Delay	3 out of 10 days	Unknown
Average Delay Time (min)	-50%	-50%
Toll Cost ($)	$1	-50%

Table A- 13. Block 2 Scenario 1

Attributes	Route 1	Route 2
Usual Travel Time (min)	-10%	-10%
Frequency of Delay	5 out of 10 days	7 out of 10 days
Average Delay Time (min)	-50%	-20%
Toll Cost ($)	$2	-100%

Table A- 14. Block 2 Scenario 2

Attributes	Route 1	Route 2
Usual Travel Time (min)	+50%	+25%
Frequency of Delay	1 out of 10 days	3 out of 10 days
Average Delay Time (min)	+20%	+50%
Toll Cost ($)	$1	-50%

Table A- 15. Block 2 Scenario 3

Attributes	Route 1	Route 2
Usual Travel Time (min)	-25%	-25%
Frequency of Delay	1 out of 10 days	3 out of 10 days
Average Delay Time (min)	-20%	-20%
Toll Cost ($)	$1	-100%

Table A- 16. Block 2 Scenario 4

Attributes	Route 1	Route 2
Usual Travel Time (min)	+25%	+50%
Frequency of Delay	5 out of 10 days	Unknown
Average Delay Time (min)	+20%	+20%
Toll Cost ($)	-50%	-50%

Table A- 17. Block 2 Scenario 5

Attributes	Route 1	Route 2
Usual Travel Time (min)	+25%	+25%
Frequency of Delay	7 out of 10 days	5 out of 10 days
Average Delay Time (min)	+50%	+20%
Toll Cost ($)	$2	$3

Table A- 18. Block 2 Scenario 6

Attributes	Route 1	Route 2
Usual Travel Time (min)	+25%	+50%
Frequency of Delay	9 out of 10 days	3 out of 10 days
Average Delay Time (min)	+50%	+50%
Toll Cost ($)	-50%	$1

Table A- 19. Block 2 Scenario 7

Attributes	Route 1	Route 2
Usual Travel Time (min)	-25%	-25%
Frequency of Delay	9 out of 10 days	1 out of 10 days
Average Delay Time (min)	-20%	-20%
Toll Cost ($)	-50%	$1

Table A- 20. Block 2 Scenario 8

Attributes	Route 1	Route 2
Usual Travel Time (min)	+10%	+10%
Frequency of Delay	7 out of 10 days	3 out of 10 days
Average Delay Time (min)	+20%	+50%
Toll Cost ($)	$3	$3

Table A- 21. Block 2 Scenario 9

Attributes	Route 1	Route 2
Usual Travel Time (min)	-25%	-10%
Frequency of Delay	Unknown	1 out of 10 days
Average Delay Time (min)	-20%	-20%
Toll Cost ($)	$2	$1

Table A- 22. Block 2 Scenario 10

Attributes	Route 1	Route 2
Usual Travel Time (min)	-25%	-25%
Frequency of Delay	Unknown	5 out of 10 days
Average Delay Time (min)	-20%	-20%
Toll Cost ($)	$2	$1

Table A- 23. Block 2 Scenario 11

Attributes	Route 1	Route 2
Usual Travel Time (min)	-50%	-50%
Frequency of Delay	9 out of 10 days	1 out of 10 days
Average Delay Time (min)	-20%	-20%
Toll Cost ($)	-100%	$3

Table A- 24. Block 2 Scenario 12

Attributes	Route 1	Route 2
Usual Travel Time (min)	+25%	+10%
Frequency of Delay	7 out of 10 days	Unknown
Average Delay Time (min)	+20%	+20%
Toll Cost ($)	$2	$3

Table A- 25. Block 3 Scenario 1

Attributes	Route 1	Route 2
Usual Travel Time (min)	-50%	-50%
Frequency of Delay	1 out of 10 days	7 out of 10 days
Average Delay Time (min)	-20%	-50%
Toll Cost ($)	$1	-100%

Table A- 26. Block 3 Scenario 2

Attributes	Route 1	Route 2
Usual Travel Time (min)	+25%	+50%
Frequency of Delay	Unknown	5 out of 10 days
Average Delay Time (min)	+20%	+20%
Toll Cost ($)	$1	$1

Table A- 27. Block 3 Scenario 3

Attributes	Route 1	Route 2
Usual Travel Time (min)	-25%	-25%
Frequency of Delay	5 out of 10 days	7 out of 10 days
Average Delay Time (min)	-50%	-20%
Toll Cost ($)	$2	$1

Table A- 28. Block 3 Scenario 4

Attributes	Route 1	Route 2
Usual Travel Time (min)	+25%	+10%
Frequency of Delay	3 out of 10 days	7 out of 10 days
Average Delay Time (min)	+20%	+50%
Toll Cost ($)	-100%	-100%

Table A- 29. Block 3 Scenario 5

Attributes	Route 1	Route 2
Usual Travel Time (min)	+25%	+50%
Frequency of Delay	9 out of 10 days	1 out of 10 days
Average Delay Time (min)	+50%	+20%
Toll Cost ($)	$1	$3

Table A- 30. Block 3 Scenario 6

Attributes	Route 1	Route 2
Usual Travel Time (min)	-10%	-10%
Frequency of Delay	7 out of 10 days	9 out of 10 days
Average Delay Time (min)	-20%	-50%
Toll Cost ($)	$1	-50%

Table A- 31. Block 3 Scenario 7

Attributes	Route 1	Route 2
Usual Travel Time (min)	+25%	+50%
Frequency of Delay	Unknown	5 out of 10 days
Average Delay Time (min)	+20%	+20%
Toll Cost ($)	$3	$1

Table A- 32. Block 3 Scenario 8

Attributes	Route 1	Route 2
Usual Travel Time (min)	+50%	+25%
Frequency of Delay	5 out of 10 days	1 out of 10 days
Average Delay Time (min)	+20%	+20%
Toll Cost ($)	$1	$2

Table A- 33. Block 3 Scenario 9

Attributes	Route 1	Route 2
Usual Travel Time (min)	+50%	+25%
Frequency of Delay	7 out of 10 days	9 out of 10 days
Average Delay Time (min)	+20%	+50%
Toll Cost ($)	-100%	-50%

Table A- 34. Block 3 Scenario 10

Attributes	Route 1	Route 2
Usual Travel Time (min)	-10%	-10%
Frequency of Delay	5 out of 10 days	Unknown
Average Delay Time (min)	-20%	-20%
Toll Cost ($)	$1	-50%

Table A- 35. Block 3 Scenario 11

Attributes	Route 1	Route 2
Usual Travel Time (min)	-25%	-25%
Frequency of Delay	9 out of 10 days	3 out of 10 days
Average Delay Time (min)	-50%	-20%
Toll Cost ($)	-100%	$2

Table A- 36. Block 3 Scenario 12

Attributes	Route 1	Route 2
Usual Travel Time (min)	-50%	-50%
Frequency of Delay	7 out of 10 days	Unknown
Average Delay Time (min)	-20%	-20%
Toll Cost ($)	-100%	$1

Table A- 37. Block 4 Scenario 1

Attributes	Route 1	Route 2
Usual Travel Time (min)	+25%	+25%
Frequency of Delay	3 out of 10 days	9 out of 10 days
Average Delay Time (min)	+50%	+20%
Toll Cost ($)	$3	$1

Table A- 38. Block 4 Scenario 2

Attributes	Route 1	Route 2
Usual Travel Time (min)	-25%	-10%
Frequency of Delay	7 out of 10 days	3 out of 10 days
Average Delay Time (min)	-20%	-50%
Toll Cost ($)	$2	$1

Table A- 39. Block 4 Scenario 3

Attributes	Route 1	Route 2
Usual Travel Time (min)	-25%	-25%
Frequency of Delay	7 out of 10 days	3 out of 10 days
Average Delay Time (min)	-50%	-20%
Toll Cost ($)	-50%	$2

Table A- 40. Block 4 Scenario 4

Attributes	Route 1	Route 2
Usual Travel Time (min)	-25%	-25%
Frequency of Delay	7 out of 10 days	9 out of 10 days
Average Delay Time (min)	-20%	-20%
Toll Cost ($)	$1	-100%

Table A- 41. Block 4 Scenario 5

Attributes	Route 1	Route 2
Usual Travel Time (min)	+50%	+25%
Frequency of Delay	5 out of 10 days	9 out of 10 days
Average Delay Time (min)	+20%	+50%
Toll Cost ($)	$2	-50%

Table A- 42. Block 4 Scenario 6

Attributes	Route 1	Route 2
Usual Travel Time (min)	+25%	+10%
Frequency of Delay	Unknown	7 out of 10 days
Average Delay Time (min)	+20%	+20%
Toll Cost ($)	$2	-50%

Table A- 43. Block 4 Scenario 7

Attributes	Route 1	Route 2
Usual Travel Time (min)	-10%	-10%
Frequency of Delay	7 out of 10 days	5 out of 10 days
Average Delay Time (min)	-20%	-20%
Toll Cost ($)	$1	$3

Table A- 44. Block 4 Scenario 8

Attributes	Route 1	Route 2
Usual Travel Time (min)	-50%	-25%
Frequency of Delay	5 out of 10 days	Unknown
Average Delay Time (min)	-20%	-20%
Toll Cost ($)	-50%	$2

Table A- 45. Block 4 Scenario 9

Attributes	Route 1	Route 2
Usual Travel Time (min)	+10%	+25%
Frequency of Delay	1 out of 10 days	3 out of 10 days
Average Delay Time (min)	+20%	+50%
Toll Cost ($)	$3	-100%

Table A- 46. Block 4 Scenario 10

Attributes	Route 1	Route 2
Usual Travel Time (min)	+25%	+50%
Frequency of Delay	9 out of 10 days	1 out of 10 days
Average Delay Time (min)	+50%	+50%
Toll Cost ($)	$1	$3

Table A- 47. Block 4 Scenario 11

Attributes	Route 1	Route 2
Usual Travel Time (min)	-25%	-10%
Frequency of Delay	Unknown	5 out of 10 days
Average Delay Time (min)	-20%	-20%
Toll Cost ($)	$1	-50%

Table A- 48. Block 4 Scenario 12

Attributes	Route 1	Route 2
Usual Travel Time (min)	+10%	+25%
Frequency of Delay	5 out of 10 days	Unknown
Average Delay Time (min)	+20%	+50%
Toll Cost ($)	$3	-50%

Table A- 49. Block 5 Scenario 1

Attributes	Route 1	Route 2
Usual Travel Time (min)	-10%	-10%
Frequency of Delay	3 out of 10 days	1 out of 10 days
Average Delay Time (min)	-20%	-20%
Toll Cost ($)	-100%	$1

Table A- 50. Block 5 Scenario 2

Attributes	Route 1	Route 2
Usual Travel Time (min)	-25%	-10%
Frequency of Delay	7 out of 10 days	3 out of 10 days
Average Delay Time (min)	-50%	-20%
Toll Cost ($)	$2	-100%

Table A- 51. Block 5 Scenario 3

Attributes	Route 1	Route 2
Usual Travel Time (min)	+25%	+10%
Frequency of Delay	3 out of 10 days	Unknown
Average Delay Time (min)	+20%	+20%
Toll Cost ($)	$3	$1

Table A- 52. Block 5 Scenario 4

Attributes	Route 1	Route 2
Usual Travel Time (min)	-25%	-50%
Frequency of Delay	5 out of 10 days	1 out of 10 days
Average Delay Time (min)	-20%	-20%
Toll Cost ($)	$1	$2

Table A- 53. Block 5 Scenario 5

Attributes	Route 1	Route 2
Usual Travel Time (min)	+10%	+10%
Frequency of Delay	1 out of 10 days	5 out of 10 days
Average Delay Time (min)	+50%	+50%
Toll Cost ($)	$1	-100%

Table A- 54. Block 5 Scenario 6

Attributes	Route 1	Route 2
Usual Travel Time (min)	-25%	-25%
Frequency of Delay	1 out of 10 days	7 out of 10 days
Average Delay Time (min)	-50%	-20%
Toll Cost ($)	$1	-100%

Table A- 55. Block 5 Scenario 7

Attributes	Route 1	Route 2
Usual Travel Time (min)	+25%	+10%
Frequency of Delay	9 out of 10 days	7 out of 10 days
Average Delay Time (min)	+20%	+20%
Toll Cost ($)	-50%	$3

Table A- 56. Block 5 Scenario 8

Attributes	Route 1	Route 2
Usual Travel Time (min)	-25%	-50%
Frequency of Delay	5 out of 10 days	Unknown
Average Delay Time (min)	-20%	-20%
Toll Cost ($)	-100%	$1

Table A- 57. Block 5 Scenario 9

Attributes	Route 1	Route 2
Usual Travel Time (min)	+50%	+50%
Frequency of Delay	5 out of 10 days	3 out of 10 days
Average Delay Time (min)	+50%	+20%
Toll Cost ($)	$2	$3

Table A- 58. Block 5 Scenario 10

Attributes	Route 1	Route 2
Usual Travel Time (min)	+25%	+25%
Frequency of Delay	3 out of 10 days	7 out of 10 days
Average Delay Time (min)	+50%	+20%
Toll Cost ($)	$1	-100%

Table A- 59. Block 5 Scenario 11

Attributes	Route 1	Route 2
Usual Travel Time (min)	-10%	-25%
Frequency of Delay	5 out of 10 days	Unknown
Average Delay Time (min)	-50%	-20%
Toll Cost ($)	-100%	$2

Table A- 60. Block 5 Scenario 12

Attributes	Route 1	Route 2
Usual Travel Time (min)	+10%	+25%
Frequency of Delay	Unknown	5 out of 10 days
Average Delay Time (min)	+20%	+20%
Toll Cost ($)	$3	$3

Table A- 61. Block 6 Scenario 1

Attributes	Route 1	Route 2
Usual Travel Time (min)	-10%	-25%
Frequency of Delay	3 out of 10 days	1 out of 10 days
Average Delay Time (min)	-50%	-20%
Toll Cost ($)	$1	$2

Table A- 62. Block 6 Scenario 2

Attributes	Route 1	Route 2
Usual Travel Time (min)	+10%	+10%
Frequency of Delay	1 out of 10 days	5 out of 10 days
Average Delay Time (min)	+20%	+20%
Toll Cost ($)	$2	-50%

Table A- 63. Block 6 Scenario 3

Attributes	Route 1	Route 2
Usual Travel Time (min)	-50%	-25%
Frequency of Delay	Unknown	7 out of 10 days
Average Delay Time (min)	-20%	-50%
Toll Cost ($)	$2	$1

Table A- 64. Block 6 Scenario 4

Attributes	Route 1	Route 2
Usual Travel Time (min)	-25%	-25%
Frequency of Delay	9 out of 10 days	1 out of 10 days
Average Delay Time (min)	-50%	-20%
Toll Cost ($)	-50%	$1

Table A- 65. Block 6 Scenario 5

Attributes	Route 1	Route 2
Usual Travel Time (min)	-50%	-25%
Frequency of Delay	3 out of 10 days	7 out of 10 days
Average Delay Time (min)	-50%	-20%
Toll Cost ($)	$3	$1

Table A- 66. Block 6 Scenario 6

Attributes	Route 1	Route 2
Usual Travel Time (min)	+10%	+10%
Frequency of Delay	9 out of 10 days	5 out of 10 days
Average Delay Time (min)	+20%	+50%
Toll Cost ($)	-100%	$1

Table A- 67. Block 6 Scenario 7

Attributes	Route 1	Route 2
Usual Travel Time (min)	-25%	-25%
Frequency of Delay	Unknown	5 out of 10 days
Average Delay Time (min)	-20%	-20%
Toll Cost ($)	$1	$2

Table A- 68. Block 6 Scenario 8

Attributes	Route 1	Route 2
Usual Travel Time (min)	+25%	+25%
Frequency of Delay	7 out of 10 days	Unknown
Average Delay Time (min)	+20%	+50%
Toll Cost ($)	-100%	$1

Table A- 69. Block 6 Scenario 9

Attributes	Route 1	Route 2
Usual Travel Time (min)	-50%	-50%
Frequency of Delay	1 out of 10 days	7 out of 10 days
Average Delay Time (min)	-20%	-50%
Toll Cost ($)	-100%	-100%

Table A- 70. Block 6 Scenario 10

Attributes	Route 1	Route 2
Usual Travel Time (min)	+25%	+10%
Frequency of Delay	1 out of 10 days	9 out of 10 days
Average Delay Time (min)	+50%	+50%
Toll Cost ($)	$2	$1

Table A- 71. Block 6 Scenario 11

Attributes	Route 1	Route 2
Usual Travel Time (min)	+25%	+25%
Frequency of Delay	9 out of 10 days	7 out of 10 days
Average Delay Time (min)	+50%	+20%
Toll Cost ($)	$1	$3

Table A- 72. Block 6 Scenario 12

Attributes	Route 1	Route 2
Usual Travel Time (min)	+25%	+25%
Frequency of Delay	5 out of 10 days	Unknown
Average Delay Time (min)	+50%	+20%
Toll Cost ($)	$2	$1